Willingness to wait with real-time crowding information in urban public transport – before vs. after COVID-19 pandemic

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SHORT SUMMARY

Passenger overcrowding is a major problem influencing travel behaviour in urban public transport (PT). Its relevance has been presumably shaped by the covid-19 pandemic impacts, which have to be yet fully understood. Real-time crowding information (RTCI) is therefore potentially instrumental in the post-covid recovery of PT ridership. This study investigates the willingness to wait (WTW) to reduce overcrowding in urban PT, analysing pre- vs. post-covid travel behaviour attitudes. Ex-post stated-preference data and (subsequently estimated) choice models indicate, compared to pre-covid findings, a higher propensity to skip overcrowded services with RTCI on seats available in later departures, and lower utility of RTCI on moderately crowded services. The WTW with RTCI seems to have become less dependent on individual characteristics and more prominent for time-critical (obligatory) trips as well. Implications of these findings are discussed in final study sections.

Keywords: public transport; passenger crowding; discrete choice modelling; real-time crowding information; RTCI; willingness to wait; COVID-19

1. INTRODUCTION

Travel behaviour in public transport (PT) systems is shaped by multiple factors, including passenger overcrowding - a recurrent problem in high-density urban transportation networks. Rising (over)crowding influences the relative (un)attractiveness, comfort and safety perceptions of PT travel options. Moreover, it may lead to system failure in oversaturated PT networks - manifested in form of denied boardings, demand-supply feedback deteriorations etc. (Tirachini et al, 2013; Cats, West, Elliasson 2016). Crowding impacts upon travel behaviour have been widely studied in state-of-the-art literature (e.g. (Wardman and Whelan, 2011; Tirachini et al, 2013; Hoercher et al, 2017; Yap et al, 2018) and references cited therein).

Meanwhile, the recent COVID-19 pandemic has profoundly impacted the urban PT systems worldwide, with yet lingering ramifications for passengers' travel behaviour (Tirachini and Cats, 2020; Gkiotsalitis, Cats 2021). Its experience has exacerbated the perceived risks of travelling in higher crowding conditions. The emerging stream of literature underlines that crowding valuations have increased by up to 25% compared to pre-pandemic levels (Cho and Park, 2021; Shelat et al, 2022b). Various user groups (e.g. female and elderly travellers, but also across wider population) have become much more apprehensive of exposure to PT overcrowding, especially if considering the associated infection risks (Shelat et al, 2022a; Aghabayk et al, 2021; Basnak et al, 2022).

As a consequence, PT ridership is often still struggling to recover to pre-pandemic levels. This underpins the need for tools addressing the post-pandemic travel safety concerns in urban PT systems. A prospective ITS-based solution emerges in form of providing **real-time crowding information (RTCI)** on (in-vehicle) passenger loads of urban PT services. The RTCI can help passengers mitigate the PT overcrowding experience, as demonstrated in simulation studies (Nuzzolo et al, 2016; Noursalehi et al, 2021; Drabicki et al, 2021, 2022). Moreover, RTCI provision may incite a novel (and not fully understood yet) travel behaviour phenomenon in form of willingness to wait (WTW) to reduce overcrowding. Namely, passengers may opt to skip deliberately an (over)crowded departure and wait for a less-crowded service at the same PT stop. This notion has been hitherto explored in a number of studies, though conducted either before the onset of COVID-19 pandemic (Kim et al, 2009; Kroes et al, 2014; Preston et al, 2017; Drabicki et al, 2023), or afterwards (Shelat et al, 2022a; Singh et al, 2023). To the best of our knowledge, no comparative analysis of pre- vs. post-covid changes in passengers' WTW with RTCI is yet available in state-of-the-art literature.

The objective of this study is to contribute to the above research gap with a pre- vs. post-covid investigation of passengers' WTW to reduce overcrowding with RTCI in urban PT journeys. To this end, we design a stated-preference (SP) survey and estimate discrete choice models, using a mixed logit specification. A comparison of our investigation results conducted in two stages – pre-covid (2019) and post-covid (2022) – highlights the shifts arising in passengers' WTW preferences. Findings and conclusions from our research underline how the RTCI may play an even more instrumental and effective role in post-pandemic urban PT networks.

2. METHODOLOGY

Research investigation has been conducted in two data collection stages:

- 'pre-covid' investigation – in March 2019 (sample size: n = 377 respondents),
- 'post-covid' investigation – in May 2022 (sample size: n = 424 respondents).

Both stages of our research investigation follow the methodology elaborated in (Drabicki et al, 2023), summarized below. Moreover, timing of both survey stages ensured that the case-study urban PT system was free of any disruptions or social distancing restrictions, which could have impaired the reliability and plausibility of collected responses.

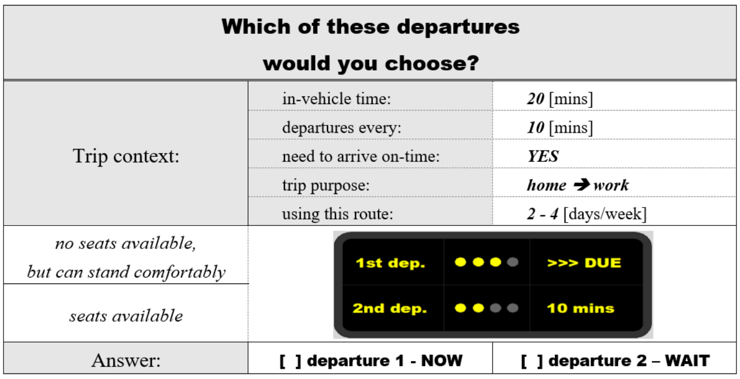


Figure 1: Example of the SP choice experiment question.

The SP survey has been designed as a field survey, conducted among passengers at urban PT stops within the city of Krakow (Poland), with completion time no greater than 3 – 5 minutes. This allowed a vast majority of interviewees to answer it successfully. A randomized sampling strategy aimed to reflect the typical demand pattern of urban PT users in Krakow.

The SP survey started with questions on the respondents' current trip context – trip motivation, propensity to arrive on-time (at destination), elapsed journey time, service frequency. This followed then with core part of SP survey – i.e., a panel series of stated choice experiments. Respondents were presented with a hypothetical RTCI on the 2 nearest bus/tram departures from their current stop, and were asked to choose the preferred travel option: first departure – departing now, but with higher (over)crowding on-board, vs. second departure – less crowded but requiring a 5- or a 10-minute wait. All the remaining trip characteristics remained equal for both travel options, as specified by respondents themselves. Socio-demographic information (age, gender, PT usage frequency) was also collected for statistical purposes.

In total, each respondent was presented with 6 stated-choice scenarios. Each scenario was set up as a combination of 2 possible waiting time values (5 or 10 minutes) and 3 possible RTCI values of the nearest 2 departures:

- 1st dep. – moderately crowded (RTCI level 3), 2nd dep. – seats available (RTCI level 2),
- 1st dep. – highly overcrowded (RTCI lvl. 4), 2nd dep. – moderately crowded (RTCI lvl. 3),
- 1st dep. – highly overcrowded (RTCI lvl. 4), 2nd dep. – seats available (RTCI lvl. 2),

The SP answers serve next as basis for estimation of discrete choice models of the WTW with RTCI. Our WTW experimental setup essentially reflects a binary choice context, formulated in accordance with the random utility maximization (RUM) theory (Ben-Akiva, Lerman 1985). Choice probability is evaluated between the utility U_1 of boarding now the first departure vs. utility U_2 associated with waiting and boarding (later) the second departure. Once we assume a fixed reference utility rate of $U_1 = 0$, the utility $U_2 = U_{WTW}$ expresses then the relative (dis)utility associated with deliberately waiting for a second, less-crowded PT departure:

$$P(U_2) = \frac{exp(U_2)}{exp(U_1)+exp(U_2)} = \frac{exp(U_{WTW})}{1+exp(U_{WTW})} \qquad (1)$$

This U_{WTW} utility is composed of systematic utility V_{WTW} plus a random error term ε_{WTW} (normally distributed with mean equal to zero). The systematic WTW utility is, in turn, a function of a vector of taste (preference) co-efficients $\boldsymbol{\beta_k}$ and corresponding attribute values $\boldsymbol{X_k}$:

$$V_{WTW} = \sum_{k=1}^{K} \boldsymbol{\beta_k} * \boldsymbol{X_k} \qquad (2)$$

The attribute set K contains various trip- and population-related characteristics, valid for a given choice situation. We hereby test various model specifications, utilizing the mixed logit (MXL) approach. The MXL allows to capture unobserved heterogeneity effects in our panel survey data. The default MXL model specification consists of RTCI utility $\beta^s_{RTCI} \cdot \delta^s_{RTCI}$ (represented by case-specific dummy variables, denoted by RTCI levels of both PT departures in the choice scenario s) and waiting time (dis)utility $\beta_{wt} \cdot t_{wt}$. The MXL mixing distribution is applied to the waiting time co-efficient, assumed to be a normally distributed variable $\beta_{wt}(\mu,\sigma)$:

$$V_{WTW} = \beta^{3-2}_{RTCI} * \delta^{3-2}_{RTCI} + \beta^{4-3}_{RTCI} * \delta^{4-3}_{RTCI} + \beta^{4-2}_{RTCI} * \delta^{4-2}_{RTCI} + \beta_{wt}(\mu,\sigma) * t_{wt} \qquad (3)$$

3. RESULTS AND DISCUSSION

Starting from descriptive statistics, a comparative analysis of both survey stages (2019 vs. 2022) reveals substantial differences in reported WTW with RTCI (Fig. 2). The 2019 pre-covid survey indicates a substantial propensity to avoid high overcrowding (RTCI level 4) in the first vehicle, regardless of crowding level inside the second departure. Ca. 75% of respondents would choose the less-crowded option arriving in 5 [mins], and for a 10-minute wait this rate oscillates around 45%. Meanwhile, the post-covid (2022) findings show that WTW decisions are more dependent on crowding level of the second departure as well. If this involves moderate standing crowding (RTCI level 3), ca. 57% of respondents would wait for 5 [mins], and just above 20% for 10 [mins]. However, if the second arrival has seats available (RTCI level 2), these rates surge to over 90% and 55%, respectively. In the third (alternative) scenario, passengers' willingness to avoid a moderately crowded vehicle (RTCI level 3) in exchange for seat availability (RTCI level 2) remains analogous across both survey samples. Approx. 30% of respondents would accept a 5-minute wait, and ca. 10% would wait for 10 [mins].

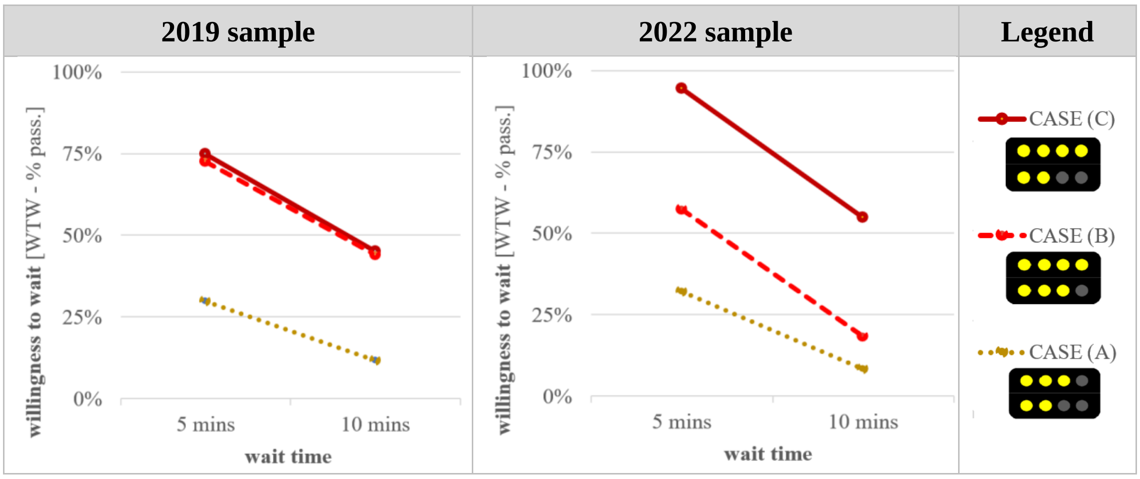


Figure 2: Survey results – overall WTW with RTCI in the pre- (left) vs. post-covid (right) sample.

The post-covid evaluation also indicates a variable and generally lower influence of trip- and demographic-related factors upon WTW with RTCI. For example, the pre-covid survey pointed towards a more substantial role of trip time-criticality, i.e. propensity to arrive on-time at the destination (Drabicki et al, 2023). In the post-covid sample, passengers' preferences are more uniform across the whole sample. This suggests relatively higher WTW probability for time-critical trips, especially with abrupt difference in crowding conditions between consecutive departures (i.e. the RTCI level 4 vs. 2 'scenario'). Otherwise, respondent's age remains a relevant choice factor, as the WTW increases for those aged 50 - 65 years, and even further for the 65+ year-olds.

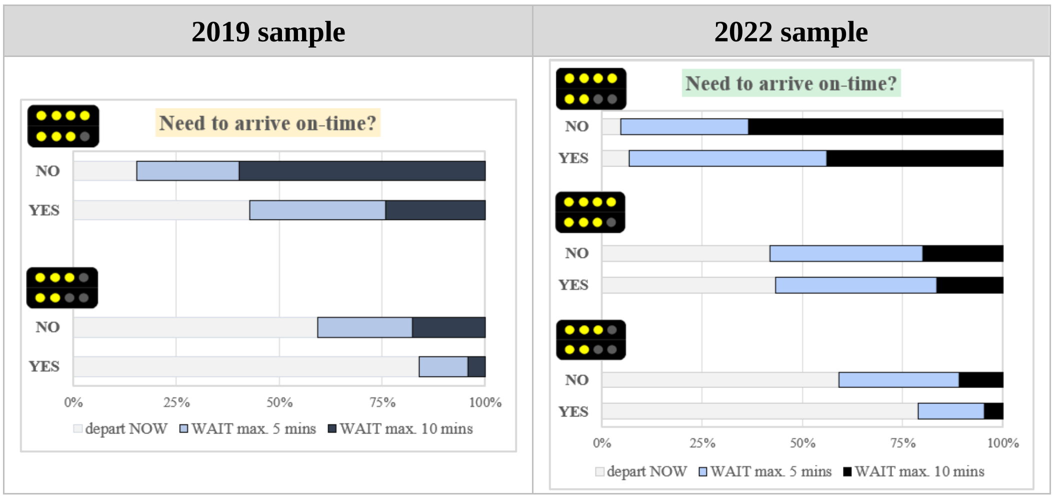


Figure 3: Survey results – reported WTW with RTCI, distinguished by trip time-criticality.

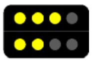
Survey outputs serve then for MXL model estimation purposes (Tab. 1). Model co-efficients essentially represent the β^{s}_{RTCI} RTCI utility versus the β_{wt} waiting time (dis)utility rate. In other words, the former denotes the expected utility gain from reducing the on-board overcrowding if choosing the later departure, whilst the latter reflects the perceived unit utility loss per minute of waiting time (hence the negative symbol). All the co-efficients are statistically significant at $p < 0.05$, and panel effects are included in mixing distribution applied to β_{wt}. In general, post-covid data shows a relative increase in RTCI utility in case of information on seats available in the second departure. This is especially valid if the first departure implies high overcrowding conditions $\beta^{4\text{-}2}_{RTCI}$. On the other hand, when RTCI indicates only the possibility of decreasing the standing crowding ($\beta^{4\text{-}3}_{RTCI}$), its utility seems lower compared to pre-covid estimates.

Table 1: Mixed logit estimation results of the WTW with RTCI.

Coefficients mean, *(t-stat.)*		**2019 sample**		**2022 sample**	
$\beta^{3\text{-}2}_{RTCI}$		1.828	*(8.09)*	2.144	*(10.11)*
$\beta^{4\text{-}3}_{RTCI}$		5.294	*(15.90)*	3.540	*(15.14)*
$\beta^{4\text{-}2}_{RTCI}$		5.510	*(11.46)*	6.598	*(18.92)*
β_{wt}	μ	- 0.705	*(11.82)*	- 0.628	*(16.62)*
	σ	0.286	*(6.33)*	0.244	*(13.10)*
initial log-likelihood:		- 1380.9		- 1734.3	
final log-likelihood:		- 816.5		- 1141.6	
LL ratio test:		1128.4		1243.4	
adjusted rho-square:		0.396		0.349	
sample size:		377		424	

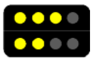
Discrete choice modelling results can be further used to compute the ratio of marginal utilities of RTCI and waiting time. This yields the average acceptable waiting times for a second, less-crowded PT departure (Tab. 2). Seemingly, acceptable WTW thresholds have increased in the post-covid period with RTCI indicating the possibility to mitigate standing crowding in the second departure. On average, waiting times have risen from (roughly) 3 to 4 [mins] for the $\beta^{3\text{-}2}_{RTCI}$ case, and even more from 9 to 12 [mins] for the $\beta^{3\text{-}2}_{RTCI}$ case. In contrast, mean acceptable waiting time has dropped from ca. 9 to 7 [mins] for the $\beta^{4\text{-}3}_{RTCI}$ case.

Table 2: Acceptable waiting times in [mins] with the RTCI, acc. to MXL modelling results.

RTCI case	**2019 sample** (mean, (*st. dev.*))	**2022 sample** (mean, (*st. dev.*))
	3.2	4.2
	(3.5)	*(3.7)*
	8.9	6.8
	(5.8)	*(4.7)*
	9.2	12.1
	(5.9)	*(6.4)*

Based on above findings, we compute the value-of-time crowding multipliers for a sample 15-minute journey in urban PT network (Tab. 3). These are calculated according to the methodology in Preston et al (2017) and Drabicki et al (2023)). The post-covid crowding multipliers are, likewise, higher for the $\beta^{4\text{-}2}_{RTCI}$ and $\beta^{3\text{-}2}_{RTCI}$ cases and lower for the $\beta^{4\text{-}3}_{RTCI}$ cases. Relative changes versus the pre-covid rates amount to ca. 5 – 10%. This compares similar (albeit somewhat lower) to findings in the recent literature (Cho and Park, 2021).

Table 3: Crowding multipliers for a 15-minute PT journey, acc. to MXL modelling results.

RTCI case	**2019 sample** (mean)	**2022 sample** (mean)
	1.21	1.28
	1.59	1.45
	1.62	1.81

4. CONCLUSIONS

This study contributes with a pre- vs. post-covid analysis of passengers' willingness to wait (WTW) to reduce overcrowding in urban PT networks. Based on survey data from 2019 and 2022 conducted in Krakow (Poland), we observe how the prospective utility of real-time crowding information (RTCI) has changed in the aftermath of COVID-19 pandemic. While pre-covid estimates showed that the WTW was primarily driven by sole possibility of avoiding overcrowding in the first departure, the expected crowding reduction in the second departure wields greater influence upon post-covid passengers' preferences. Compared to pre-covid data, fewer passengers are willing to skip a highly overcrowded vehicle and wait for a moderately crowded one. However, the WTW probability has substantially increased with seats available in the later departure. While seat availability itself may not be a crucial decision factor in short-range, urban PT trips, these findings suggest that passengers nowadays attach relatively greater weight to the RTCI content and displayed difference(s) between crowding levels of PT vehicles.

Our findings also underpin the prospective application of RTCI systems in future urban PT networks. The WTW incited by RTCI provision can lead to more balanced distribution of passenger loads between PT vehicles. This will improve operational efficiency and decrease exposure to overcrowding. Hence, timely and accurate RTCI can reassure the crowding-aware passengers about current travel conditions. Moreover, it can serve as an effective travel demand management tool, playing thus an instrumental role in post-covid recovery of PT ridership.

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