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Route Choice Strategies and Usage of Real Time Information in Public Transport – an empirical survey based on dedicated smartphone application

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Abstract This paper reports results from a travel survey based on a dedicated smartphone application applied in a field study in a Swedish mid-size urban context. Implications from the use of information regarding departure times by passengers on their route choice strategies has been emphasised during analyses of resulting data, where also auxiliary sources such as timetable data and Automatic Vehicle Location (AVL) ground truth trajectories have been utilised along with contextual factors and respondent characteristics.

Keywords: Public transport · Travel survey· Route choice strategies

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1 Introduction

Accurate and precise models regarding passenger route choice between trip origin and destination points facilitate efficient planning of public transport (PT) supply in systems, with a moderate to high level of complexity. Liu et al. (2010) describe two different schools regarding static assignment for network formation, based on the frequency based and the scheduled based assignment approach respectively. The former is based on the notion of optimal choice strategies among attractive sets of lines to calculate link volumes based on the minimisation of total travel time and assumes random (uniformly distributed) arrival of oncoming passengers to the first stop of a PT trip. The theory was introduced by Spiess and Florian (1989) and is regarded as mostly applicable in dense or unreliable transport networks. In addition, the first waiting time (FWT) of a PT trip has been shown by *inter alia* Ceder and Marguier (1985) to adhere to the function

$$E(W) = \frac{E(H^2)}{2E(H)},$$

where FWTs are to follow Poisson distribution.

The optimal strategy approach was further elaborated by Nguyen and Pallottino (1989), the application and implications of which is described by Liu, Bunker, and Ferreira (2010), into the concept of hyperpath formation, where passengers choose from attractive sets of lines in the form of paths. The latter has been exhaustively specified by Nuzzolo and Crisalli (2004) where they apply it into a schedule-based assignment. This latter assignment approach has become increasingly recognised as producing more realistic results in sparsely serviced and reliable PT systems with irregular headways (Liu et al., 2010; Nuzzolo & Crisalli, 2004).

The actual existence of strategies has been somewhat verified by empirical studies of travel behaviour. Ingvardson, Nielsen, Raveau, and Nielsen (2018) and Luethi (2007) define distributions for FWT and relate the FWT of different PT systems to reliability, information provision and stop or station characteristics. Csikos and Currie (2008) use smart card data to identify four distinct archetypes of passenger behaviour with respect to FWT, based on the distribution of waiting times for individuals and in relation to number of departing lines.

The growing availability to different forms of information regarding PT connections, e.g. with respect to both scheduled and actual departures, has motivated research on how the existence of this information affects route choice. To validate the different route choice modelling approaches, also with respect to passengers having access to real time information (RTI) regarding departure times, Fonzone and Schmöcker (2014) apply three choice strategies on the classical linear formation, specified by Spiess and Florian (1989). Moreover, Fonzone and Schmöcker (2014), discuss effects on passenger behaviour from availability to RTI with respect to the adaption of duration and location, i.e. which stop to choose for the first waiting times of a trip and when to depart from the previous location or activity. The optimisation strategy of the passenger would then target the maximisation of productive time, rather than just minimising travel time. Results from Monte Carlo simulations indicate the significance of how RTI is visualised and used by the passenger on route choice.

Some researchers (Wang, He, & Leung, 2017), (Liu, Bunker, & Ferreira, 2010), (Gadziński, 2018; Lee, Sener, & Mullins, 2016) conclude that new, emerging sources of trip data have the potential of delving further into revealed behaviour among PT passengers. This indicates the relevance of both applying the theoretical models used in this discipline and capturing the information about actual choice strategies used by passengers. Liu et al. (2010) provide examples in their summary of the current state-of-the-art regarding modelling of PT users' route choice, so do Fonzone and Schmöcker (2014) when reporting their simulation results regarding route choices based on RTI informed decisions.

Thus, drawing upon such conclusions, in this paper we analyse data obtained from a user-mediated prompted recall (Stopher, Shen, Liu, and Ahmed, 2015) mobile application based travel survey. The data from the survey include, in addition to user-revised trip trajectories and activities, also stated passenger strategies and the usage rate of departure time information ahead of PT trips based on context-aware notification prompting (Turner, Allen, & Whitaker, 2017). Hereby, the overarching aim is to contribute to the indicated need for empiricism regarding the relationships and possible correlation between use of RTI, route choice strategies and PT supply characteristics such as headway, departure reliability and in-vehicle travel time.

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

1) Which characteristics of different passenger groups, and contextual factors during trips, matter when it comes to the utilisation of planning and choice strategies? What can explain the usage of strategies formulated by e g Fonzone and Schmöcker (2014) and FWT behaviour as measured by Csikos and Currie (2008)?
2) Is it feasible to use stated strategies such as maximization of productive time, other than travelling and minimizing travel time to determine actual route choice strategies? I.e., can the stated choices of strategy be corroborated empirically?
3) Is there a correlation between waiting times and (a) common departure and travel time reliability of particular PT lines and (b) real headways, based on AVL data? If there are correlations in these cases, how can these be specified?

The rest of the paper is organised as follows. Section 2 outlines materials, methods analyses, and contains specifications of the models we applied to test our assumptions. Section 3 contains the main results. Finally, in section 4 we conclude our findings and point to directions for further endeavours in the field of route choice validation.

2 Method

2.1 Data collection

The survey, where 136 persons during a 14-day period in November 2017 collected a total of 13,495 trip segments out of which 2,980 were undertaken by PT modes (bus and train), was done in the Malmö-Lund area in southern Sweden. Survey participants were recruited in the PT system, making the sample very suitable for directed analyses of travel behaviour in this system. The smartphone survey application, TravelVU (Clark, Adell, Nilsson, & Indebetou, 2017), was semi-automated, meaning that context data such as GPS readings and accelerometer data, were collected automatically by the phones of the participants. Thus, positions for trip breaks such as boarding, alighting and change of transport modes were recorded, and transport modes were inferred in a back-end support system in continuous connection with the phones involved. In addition, context-sensitive notifications were transmitted to the respondents once a PT trip segment, preceded by a segment consisting of access walk, bike or car, was completed, asking for planning strategies and information used for this purpose. 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. This enabled us to relate travel behaviour at each trip segment to corresponding PT service trip characteristics and level of service.

There were a few important definitions used by the application to distinguish between activities and movements (Linse, 2017). Thus, an activity was recorded if the phone was within a square of 100 by 100 meters for at least two minutes. Consequently, the *en-route* activities transfer or wait were only recorded by the application if the duration was at least two minutes, but other transfers and wait times were extracted from the produced itineraries by utilising the sequence of used transport modes. These transfers and waits, below two minutes, were set random durations in the interval [0,2].

2.2 Data analyses

The three research questions were tested using straightforward statistical tests including chi-square, linear regression and univariate ANOVA models, specified based on our empirical data regarding stated and revealed passenger strategies in relation to explanatory variables such as individual characteristics and trip attributes based on real and scheduled PT vehicle trajectories. The models we deployed, including dependent and independent variables, are listed in ***Table 1***. We used First Waiting Time (FWT and Transfer Wait Time as proxy variables for route choice strategies. 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 during a PT journey, in both time and space.

Table 1 Models and variables used to explore our research questions (results are presented in Section 3)

Model type	**Dependent variable**	**Independent variables**
Univariate ANOVA	First wait time	Stated strategy*Stated information use; Stated information use*Information vs previous knowledge; Stated strategy*Information vs previous knowledge; Stated strategy; Information vs previous knowledge; Stated optimization strategy
	First wait time	Stated strategy*Stated information use; Stated information use*Information vs previous knowledge; Stated strategy*Information vs previous knowledge; Stated strategy; Information vs previous knowledge; Stated optimization strategy; Type of day; Time period; Gender; Trip purpose; Stop type; Previous activity; Occupation; Flex time
	Transfer wait time	Stated strategy*Stated information use; Stated information use*Information vs previous knowledge; Stated strategy*Information vs previous knowledge; Stated strategy; Information vs previous knowledge; Stated optimization strategy
	Transfer wait time	Stated strategy*Stated information use; Stated information use*Information vs previous knowledge; Stated strategy*Information vs previous knowledge; Stated strategy; Information vs previous knowledge; Stated optimization strategy; Type of day; Time period; Gender; Trip purpose; Stop type; Previous activity; Occupation; Flex time
Linear regression	First wait time	Trip duration
	Transfer wait time	Trip duration

Trip purpose was inferred from the stated activity at the end of each trip – previous activity was consequently the activity recorded ahead of each trip. Stop type was inferred from line trajectories - the algorithm by which these were inferred in turn, is further described in section 3.1 below. Gender, Occupation and Flex time was taken from responses of enquiry in the survey app.

In addition, non-parametric chi-square tests were applied to test potential influence of person characteristics and trip attributes on stated strategy or information usage (***Table 2***).

Table 2 Non-parametric tests applied to explore various impacts on stated strategies and information access (results are presented in Section 3)

Test	Row variable	Column variable
Chi-square	Actual headway (binned)	Stated strategy
	Actual headway (binned)	Information vs previous knowledge
	Departure reliability (binned)	Stated strategy
	Departure reliability (binned)	Information vs previous knowledge
	Stated strategy	Trip duration (binned)
	Stated strategy	Trip purpose
	Stated strategy	Previous activity
	Stated information use	Trip purpose
	Stated information use	Previous activity
	Information vs previous knowledge	Trip purpose
	Information vs previous knowledge	Previous activity
	Stated optimization strategy	Trip purpose
	Stated optimization strategy	Previous activity

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

Influenced by Csikos and Currie (2008), we also analysed FWT distributions defined by the mentioned author's four archetypes – "Like clockwork", with minimal FWT of at most a few minutes; "Consistent within a wider window"; "Consistent plus outliers" and "Largely random" respectively. We used median differences between upper and lower quartiles as measure of FWT variability and defined the four archetypes by using the four quartiles of these medians. The rationale behind these choice of measures, as also discussed by Csikos and Currie (2008), was to eliminate outliers. Based on these definitions, we performed chi-square tests between the four FWT archetypes and the stated strategy variables, to elucidate tie validity of the former.

3 Results

3.1 Overview of responses

Shares of trip segments performed under different strategies, regarding information and planning, according to responses to phone notifications of our survey participants are presented in Table 3, 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 shares refer to trip segments and not to individuals, meaning there being a risk of overrepresentation by single individuals. However, only 4 out of 136 respondents did not respond at all to these questions.

Table 3a-d Information usage strategies as indicated by survey responses (based on trip segments)

Table 3a

Strategy	Share of responses (trip segments)
Planning ahead	61.6%
Not planning ahead	37.1%
Don't know	1.3%

Table 3b

If planning ahead: Source of trip information	Share of responses (trip segments)
Pre-existing knowledge of timetable	48.3%
Digital travel planner	51.5%
Other	0.2%

Table 3c

If not planning ahead – source of information	Share of responses (trip segments)
Pre-existing knowledge of timetable	23,8%
No information	74,5%

Table 3d

Strategy[1]	Share of responses (trip segments)
"Busy (4)"[2]	67.0%
"ASAYC"[3]	33.0%

[1] Adjusted to strategy terminology used by Fonzone and Schmöcker (2014)

[2] Here interpreted as being the potential passenger choosing desired origin **departure time** in travel planner

[3] As Soon As You Can, here interpreted as being the potential passenger choosing desired destination **arrival time** in travel planner

The spread of strategies (planning or not planning ahead of a trip) was analysed with respect to individual respondents. Out of the 132 respondents delivering valid data, only 1.6% stated “Planning ahead” for all trip segments, the mean share of planned trip segments was 55% with a standard deviation of 0.4. Note that these figures are a trip segment-based, and the number of PT trip segments per trip was 2.46 in the sample. However, we were also able to measure the share of planned PT *trips* instead of trip segments, and we found this to be that 57% of PT trips were actually planned ahead (or contained at least one trip segment which had been pre-planned) using timetable of journey planner, according to replies in the prompted-recall survey.

3.2 Correlation between responses

The correlation between the *stated strategies* and *information use* is highest between Stated strategy and Stated information use, where there was some positive influence of previous knowledge of timetable or use of journey planner respectively and stated use of a strategy (observed: 625 and 534, expected: 449.8 and 473.5 respectively in a significant chi-square test). However, there was only very weak correlation between *pre-knowledge of the time table* and stating *not using written information ahead* of going to the first bus stop of a journey (observed: 229, expected: 274,4), which is reasonable assuming respondents interpreting this alternative as already being in possession of the information needed (thus no support for an assumption of purely random, non-planned behaviour).

3.3 Possible relationships between stated information and strategy use and revealed waiting times

Results from our ANOVA tests of FWT and TWT with respect to stated use of strategies and information, as well as a number of other explanatory variables, are shown in ***Table 4*** and ***Table 5***. As indicated, only Information vs Previous knowledge had a significant contribution to each model. A post-hoc Least square difference (LSD) test revealed that *not having pre-knowledge of the time table* rendered a mean of 0.7 minutes longer FWT than actually being in possession of this information. Moreover, using strategy "As soon as you can – ASAYC", or stating Departure time" as specified in a journey planner, meant spending on average 0.7 minutes longer on FWTs than when using the strategy Busy(4), or stating to have specified Arrival time in a journey planner. The number of observations of TWT is too small for being able to conduct an LSD test for the variable *Information vs previous knowledge*, but using the similar variable *Stated information use* instead indicates a 2-minute reduction in waiting time for those who used travel planner, compared to those who claimed to know the timetable by heart.

Table 4 Results from univariate ANOVA with FWT as dependent variable

Source	Degrees of freedom	F-statistic	P-value
Corrected Model	121	5.965	0.000*
Intercept	1	2.131	0.145
RespGender * TripPurpose	14	0.869	0.593
TripPurpose * StopType	38	2.437	0.000*
RespGender * StopType	4	2.716	0.029*
Daytype	2	4.56	0.011*
Time period (peak/offpeak)	3	2.265	0.079
RespGender	1	1.193	0.275
TripPurpose	16	2.753	0.000*
StopType	5	2.812	0.016*
PreviousAct	18	22.833	0.000
Occupation	3	0.417	0.741*
Flex	3	1.344	0.259
Stated strategy	4	0.991	0.411
Stated information source	3	0.719	0.541
Information vs previous knowledge	3	3.062	0.027*
Stated optimization strategy	2	0.495	0.61
Error	1,147		
Total	1,269		
Corrected Total	1,268		
R^2=0.386			
$R^{2,\ adjusted}$=0.321			

However. when analysing TWT with respect to planning strategy (see ANOVA results in ***Table 5***), the LSD post hoc tests indicate a two and a half minutes *longer* waiting times for those respondents who claimed to have planned ahead of their trip, compared to those who went to the stop without using any information. When controlling for trip duration (see ***Figure 1*** for a graphical representation), there is a weak positive correlation between TWT and trip duration, which indicates that trip duration might be an underlying factor affecting both transfer waiting time *and* planning strategy. This thesis is further corroborated by results from a chi-square test of Planning strategy against Trip duration, where there is an overrepresentation of trip segments where respondents state use of planning ahead of the trip among trips exceeding one hour in duration (observed:200; expected 157). On the other hand, there is an underrepresentation of pre-planned trips among those below 30 minutes in duration (observed: 19; expected: 32) and the reverse is valid for trips where the respondent stated not planning ahead (observed: 54; expected: 95 for trips exceeding 60 minutes and observed: 34 while expected: 19.4 for trips below 30 minutes in duration).

Table 5 Results from univariate ANOVA with TWT as dependent variable

Source	**Degrees of freedom**	**F-statistic**	**P-value**
Corrected Model	102	2.18	0.000*
Intercept	1	5.895	0.016*
RespGender * TripPurpose	12	1.249	0.247
TripPurpose * StopType	29	0.981	0.496
RespGender * StopType	4	1.677	0.154
Stated strategy	4	1.251	0.289
Stated information source	2	0.932	0.395
Information vs previous knowledge	3	3.297	0.020*
Stated optimization strategy	2	0.159	0.853
Daytype	2	4.422	0.013*
tidsp	3	2.344	0.072
RespGender	1	0.496	0.481
TripPurpose	15	1.463	0.115
StopType	5	0.7	0.624
PreviousAct	13	4.774	0.000*
Occupation	3	0.785	0.503
Flex	3	1.128	0.337
Error	421		
Total	524		
Corrected Total	523		
R^2=0.346			
$R^{2,\ adjusted}$=0.187			

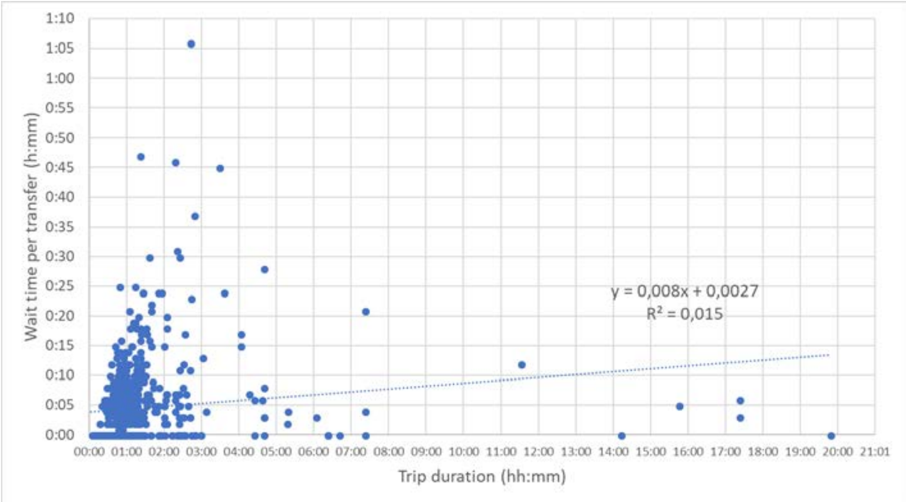

Figure 1 Individual transfer waiting times regressed against trip durations (origin to destination).

3.4 Other potential factors influencing stated use of strategies

Analysing possible explanations for the use or planning strategies in our data, we found no significant effect from previous activity, but the purpose of trips had significant influence on the choice of ASAC or Busy (4). The clearest results were obtained for School trips, where there was an over-representation of ASAYC (Arrival time specified in journey planner) with an observed number of 61 compared to an expected value of 48.2. For trips to work, the Busy (4) strategy (departure time specified) was somewhat over-represented with observed: 272 and expected: 265.3. Also, time of day had a significant effect on the choice of planning strategy, where Busy (4) was under-represented for trips during the PM rush hour period (observed: 338, expected: 373,2), while it was over-represented during daytime (9 AM to 3 PM, observed: 248; expected: 211.3). Also, Gender had a significant influence, where men were under-represented in the ASAYC category while women were over-represented using this strategy (observed: 128 and 356; expected: 199.1 and 284.9 for men and women respectively). The reverse condition applies for the Busy (4) strategy (observed: 408 and 524; expected: 383.3 and 548.7 for men and women respectively). There are also significant influence on the choice of strategy from Stop type (urban locations have over-representation of Busy (4)), respondent occupation (students are over-represented for the ASAYC-strategy), Flex time (over-representation for ASAYC for respondents who do not have this employment type), age (over-representation for ASAYC for 20-35 year olds) number of PT trips made during the survey period (under-representation for ASAYC for respondents who made less than one trip a day on average).

3.4 Waiting time archetypes and potential explanatory factors

When analysing the spread of waiting times in relation to 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 times Arrival Offset instead of FWT). In Figure 2 - Figure 5, CDFs of median FWTs across individuals are shown for each archetype, or quartile of differences between upper and lower quartile of FWTs from the total sample. When compared to the corresponding profiles in the paper of Csikos & Currie, there are some resemblances for 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") has less consistency for our data. In general, our data contains a narrower range of FWTs than Csikos and Currie, with a mean difference between the upper and lower quartiles of just 3 minutes and a standard deviation of 2.25 minutes (for Csikos and Currie, this mean range between 11.8-16.6 with standard deviations in the interval [16.6,25.3] depending on the analysed station).

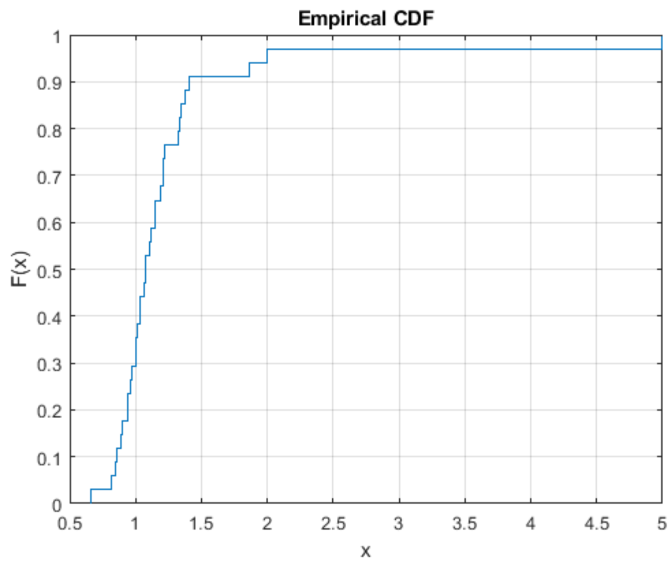

Figure 2 Cumulative distribution of median First Waiting Times (FWT=x) for first quartile of differences between upper and lower quartile of FWT (archetype “like clockwork” according to Csikos & Currie, 2008)

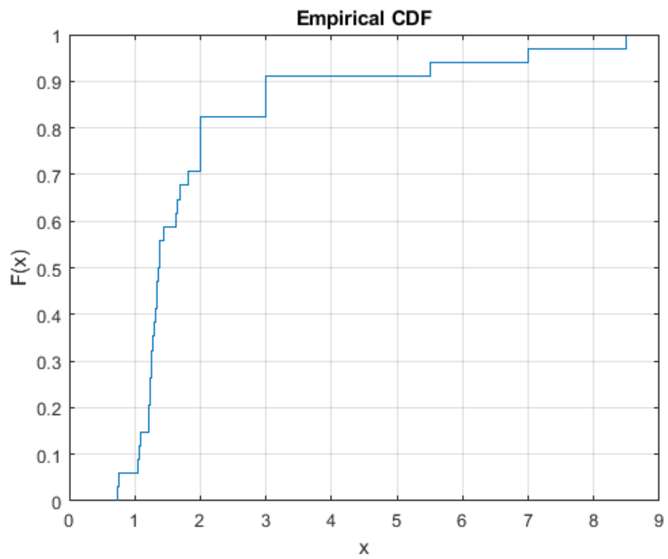

Figure 3 Cumulative distribution of median First Waiting Times (FWT=x) for second quartile of differences between upper and lower quartile of FWT (archetype “consistent within a wider window” according to Csikos & Currie, 2008)

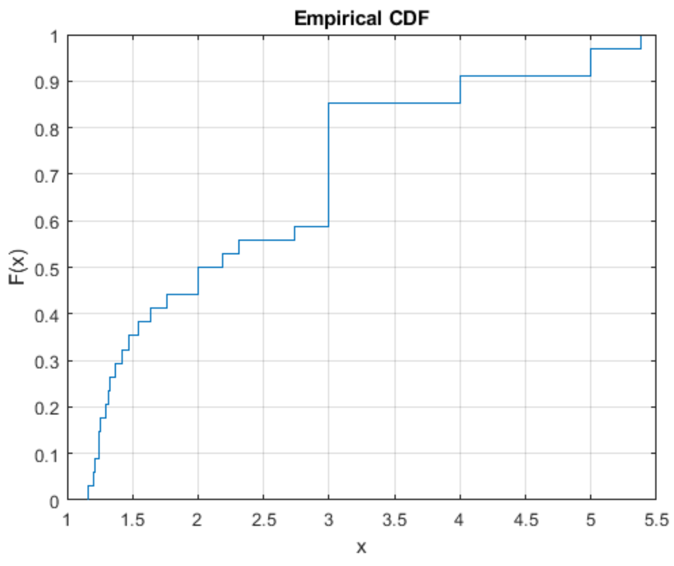

Figure 4 Cumulative distribution of median First Waiting Times (FWT=x) for third quartile of differences between upper and lower quartile of FWT (archetype “consistent plus outliers” according to Csikos & Currie, 2008)

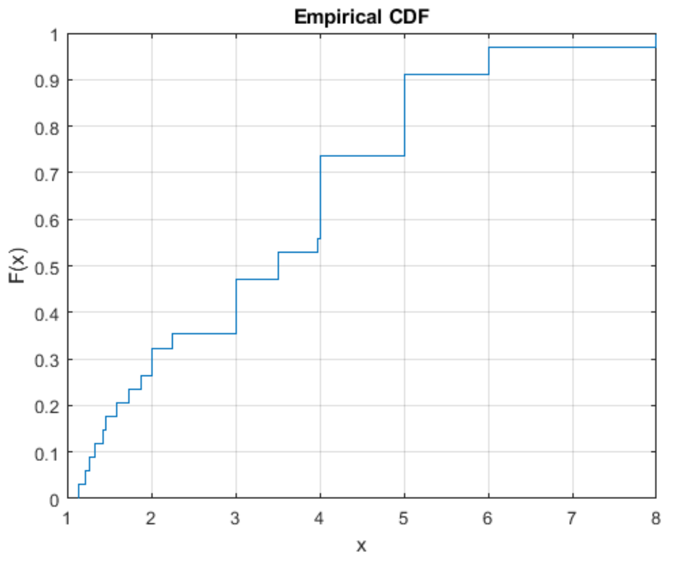

Figure 5 Cumulative distribution of median First Waiting Times (FWT=x) for fourth quartile of differences between upper and lower quartile of FWT (archetype “largely random” according to Csikos & Currie, 2008)

When analysing FWT spread archetype characteristics of the respondents using chi-square tests, we found – significantly - that employees are over- represented in the first archetype (“like clockwork”, observed: 276; expected: 238.7) while students are over-represented in the “largely random” quartile (observed: 278; expected: 202.7). There is also a significant influence of age on FWT archetype (respondents 20-35 years old are over-represented in the “like clockwork” quartile – observed: 216; expected: 158.6 - while those in the 51-65 age group are over-represented in the “largely random” quartile – observed: 36; expected: 87.0). Concerning gender, there is 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 the uppermost quartile (observed: 275 and 410 respectively; expected: 229 and 350 respectively) while men are overrepresented in the “Consistent within a wider window” and “Consistent plus outliers” archetypes (observed: 319 and 291 respectively; expected: 242.3 and 262 respectively).

Unfortunately, we were not able to link the FWT archetypes to stated strategies in the recall survey. We actually got the quite counter-intuitive results regarding FWT quartiles; over-representation in the “largely random” archetype for trips where respondents stated using a planning strategy. Perhaps, this result can be related to the issue of durations mentioned earlier (longer trips→more planning, but also longer waiting times). The correlation between FWT archetype and reliability was also quite weak, with a linear-by-linear association significance of 0.069. Finally, a chi-square test for archetype versus stated strategy according to Fonzone and Schmöcker (2014) indicated weak correlations between the two variables.

4. Conclusions

We used results from a user-mediated smartphone survey, utilising a dedicated application to collect trip data, to investigate and explore actual route choice strategies in a reasonably simple PT route network with frequent occurrence of departure time unreliability. Our results corroborate the findings made previously that FWT behaviour may be categorised into archetypes depending on the degree of randomness in waiting time behaviour. We found that use of timetable information had a significant effect on first waiting times and that stated use of strategies was related to trip purpose, time of day, respondent age, gender and employment type, stop location and number of trips made. In addition, we were able to relate waiting time behaviour to explanatory trip attributes and found previous activity and trip purpose to be significant factors.

We were able to obtain reasonable FWT archetypes, as proposed by Csikos and Currie (2008), and discussed how to use these as proxies for strategic passenger behaviour by relating them to respondent characteristics. However, we were not able to fully corroborate the responses from the recall survey by using the archetypes and waiting times as proxies for revealed travel behaviour. Underlying factors with a large degree of influence dominated over the weak relationships we found. Further research will shed more light into what approaches should be attempted to provide stronger tools to measure the revealed use of PT route choice strategies.

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