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Modelling passengers' willingness to wait in the presence of real-time crowding information (RTCI)

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Abstract: In this study we model the stated willingness to wait (WTW) for a less-crowded public transport (PT) service departure in the presence of real-time crowding information (RTCI). We conduct a stated-preference survey and investigate passengers' preferences in relation to boarding the first (more crowded) departure vs. waiting for the second, less-crowded one. We then estimate a series of multinomial and mixed logit models. Results show that the possibility to avoid overcrowding in the first departure induces a significant WTW rate, ranging from 10% to 70% - notably, depending on the crowding level of first departure, wait time for next departure and users' perceived propensity to arrive on-time. Acceptable wait times range on average between 2 – 10 minutes, reaching even up to ca. 20 minutes in individual cases. Our findings for urban PT (i.e. bus or tram) services differ from those previously reported in the context of regional or rail transport. The estimated value-of-time multipliers are applicable for simulation and analytical purposes. We also discuss implications for developing the RTCI as a travel demand management tool, potentially effective in mitigating PT service disruptions.

Keywords: public transport; crowding; willingness to wait; real-time crowding information; RTCI

1. Introduction

Passenger overcrowding is an important phenomenon affecting the travel experience and performance of public transport (PT) networks. An interesting development that has the potential to alleviate some of the ramifications of crowding is the provisioning of real-time crowding information (RTCI) on current on-board passenger loads of PT services. RTCI is a novel solution whose effects upon travel behaviour and system performance need to be yet properly understood. A major behaviour impact of RTCI availability might be associated with passengers' willingness to wait (WTW) to avoid an overcrowded first departure and board a less-crowded departure later at the same PT stop. This notion has been hitherto explored in a few studies only, mostly stated-preference (SP) works. The study of (Kim et al, 2009) in Seoul concluded that stated propensity to wait for a second, less-crowded bus is likely to be higher for non-commuting trips, longer journey time, selected user groups (e.g. elderly people) and if there are seats available. Kroes et al (2014) find that WTW in Paris metro system is primarily determined by crowding level in the first incoming PT departure. SP results range even as high as 75% in case of severe overcrowding, but rough illustrative RP estimates are much lower at 15 – 25% of all passengers. In a British Rail study, Preston et al, (2017) observe that trip purpose is an influential WTW factor. SP waiting time acceptance oscillates between 8 – 23 minutes and corresponding value-of-time multipliers for a 30-minute rail journey range from 1.3 to 1.7, with lower values for time-critical trips. Finally, a study in Calgary (Kattan and Bai, 2018) examines stated WTW with crowding information on first train only, with output waiting probability between 45% - 65%.

However, current studies do not fully explain the properties of potential WTW phenomenon that can emerge with future RTCI provision. State-of-the-art findings are mostly applicable to rail systems and regional, long-distance trips. In contrast, different comfort considerations might be invoked in high-frequency urban PT networks, dominated by short-range trips, that are arguably governed by different travel behaviour patterns. These aspects have been subject to limited research attention, and in particular choice models describing the WTW in the presence of RTCI are lacking. Such model estimations will be useful input for analytical and simulation studies aimed at assessing the impacts of RTCI on passenger flow distribution and consequently its potential in mitigating overcrowding in congested urban PT networks.

The aim of this study is to obtain estimations of WTW in the presence of RTCI. To this end, we conduct a SP survey among urban PT users (i.e. bus and tram passengers) in Krakow (Poland) that is designed to investigate the response to hypothetical RTCI for the respective trip context, i.e. departing now vs. waiting for the next bus/tram departure that is less crowded. Based on these, we estimate discrete choice models, including the multinomial logit (MNL) and mixed logit (MXL) results and discuss their implications.

2. Method

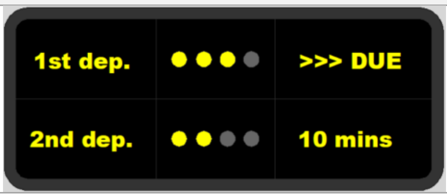
In order to measure and examine the influence of RTCI on potential WTW, we conduct a stated-preference (SP) passenger survey. This was preceded by a series of focus-group discussions which helped designed the proper survey experiment. The questionnaire consists of four parts that contain questions about passengers' crowding experience, current trip context (trip purpose, journey time, travel route), socio-demographic data and stated-choice questions.

The stated-choice part forms the central part of our WTW investigation. Passengers are presented with hypothetical RTCI for their current trip and are asked to choose between two alternatives: boarding the first PT departure (due to depart now) – vs. skipping the first option and waiting for the second PT departure instead (which is always less crowded in the experiments) (fig. 1). Alternatives are described by two attributes, i.e. on-board crowding conditions and wait time. Wait time for the second departure is equal to 5 minutes or 10 minutes. Crowding conditions are represented by means of a 4-level RTCI scale with 3 possible combinations of RTCI values:

- 1st departure: moderately crowded (RTCI level 3), 2nd departure: seats available (RTCI level 2),
- 1st departure: severely overcrowded (RTCI level 4), 2nd departure: moderately crowded (RTCI level 3),
- 1st departure: severely overcrowded (RTCI level 4), 2nd departure: seats available (RTCI level 2).

All other trip characteristics – journey time, time-criticality etc. – remain equal for both alternatives, as specified earlier by the respondent. Thus, in total, we analyse 6 possible choice scenarios.

Q9: Which of these departures would you be willing to choose for your current trip?
- journey time: ***20*** [mins], departures every: ***10*** [mins],
- need to arrive on-time: ***YES***, trip purpose: ***home → work***



1st dep.: no seats available, but can stand comfortably

2nd dep.: seats available

A9: [ ] **1st departure** – NOW / [ ] **2nd departure** – in 10 minutes

Fig. 1. Illustration from the stated-choice experiment – 2 alternatives (depart now vs. depart later), with 6 possible scenarios in total (3 RTCI cases vs. 2 wait time cases). Remaining trip attributes (choice context) are held constant.

Survey data is then used to estimate discrete choice models. The WTW model is essentially a binary choice model formulated in accordance with random utility maximization (RUM) theory, where the utility of boarding the first departure (due now) U_0 is evaluated against the utility of waiting for the second departure U_{wt}. The resultant choice probability $P(U_{wt})$ corresponds to the stated WTW for a less-crowded departure with RTCI (eq. 1):

$$P(U_{wt}) = \frac{e^{U_{wt}}}{e^{U_0} + e^{U_{wt}}} = \frac{e^{U_{wt}}}{1 + e^{U_{wt}}} \tag{1}$$

Utility of first departure is assumed as a fixed reference value $U_0 = 0$. WTW is thus calculated in relation to waiting utility U_{wt}, which consists of systematic waiting utility V_{wt} plus a random error term ε_{wt} (normally distributed, with mean value equal to zero) (eq. 2):

$$U_{wt} = V_{wt} + \varepsilon_{wt} = \sum_{i \in I} \beta_i \cdot x_i + \varepsilon_{wt} \tag{2}$$

The systematic part of waiting utility V_{wt} is a function of RTCI and wait time utilities (eq. 3). The former values reflect the relative difference in on-board crowding levels (as depicted on the 4-level RTCI scale) between 2 next departures. These are represented by dummy variables δ^{s}_{cr} (equal 1 for a specific SC scenario s and 0 otherwise). The latter value t_{wt} can be equal to 5 or 10 minutes.

$$V_{wt} = \beta_{cr}^{4-3} \cdot \delta_{cr}^{4-3} + \beta_{cr}^{4-2} \cdot \delta_{cr}^{4-2} + \beta_{cr}^{3-2} \cdot \delta_{cr}^{3-2} + \beta_{wt} \cdot t_{wt} \tag{3}$$

Essentially, this implies that WTW is a function of acceptable trade-offs between reduced crowding level (represented by RTCI utility β^{x}_{cr}) vs. additional wait time (utility β_{wt}). We consider here two possible specifications of the choice function. In the first approach, β_i coefficients are derived as discrete values according to the classical multinomial logit (MNL) formulation. In the second specification, we employ the mixed logit (MXL) model and assume that there is an unobserved heterogeneity in β_i across the respondents. In the MXL formulation, β_i are normally distributed parameters, characterized by mean μ_i and standard deviation σ_i. This allows us to investigate whether accounting for panel and heterogeneity effects provides additional insights into crowding valuations.

3. Findings

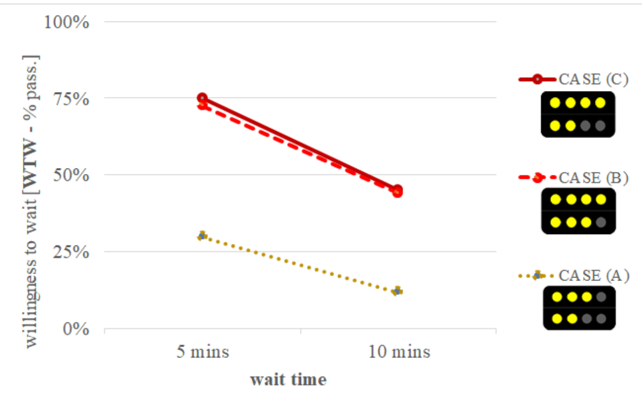


Fig. 2. Overview of SC results – stated WTW to reduce overcrowding with RTCI. Share of respondents willing to wait for a second, less-crowded urban PT departure oscillates from 12% (for a 10-minute wait) to 30% (for a 5-minute wait) if the first vehicle has standing space only (RTCI level 3). However, in case it becomes overcrowded (RTCI level 4) and second vehicle is moderately crowded (RTCI level 3) these rates are substantially higher: 44% and 72% respectively. Interestingly, in the latter case, a further improvement in comfort conditions in the second vehicle (seats available – RTCI level 2) does not provide additional incentive, with just ca. 3% more respondents opting to wait.

Surveys were conducted in March 2019 among PT passengers waiting at bus and tram stops in Krakow, with ca. 375 fully valid responses. General results indicate a substantial rate of potential WTW among respondents to reduce overcrowding. This is primarily correlated with crowding conditions on-board the first departure and wait time (fig. 2). Further statistical analysis indicates that trip purpose and time-criticality (i.e. flexibility of arrival time) are potential influential factors (fig. 3). Users above 50 years of age are also more willing to accept an additional wait for a less-crowded vehicle. In contrast, factors such as journey time or gender do not seem to have a significant impact on reported choices, and the influence of other aspects considered (trip and service frequency) is also fairly limited.

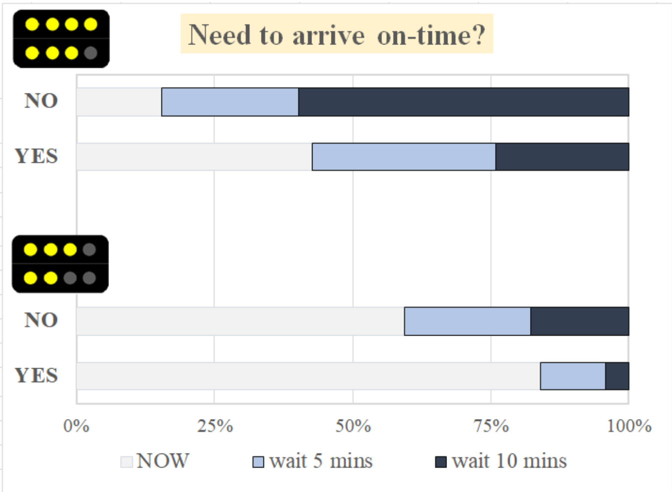
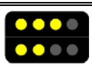


Fig. 3. Overview of SC results – stated WTW depending on trip time-criticality. WTW is noticeably higher for respondents who do not perceive any propensity to arrive on-time at the destination, with 20 – 30% higher probability depending on the RTCI level and wait time. Likewise, home-bound and leisure trips involve greater WTW than other trip purposes (e.g. work- or school-bound trips).

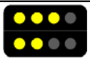
We then proceed with estimating discrete choice models, firstly – a general model for all trips (tab. 1), and also separate models for time-critical vs. non-time-critical trips. As expected, time-criticality influences the estimation results, with higher sensitivity to overcrowding exposed for the latter case. Journey time was excluded from the eventual model formulation (eq. 3) as its impact is negligible in comparison to wait time or RTCI level (similar observations are reported by Preston et al (2017)).

Tab. 1. MNL estimation results: WTW estimated as a function of RTCI vs. wait time utility - firstly for all trips, and then distinguished on trip time-criticality. RTCI utility is noticeably higher for trips where passengers do not need to arrive on-time at the destination (i.e. non-time-critical trips).

Coefficient	Case	**all trips**		**time-critical only**		**non-time-critical only**	
		estimate - mean, *(std)*	p-value	estimate - mean, *(std)*	p-value	estimate - mean, *(std)*	p-value
β_{cr}^{3-2}		0.387 *(0.158)*	0.0143	*-0.19* *(0.272)*	*0.486*	0.951 (0.219)	0
β_{cr}^{4-3}		2.22 *(0.169)*	0	1.84 *(0.257)*	0	2.97 *(0.253)*	0
β_{cr}^{4-2}		2.29 *(0.17)*	0	1.91 *(0.258)*	0	3.06 *(0.256)*	0
β_{wt}	*(n/a)*	-0.246 *(0.019)*	0	-0.303 *(0.032)*	0	-0.256 *(0.028)*	0
Log-likelihood:		-1305.937		-690.375		-865.048	
Rho-square:		0.16		0.27		0.20	

In the next step, Logit model results are used to evaluate acceptable wait time thresholds and WTW crowding multipliers. On average, max. wait times oscillate around 2 minutes if the first vehicle is moderately crowded (RTCI level 3) and 9 minutes if it is highly overcrowded (RTCI level 4). Output crowding multipliers in terms of total travel time (tab. 2) are ca. 0.95 – 1.6 for time-critical trips, and reach even between 1.2 – 2.2 for non-time-critical trips. Additionally, preliminary MXL estimates allow us to observe the resultant wait time distribution in each scenario (fig. 4). This seems to indicate that applying the MXL specification and including the panel effects will play an important role in the eventual results of WTW choice modelling.

Tab. 2. Output crowding multipliers based on multinomial logit (MNL) estimates, distinguished on trip time-criticality. These are presented as total travel time multipliers (i.e. wait time + in-vehicle time). Values can be interpreted as the ratio of travel time weight of first departure (due now) relative to the travel time weight of second departure (due later).

travel time multiplier - mean		**Time-critical trips**		**Non-time-critical trips**	
	in-vehicle time t_{ivt} =	10 [mins]	20 [mins]	10 [mins]	20 [mins]
$CM\left(\beta_{cr}^{3-2}\right)$		0.94	0.97	1.37	1.19
$CM\left(\beta_{cr}^{4-3}\right)$		1.61	1.30	2.16	1.58
$CM\left(\beta_{cr}^{4-2}\right)$		1.63	1.32	2.20	1.60

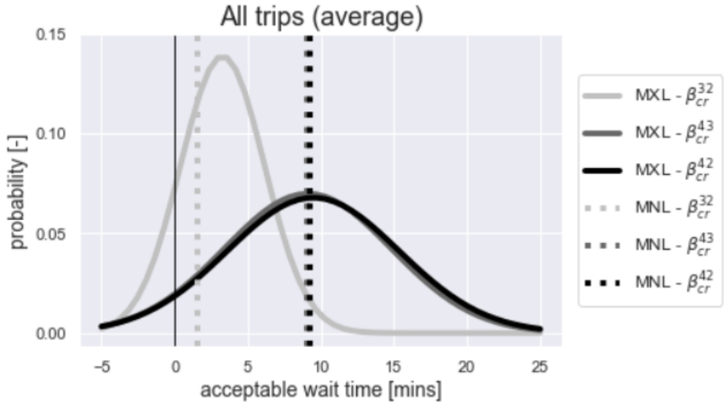


Fig. 4. Max. acceptable wait time in [mins] with RTCI, based on two choice modelling approaches. According to MNL estimates, stated wait time tolerance is on average equal to 2 – 9 [mins]. While preliminary MXL results indicate similar mean values, they also reveal an important dispersion emerging from model estimates. This implies that potential WTW with RTCI is observable even up to 12 - 23 [mins] of wait time among individual passengers.

4. Discussion

The objective of this study is to estimate the waiting probability for a less-crowded vehicle in the presence of RTCI in urban PT networks. We conduct a SP survey to examine the potential WTW among bus and tram users. We obtained as output the acceptable wait time thresholds and value-of-time crowding multipliers, depending on in-vehicle crowding levels (RTCI) and trip time-criticality. Our findings show that WTW with RTCI can potentially have significant implications in the context of high-frequency urban PT networks. It is primarily facilitated by the possibility to avoid high overcrowding on-board the first PT departure: ca. 50% of survey respondents state that they would consider waiting up to 10 minutes for a less-crowded departure, while for a moderately crowded first PT departure this rate decreases to 10% (fig. 2). Interestingly, in the former case, further improvement in comfort conditions on-board the second PT departure (i.e. seat availability) barely influences the WTW rate. One of the key determinants of the WTW pertains to the perceived trip time-criticality, i.e. acceptable wait times are visibly lower if the passenger has to arrive on-time at the destination. Preliminary model estimation results also indicate that PT users exercise might considerable taste variations with respect to WTW. These aspects will be further examined in the MXL model estimates and discussed in final conclusions from our study.

Our findings can be used for investigating the impacts of future RTCI systems in simulation and analytical models, travel behaviour and cost-benefit analysis. The following research directions and policy aspects are believed to be particularly interesting as subjects of further investigation. Firstly, in terms of designing and conveying the RTCI, distinguishing between higher crowding conditions (i.e. excessive vs. moderate standing crowding) seems to be particularly important in the context of short-range, urban PT trips. In contrast, information on number of seats available might not be as relevant as in the case of regional and/or rail PT transport. Secondly, the prevalence of WTW phenomenon reported in our SP survey indicates that reliable and timely RTCI provision can facilitate major travel behaviour shifts in congested urban PT networks. This can be beneficial both for passengers (reduced overcrowding experience, more informed choices) and operators (improved service capacity utilization). Finally, this shows the potential of future RTCI system to become an effective travel demand management feature in counteracting PT service disruptions, such as bus bunching effects. Given the passengers' stated wait time acceptance (extra 5 – 10 minutes and even higher) to avoid overcrowding, a major share of them could be encouraged to *spread themselves out* over the next, less-crowded PT departures arriving in the next few minutes by providing relevant information. Thus, WTW with RTCI can become a certain *soft* holding strategy, effectively reversing the negative bus bunching feedback loop. Notwithstanding, for such measures to be effective, efforts need to be devoted to ensure the trustworthiness of the RTCI provisioned, including the consideration of demand-anticipatory techniques. Further empirical and simulation studies will help better understand these interesting prospects of RTCI applications.

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