Research in Transportation Business & Management 47 (2023) 100963

Contents lists available at ScienceDirect

Research in Transportation Business & Management

journal homepage: www.elsevier.com/locate/rtbm

Should I stay or should I board? Willingness to wait with real-time crowding information in urban public transport

Arkadiusz Drabicki [a,b,*], Oded Cats [a], Rafał Kucharski [a,c], Achille Fonzone [d], Andrzej Szarata [b]

[a] Department of Transport and Planning, Delft University of Technology, the Netherlands
[b] Department of Transportation Systems, Cracow University of Technology, Poland
[c] Group of Machine Learning Research, Jagiellonian University, Poland
[d] Transport Research Institute, Edinburgh Napier University, United Kingdom

ARTICLE INFO

Keywords:
Public transport
Overcrowding
Real-time crowding information
RTCI
Willingness to wait

ABSTRACT

Overcrowding is a major phenomenon affecting travel experience in urban public transport, whose negative impacts can be potentially mitigated with real-time crowding information (RTCI) on public transport vehicle departures. In this study, we investigate the willingness to wait (WTW) with instantaneous RTCI to avoid the in-vehicle (over)crowding the passenger faces, focusing specifically on urban crowding context (i.e. bus and tram systems). We conduct a stated-preference survey in Krakow (Poland), where we examine the choice probability between boarding now a more crowded vehicle vs. waiting at the stop for a less-crowded PT departure, and estimate a series of discrete choice models.

Results show that 50–70% of respondents consider skipping a first departure which is excessively overcrowded and 10–30% would skip a vehicle with moderate standing crowding on-board. Acceptable waiting times typically range between 2 and 13 min, depending on crowding level and propensity to arrive on-time, but may even exceed 20 min in individual cases. These findings indicate that RTCI can induce a substantial WTW, affecting travel behaviour. We discuss its implications for mitigating service disruptions and demand management policies, including prospective support for public transport recovery in the aftermath of covid-19 crisis.

1. Introduction

Passenger overcrowding is an important phenomenon affecting travel experience and performance of public transport (PT) networks. The finite capacity of PT systems may become eventually outstripped by ever increasing PT transportation demand, especially in urban areas. This leads to overcrowding, which has significant consequences for the perceived quality of PT service (Tirachini, Hensher, & Rose, 2013) and whose vast economic costs are yet often underestimated in cost-benefit analyses (Batarce, Muñoz, & de Dios Ortúzar, 2016; De Palma, Lindsey, & Monchambert, 2017).

An increasing interest in 'soft' travel demand management (TDM) solutions offers opportunities to utilise more effectively the available system capacity and mitigate the impacts of overcrowding. Reliable and useful real-time information, available from data collected by the ITS (Intelligent Transport Systems) in PT networks, can increase passengers' awareness about current travelling conditions, help them make more informed choices (Fonzone & Schmöcker, 2014; Islam & Fonzone, 2021) and potentially the best travel decisions possible (Noursalehi, 2017). Moreover, estimating and predicting current and future passenger volumes in the PT network can help in application of real-time strategies that facilitate better passenger load distribution among PT vehicles (Ceder, 2015; Gavriilidou & Cats, 2019) and thus shift network towards optimum state (van Essen, Thomas, van Berkum, & Chorus, 2016). It is thus key to understand how information on crowding levels impacts user behaviour in urban PT services.

1.1. Literature review

Crowding is an influential travel choice factor in PT networks (Tirachini et al., 2013; Whelan & Crockett, 2009). Passenger reactions to crowding range from route, modal and temporal shifts towards more complex changes in trip frequency, trip destination, trip chains or even cancelling the journey altogether (Gentile & Noekel, 2016; Tirachini et al., 2013). Passengers may be willing to pay (Whelan & Crockett, 2009) or make an extra detour (Kim, Hong, Ko, & Kim, 2015) to avoid

* Corresponding author at: Department of Transportation Systems, Cracow University of Technology, Poland.
E-mail address: arkadiusz.drabicki@pk.edu.pl (A. Drabicki).

https://doi.org/10.1016/j.rtbm.2023.100963
Received 25 June 2022; Received in revised form 10 January 2023; Accepted 15 February 2023
Available online 1 March 2023

overcrowding, and even to travel upstream first in order to get a seated place in the desired travel direction (Tirachini, Sun, Erath, & Chakirov, 2016). Experience of overcrowding is all the more important given passengers' tendency to disproportionally remember negative travel experiences (Abenoza, Cats, & Susilo, 2017), especially once travel conditions exceed a certain discomfort threshold (Börjesson & Rubensson, 2019). An important undesired effect induced by overcrowding experience pertains to increased perceptions of travel time unreliability and the associated risk of late arrival at the destination (Tirachini et al., 2013). These concerns are especially likely to be exacerbated by the unavailability of accurate and timely travel information and resultant uncertainty (Kattan & Bai, 2018).

Effects of overcrowding disutility are quantified using value-of-crowding measures (Li & Hensher, 2011), i.e. as an equivalent of travel attribute – journey time, monetary fare or generalised travel cost – that passengers are willing to trade-off against the overcrowding experience. A common approach is to estimate the so-called temporal ***crowding penalty*** (Batarce et al., 2015; Tirachini et al., 2013). Traditionally, crowding valuations are primarily obtained through stated-preference (SP) experiments where respondents exercise trade-offs between travel times, crowding levels, and other attributes in hypothetical choice scenarios, with multiple studies published in this field (Bansal, Hurtubia, Tirachini, & Daziano, 2019; Batarce et al., 2016; Haywood & Koning, 2015; Kattan & Bai, 2018; Kroes, Kouwenhoven, Debrincat, & Pauget, 2014; Li, Gao, & Tu, 2017; Li & Hensher, 2011; Preston, Pritchard, & Waterson, 2017; Rudnicki, 1999; Tirachini et al., 2013; Tirachini, Hurtubia, Dekker, & Daziano, 2017; Wardman & Whelan, 2011; Whelan & Crockett, 2009). Their findings underpin the significance of disutility imposed by on-board overcrowding, with maximum travel time multipliers usually in the range of 1.4–1.8 for seated passengers and 2.1–2.5 for standing passengers, though studies with different methodological assumptions report even higher estimates, up to 2.5–3.6 (sitting penalty) and 3.2–5.8 (standing penalty) (e.g. Tirachini et al. (2017); Bansal et al. (2019)). An alternative, yet not always feasible approach involves revealed-preference (RP) studies, where crowding penalties are evaluated by processing real-world travel records, e.g. smartcard data transactions (Batarce et al., 2015; Hörcher, Graham, & Anderson, 2017; Tirachini et al., 2016; Yap, Cats, & van Arem, 2018). These studies report maximum travel time multipliers due to overcrowding as oscillating between 1.1 and 1.7 (sitting penalty) and 1.5–2.0 (standing penalty). In a broad overview, state-of-the-art concerns mostly the evaluation of crowding penalty as a function of in-vehicle travel time, or total journey time. Such crowding multipliers reflect how much extra time a passenger is willing to spend travelling on-board an uncrowded vehicle, compared to a shorter travel time on-board an overcrowded vehicle.

However, overcrowding may also be directly traded-off with waiting time. This is the case for instance in the event of denied boarding. Waiting time due to denied boarding imposes a substantially greater disutility, even 3.5 times higher than nominal waiting time disutility (Cats, West, & Eliasson, 2016). Furthermore, passengers may deliberately choose to accept additional wait time if boarding a later trip could imply lower on-board crowding conditions. The notion of **willingness-to-wait (WTW)** to avoid (or reduce the negative effects of) overcrowding has been hitherto explored in a few studies, mostly conducted within the SP setting (Kim, Lee, & Oh, 2009; Kroes et al., 2014; Yu, Li, Kong, Wang, & Wu, 2015; Preston et al., 2017; Kattan & Bai, 2018, Shelat et al. (2022a, b)). Below we summarise the main implications of these studies:

- The study of Kim et al. (2009) from Seoul analysed the effect of hypothetical bus occupancy information on stated choices between the next two bus departures. They found that propensity to wait for the less-crowded bus is likely to be higher in case of non-commuting trips, seats' availability, longer journey time and for selected user groups (elderly people, white- and blue-collar workers etc.).
- Kroes et al. (2014) find that WTW in Paris metro system is primarily determined by crowding level of the first incoming PT departure. SP estimates show the share of PT users willing to wait additional few minutes vary from 12% (if the first train has minor crowding) to 75% (if the first train is severely overcrowded, while second train has seats available).
- Yu et al. (2015) investigate the WTW with bus crowding information among bus passengers in Dalian (China). However, their SP survey is conducted during the morning peak-hour only and does not consider the impact of certain trip and population characteristics upon the WTW rate, such as propensity to arrive on-time.
- In another study, Preston et al. (2017) report stated WTW among British Rail commuters with information on seats available in a later, less-crowded train. Findings underline the importance of trip purpose, as WTW is likely to emerge among travellers with arrival time flexibility (leisure trips) or those concerned about travel time productivity (business trips). Average acceptable waiting time oscillates between 8 and 23 min, with estimated value-of-crowding multipliers for a 30-min journey ranging from 1.3 (time-critical trips) to 1.5–1.7 (other trip purposes).
- A study performed for a light rail transit system in Canada (Kattan & Bai, 2018) investigates waiting probability when respondents have information only on the first train (due now) being overcrowded. The stated WTW increases with infrequent system usage, perceived unreliability of ATIS system, respondents' age and longer journey time. Estimated probability of waiting for the second train, whose crowding level remains unknown in the SP experiment, ranges between 45% (commuter trips, peak trips) to 65% (non-commuter trips, off-peak trips).
- Recently published studies provide also first insights into the impacts of COVID-19 pandemic upon rising PT (over)crowding impedance and waiting time valuations. In a SP survey conducted among Dutch train passengers, Shelat, Cats, and van Cranenburgh (2022a) distinguished 2 population classes, i.e. 'infection-indifferent' and the newly emerged 'COVID-conscious' travellers. The latter group is significantly more sensitive to infection risk and crowding discomfort. The unit WTW rate is calculated for these groups respectively as about 1 and 8 [mins] of acceptable waiting time per reduction of 1 person on-board. Such values suggest a substantial increase in the WTW in relation to information provisioned on train crowding levels and the associated infection risk. Among personal traits, it is observed that females and elderly users exhibit greater crowding impedance due to COVID-19 impacts (even 20–50%), while high-income and commuting users are more resilient to these concerns (Aghabayk, Esmailpour and Shiwakoti, 2021; Basnak, Giesen, & Muñoz, 2022). Post-COVID-19 crowding valuations are also likely higher for train modes and longer-range trips (ca. 25% higher than pre-pandemic levels) than for bus modes and short-range trips (ca. 5%) (Cho & Park, 2021; Shelat, Van De Wiel, et al., 2022b)).

Passengers' WTW phenomena can be potentially facilitated and passengers can be stimulated to act upon it by providing information on current and future on-board passenger loads. This is nowadays increasingly feasible by means of generating and disseminating **real-time crowding information (RTCI)** (Gentile & Noekel, 2016; Jenelius, 2020). The RTCI systems are still in their early practical deployment stages, mostly confined to limited-scale information on individual train carriages' loads (e.g. London (Schmitt, 2017), Stockholm (Zhang, Jenelius, & Kottenhoff, 2017), Sydney (Susan, 2018), Tokyo (East Japan Railway Company, 2021)), bus occupancy loads (Seoul – (Seoul Metropolitan Government, 2017)) and travel apps supplied with expected crowding information based on historical user feedback (e.g. Moovit (Moovit Inc, 2021), Google Maps Transit (Google LLC, 2021), JakDojade.pl (City-Nav LLC, 2021)) coupled with real-time weighting data (e.g. Dutch railways (Nederlandse Spoorwegen, 2021), Singapore buses (Singapore LTA Land Transport Authority, 2021)). These developments are accompanied by an increasing scientific interest, with studies devoted to developing simulation models (Drabicki, Kucharski, Cats, & Szarata, 2020; Noursalehi, 2017; Nuzzolo, Crisalli, Comi, & Rosati, 2016), prediction algorithms (Jenelius, 2018; Jenelius, 2019; Jenelius, 2020; Więcek, Kubek, Aleksandrowicz, & Strózek, 2019) and empirically examining RTCI impacts in pilot trials (Zhang et al., 2017). Recently, RTCI provision has been gaining momentum as operators aim to tackle the ramifications of the (on-going) covid-19 pandemic crisis for perceived travel safety. This has been witnessed in several RTCI systems in the US, e.g. in Boston (MBTA (Massachusetts Bay Transportation Authority), 2021), San Jose (VTA Valley Transportation Authority, 2021) and Washington D. C. (WMATA Washington Metropolitan Area Transit Authority, 2021).

To conclude the review, we conclude that despite recent research advancements, the literature still contains major research gaps with regards to the impact of RTCI on passengers' travel behaviour – specifically, the instantaneous boarding decisions referred to as the WTW phenomenon. Firstly, the majority of state-of-the-art studies on PT (over)crowding valuations concerns the trade-offs against journey (in-vehicle) times, and as such they are not directly relevant for WTW quantification purposes. Secondly, the WTW valuations have been hitherto mostly deduced in the context of longer-distance, regional rail trips, where seat availability and/or the possibility to work whilst travelling seem to play an important role. In contrast, short-range, urban PT trips may involve different choice considerations, comfort trade-offs and sensitivity towards overcrowding. Finally, SP studies do not provide a complete description of how passengers trade-off the value of RTCI against waiting disutility with regards to trip and population characteristics, especially in the urban PT context (e.g. WTW vs. propensity to arrive on-time).

Arguably, the WTW can be transformed in actual travel behaviour – i.e., in waiting for PT departures further in time – by disseminating RTCI, especially in high-frequency PT services. It remains unknown, though, what might be the perceived value (utility) of RTCI in instantaneous boarding choice context and what factors influence the WTW with crowding information on next departures in urban PT networks. Consequently, this hampers the development of analytical support for the assessment of RTCI systems using PT network models and/or cost-benefit evaluation tools.

1.2. Objectives and contribution

This study is devoted to the analysis of passengers' willingness-to-wait to avoid overcrowding in the presence of real-time crowding information in urban public transport. Our research questions are as follows:

1. What is the stated WTW among urban PT users with RTCI for a later but less-crowded departure of the same bus/tram line?
2. What factors – in terms of trip- and individual-related characteristics - explain the WTW to avoid overcrowding with RTCI?
3. What are the implications of WTW for travel demand management strategies, also in the context of covid-19 impact upon PT sector?

To address these questions, we conduct a stated-preference survey among urban PT (i.e. bus and tram) users in the city of Krakow (Poland). The survey experiment examines their response to the hypothetical RTCI for their current trip context. In a series of choice experiments, urban PT users are asked to indicate their preference between departing now - in higher crowding conditions – vs. waiting for the next bus/tram departure - which is less-crowded. Based on these, we estimate a series of discrete choice (mixed logit) models that describe the WTW with RTCI.

The main contribution of this paper is the quantification of passengers' stated WTW for a less-crowded vehicle under provision of RTCI. Modelling outputs allow for measuring the WTW probability in form of discrete choice models and deriving the acceptable wait time thresholds and crowding multipliers. Our findings reveal the prospective importance of RTCI in instantaneous boarding decisions, as passengers are willing to trade-off (on average) an extra waiting time of 2–13 [mins] to avoid the risk of on-board overcrowding. Furthermore, up to 50–70% of all respondents would consider waiting further at the stop for a less-crowded departure with RTCI. We also observe that urban PT users place higher emphasis on avoiding the risks of excessive overcrowding in the first place, such as denial-of-boarding risk, while seat availability seems to be of secondary importance. Using a simplified example, we illustrate how the obtained findings can help with assessing the potential impacts (and benefits) of WTW behaviour stimulated by RTCI access.

The WTW with RTCI could not only improve the users' travel experience and counteract the negative PT overcrowding impacts, but also comprise a useful travel demand management strategy. In hindsight, its implications may be even more paramount in the context of the post-covid-19 recovery of PT sector. The discussion of the prospective applicability of our findings will follow in the final part of this paper.

The remainder of this paper is organized as follows. Section 2 presents the methodological framework of this study, comprising of a SP survey design and a discrete choice model formulation. In section 3, we report and discuss the survey and model estimation results. We conclude with section 4, summarising main factors influencing the WTW with RTCI, discussing the research and practical implications of this study and pointing the future research directions.

2. Method

We first present the data collection describing survey experiment design (2.1). Thereafter, we present the methodology adopted for estimating choice models and obtaining the WTW valuations (2.2).

2.1. Stated-preference (SP) survey

To design our stated-preference (SP) survey, we first conducted a series of focus-group surveys among PT users, and used them to conceptualise (and refine) our main survey questionnaire. Respondents were also asked about their preferences and interpretations of various crowding information schemes. As a result, we obtained a descriptive RTCI classification scheme rated as the most favourable and understandable, which will form the basis of our stated-choice experiment. The output RTCI scale classifies the crowding on-board the urban bus and tram vehicles in 4 levels as shown in Table 1. Each RTCI level is associated with distinctive travel (dis)comfort expectations and behavioural responses (travel decision) as specified by focus-group respondents. The RTCI scheme in our study is comparable with descriptive classification of on-board crowding assumed in other works in this research field, usually plotted on a 3-level to 6-level scale (Batarce et al., 2015; Jenelius, 2020; Kim et al., 2009; Kroes et al., 2014; Więcek et al., 2019; Zhang et al., 2017).

The main survey questionnaire contains 14 questions in total, divided into following parts:

1. Introduction to survey and (brief) explanation of its objectives.
2. Current PT trip context – trip purpose, time-criticality (i.e. propensity to arrive on-time), frequency of travelling along this route (per week), in-vehicle journey time and service frequency.
3. Choice experiments - WTW with hypothetical RTCI for the next two departures of the current urban trip.
4. Socio-demographic characteristics.

The questionnaire is designed as a field survey to be conducted among passengers waiting at the bus and tram stops.

In the choice experiments, we present respondents with hypothetical choice scenario for their current urban PT trip context (Fig. 1). The RTCI display in our SP survey is an example of crowding information conveyed in real-time to urban PT travellers, resembling e.g. state-of-

Table 1
Survey design – focus-group results. Respondents' interpretations of a descriptive 4-level RTCI representation scheme for bus and tram vehicles (urban PT trips).

RTCI level		interpretation	behavioural response
1.		• >50% of seats available • plenty of uncrowded space	• would choose this trip 'at-ease' • would find a double seat easily • expect a comfortable trip
2.		• individual seats (ca. 10–20%) available • no standing crowding	• would take this trip • not 100% sure to find a seat • *(students)* would prefer to stand inside, even with seats available
3.		• all seats taken • moderate crowding, but no overcrowding • can move inside, but not 100% freely	• would take this trip • expect a 'comfortable' standing place • expect some discomfort
4.		• all seats taken, uncomfortable standing conditions • severely overcrowded • hard to move or grab a hold inside	• unless in a hurry – would consider different travel options • expect substantial discomfort • expect denial-of-boarding risk

the-practice pilot RTCI solutions (cited in the Subsection 1.1. above). Passengers are asked to choose between two alternatives which involve either boarding first PT departure (due to depart now) or skipping the first option and waiting for the second PT departure instead. Each alternative is characterized by two attributes: i.e., on-board crowding conditions (i.e. RTCI level) and waiting time, ceteris paribus. Combination of crowding conditions of the two trips can result in the following cases:

- ***Case (A):*** First departure: moderately crowded (RTCI level 3); Second departure: seats available (RTCI level 2).
- ***Case (B):*** First departure: overcrowded (RTCI level 4); Second departure: moderately crowded (RTCI level 3).
- ***Case (C):*** First departure: overcrowded (RTCI level 4); Second departure: seats available (RTCI level 2).

Waiting time for the second departure is assumed to be 5 min or 10 min. All other trip characteristics – i.e. on-board journey time, time-criticality, trip purpose etc. – remain the same for both alternatives, as specified earlier by respondent in the second part of the survey (see previous paragraph). This design, in conjunction with the in-situ surveying method, aims to additionally accentuate the influence of contextual setting upon respondents' decisions (i.e. trip conditions are 'palpable' for them), as compared to the conventional methodology of the *off-line* SP surveys.

In total, the SP experiments contain 6 possible choice scenarios. Hence, it was designed as panel survey and each respondent was asked to answer the whole scenario set. To ensure that the survey could be credibly completed by respondents interviewed at PT stops within a short amount of time, we had to limit the number of examined choice scenarios. Pilot results from focus groups indicated a negligible difference in respondents' perceptions and choices if crowding on-board the second departure is described as either RTCI level 1 or RTCI level 2. Therefore, scenarios involving the lowest crowding conditions (RTCI level 1) were not eventually considered in the survey.

2.2. Choice modelling

We adopt the random utility maximization (RUM) theory, estimating a series of discrete choice models which describe the probability *P(i)* of choosing an alternative i characterized by its utility U_i from a given choice set. Within the RUM paradigm, the individuals' objective is to maximise their utility when performing choices. The utility U_i of an alternative i consists of the systematic V_i and random error ε utility components (Eq. 1):

$$U_i = V_i + \varepsilon \tag{1}$$

The setup of our experiments implies a binary choice context, i.e. the set consists of two alternatives i, j. Since the random error component ε is independent and identically (i.i.d.) Gumbel distributed, the choice probability *P(i)* of an alternative i is given by the following formula (Eq. 2):

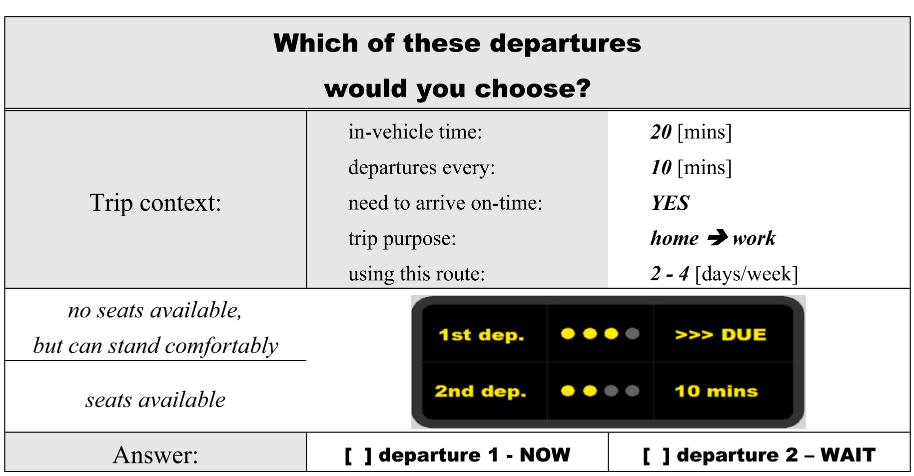


Fig. 1. Illustration from the SC experiment – sample question.

$$P(i) = \frac{e^{V_i}}{e^{V_i} + e^{V_j}} \quad (2)$$

The alternatives correspond to urban PT departures (runs) that the respondent can choose from (and board) at a given stop. The utility formulation that we adopt here is analogous to the approach presented by Preston et al. (2017). The first departure (due now) is set as the base alternative and its utility V_{dep1} is assumed as reference value fixed to zero, i.e. $V_{dep1} = 0$. The second departure (due later) is defined by utility V_{dep2} that essentially represents the **willingness to wait (WTW) utility** (Eq. 3), i.e. relative (dis)utility of deliberately skipping the first departure and waiting for the second departure, given the provisioned on-board crowding information. The WTW utility is evaluated as a sum of the vector of choice explanatory variables $\boldsymbol{X} = (x_1, x_2, \dots, x_n)$, weighted by their corresponding taste preference parameters $\boldsymbol{\beta} = (\beta_1, \beta_2, \dots, \beta_n)$ as follows:

$$V_{dep2} = V(WTW) = \sum \beta_n {}^* x_n \quad (3)$$

This WTW formulation represents in a generic way how various choice variables (attributes) contribute to a relative increase (or decrease) in waiting utility. Variables in the vector X may include both trip-related attributes referring to the specific choice context, as well as socio-demographic attributes of the respondent. Explanatory variables (attributes) x_n are mostly included in form of dummy attributes δ_n, equal to 1 if the attribute n is valid in that particular choice scenario, and 0 otherwise. This implies that the β_n parameter reflects the overall (dis) utility value related to the attribute n (if $\delta_n = 1$). Additional choice attributes x_n are included as time attributes t_n, i.e. wait time and in-vehicle journey time valid in the respective choice scenario. In these cases, β_n value represents a unit incremental (dis)utility rate per additional minute of travel time.

We consider several alternative WTW formulations, based on the mixed binary logit specification. The basic WTW model (Eq. 4) is comprised of two key attributes in our experiments:

- utility of crowding difference between the first and the second departure, denoted by RTCI system: β^s_{RTCI} * δ^s_{RTCI}, where δ^s_{RTCI} refers to specific choice scenario s (thus, for each record only a single δ^s_{RTCI} value is non-zero):
  - o case (A), i.e. reduction from RTCI level 3 to RTCI level 2: $\delta^{3\text{-}2}_{RTCI} = 1$,
  - o case (B), i.e. reduction from RTCI level 4 to RTCI level 3: $\delta^{4\text{-}3}_{RTCI} = 1$,
  - o case (C), i.e. reduction from RTCI level 4 to RTCI level 2: $\delta^{4\text{-}2}_{RTCI} = 1$,
- (dis)utility of wait time (in [mins]) for the second departure: β_{wt} * t_{wt}.

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

The extended WTW model (Eq. 5) accounts for a combination of trip- and individual-related attributes. Here, we include choice attributes that are found to be relevant after the statistical analysis of our survey sample. In addition to the basic WTW model, these include the impact upon WTW (dis)utility due to:

- trip frequency ($\delta_{commute} = 1$ if respondent performs this journey at least twice a week),
- age ($\delta_{age50-65} = 1$ if respondent is between 50 and 65 years of age; $\delta_{age65plus} = 1$ if >65 y/old),
- time-criticality ($\delta_{timecrit} = 1$ if respondent has to arrive before a specified time at the destination),
- in-vehicle journey time (t_{ivt} in [mins], remaining from this stop):

$$\begin{aligned} V(WTW) = {} & \beta^{3-2}_{RTCI} {}^* \delta^{3-2}_{RTCI} + \beta^{4-3}_{RTCI} {}^* \delta^{4-3}_{RTCI} + \beta^{4-2}_{RTCI} {}^* \delta^{4-2}_{RTCI} + \beta_{commute} {}^* \delta_{commute} \\ & + \beta_{age50-65} {}^* \delta_{age50-65} + \beta_{age65plus} {}^* \delta_{age65plus} + \beta_{timecrit} {}^* \delta_{timecrit} \\ & + \beta_{ivt} {}^* t_{ivt} + \beta_{wt}(\mu, \sigma) {}^* t_{wt} \end{aligned} \quad (5)$$

The choice of mixed logit model is advantageous and superior to the employment of conventional (linear) multinomial logit (MNL) model in our study. The mixed logit includes panel data effects, accounting for possible correlations between different observations of the same respondent. It also assumes that there is an unobserved heterogeneity across respondents. We capture these by means of mixing density applied to the wait time (dis)utility parameter $\beta_{wt} = \beta_{wt}\ (\mu, \sigma)$, which becomes here a normally distributed value, characterized by mean and standard deviation. This enables us to investigate the impact of taste variations with respect to the WTW utility among our sampled population.

Next, estimated choice model parameters are used to compute wait time thresholds and crowding multipliers related to WTW for each RTCI scenario s. By dividing the marginal utility of RTCI by the marginal utility of wait time, we obtain the threshold wait time in [mins] t^s_{WTW}, that can be interpreted as an acceptable trade-off for the necessity to wait for the second departure in order to experience lower on-board crowding later on (Eq. 6) – as we elaborate further in the subsection (3.3.):

$$t^s_{WTW} = \left| \frac{\beta^s_{RTCI}}{\beta_{wt}} \right| \quad (6)$$

Based on these, we can compute the value-of time crowding multipliers CM^s_{WTW}. The WTW crowding multiplier specification is akin to the concept of marginal rate of substitution between 2 alternatives, commonly used in monetary valuations of travel attributes (the notion of WTP - willingness-to-pay) (Tirachini et al., 2017). Assuming that passengers are willing to wait for t^s_{WTW} [mins] to board a less-crowded trip of the same in-vehicle journey time t_{ivt} [mins] to their destination, the WTW crowding multipliers correspond to the travel time disutility ratio between boarding an overcrowded departure now (t_{ivt}) vs. waiting and boarding a less-crowded departure later ($t^s_{WTW} + t_{ivt}$). Thus, the CM^s_{WTW} values are a function of the (remaining) in-vehicle journey time t_{ivt} and acceptable wait time t^s_{WTW} for a given RTCI scenario s (Eq. 7). The CM^s_{WTW} rate is essentially interpretable as total travel time multiplier of the first (overcrowded) departure, relative to the total travel time associated with the second (less-crowded) departure (Preston et al., 2017). Such formulation yields WTW crowding multipliers adequate for application e.g. in PT assignment models and cost-benefit analysis.

$$CM^s_{WTW} = \frac{t_{ivt} + t^s_{WTW}}{t_{ivt}} \quad (7)$$

3. Results

In this section, we first present the descriptive statistics of passenger survey results (3.1). We then report the results of a series of discrete WTW choice model estimations (3.2) in form of extended and base mixed logit specifications. Finally, estimation outputs are used to calculate the acceptable wait time thresholds and crowding multipliers with RTCI (3.3.).

3.1. Descriptive statistics

The survey was carried out in March and April 2019 in the city of Krakow, the second-largest city in Poland with city population of 750 k inhabitants (ca. 1.4 m in the metro area). The core of the urban PT system in Krakow is composed of tram and bus network, which are the dominant PT modes in the city, used for about half a million trips on a daily basis. This urban PT network consists of approx. 24 tram lines and 84 bus lines (plus 65 ‘feeder’ bus lines in the agglomeration area). Peak-hour headways range between 5 and 15 [mins] for all tram lines and main bus services (MPK Krakow, 2022). The internal layout of bus and tram vehicles typically implies an enlarged standing space, offset by reduced seating area.

The SP survey was carried out on portable tablet devices, face-to-face

Table 2
Survey results - descriptive (sociodemographic) statistics of the sample population (left) and comparison with the general PT user population in Krakow (right), obtained from the 2014 comprehensive travel survey (Szarata, 2015).

	Survey sample		2014 travel survey sample
Total respondents	377	100.0%	100.0%
Gender			
Women	198	52.5%	57.6%
Men	179	47.5%	42.4%
Age			
18–25	164	43.5%	26.6%
26–40	118	31.3%	28.7%
41–50	41	10.9%	11.7%
51–65	18	4.8%	14.9%
> 65	36	9.5%	18.1%

among passengers waiting at bus and tram stops. As surveying locations, we (randomly) chose 8 inner-city PT stops with relatively high passenger volumes, and conducted surveys during the daytime (both during peak and midday off-peak hours). About 75% of interviews involved PT services with headways of 5–10 [mins], and not >15 [mins] in ca. 93% of cases. Time required to fill the survey did not exceed 3.5–5.0 [minutes], with response rate oscillating around 50%. Completion rate was ca. 94% and thus a total of 377 valid questionnaires were collected. Favourably, such figures imply that a majority of interviewees were able to complete survey on-time without missing their next incoming PT departure.

Sampling strategy aimed to reflect the typical demand pattern of urban PT users in Krakow. Eventually, about 75% of answers were collected from users who are <40 years old. This overrepresentation of younger population is attributable to a lower response rate among older users, who – despite extra surveying efforts - were more reluctant to participate in the survey. Nevertheless, about 10% of survey sample are aged 65 and over. Gender split also shows (roughly) equal proportions, with a 52% share of female participants. Table 2 presents the summary of sample characteristics.

An overview of the choice experiment results (Fig. 2) shows that WTW is a relevant phenomenon that clearly rises in magnitude with higher crowding conditions. In the moderately crowded case (A), boarding the first vehicle (departing now) is the most popular option, but still 12 or 30% of respondents indicate that they would wait for a less-crowded departure, depending on required wait time (10 or 5 min, respectively). Then, a rise in overcrowded conditions in case (B) clearly influences respondents' attitudes, with WTW rising to 45–75% of all respondents. Interestingly, in case (C), where the first vehicle is still overcrowded but the second one has seats available, results are similar to those observed in the case (B). Improving comfort conditions in the second departure does not seem to provide an additional incentive to reconsider choices, however, with WTW rising by merely 1–3%. For the sake of brevity, we will therefore omit case (C) in the remainder of this subsection, and report survey results only for the moderately crowded case (A) (first departure - RTCI level 3) and overcrowded case (B) (first departure - RTCI level 4).

A detailed summary of reported WTW rates in context of main choice factors is presented in Table 3. Among these, a key issue affecting the WTW pertains to trip purpose and propensity to arrive on-time at the destination (i.e. trip time criticality (Fig. 3)). Respondents are more likely to wait for a less-crowded vehicle in case of home-bound trips (e.g. evening commute) and leisure trips. In contrast, they are more determined to board the first vehicle for trips originating at home, especially obligatory ones (i.e. commuting to workplace or school / university). Further on, we observe a limited influence of in-vehicle journey time on passengers' choices (Table 3), manifested mainly through slightly lower WTW for short trips, i.e. <10 min. Trip frequency is loosely associated with willingness-to-wait: regular users (commuters) who travel on a given PT route at least twice a week are less inclined to consider waiting for a less-crowded departure. A possible explanation is that they are more likely to encounter overcrowding and may become eventually more accustomed to the travel discomfort imposed by it.

Among demographic factors, we find that respondents above 50 years of age show greater willingness to avoid (over)crowding in their departure choices (Table 3), already in the moderately crowded case (RTCI level 3). The WTW rate rises even further among users of 65 years of age and over. As many as 60–90% of them will opt to wait additional 10 min to avoid higher crowding in the first departure. This stands in stark contrast to younger respondents (below 50 years of age), where the corresponding figure is on average between 5% - 40%. No relation is observable for gender though, with fairly uniform WTW levels among females and males.

3.2. Choice modelling results

Following the descriptive analysis of our survey sample, we proceed with estimating discrete choice models to describe the WTW phenomenon under the prospective provision of RTCI. We select and present below the choice models which were found statistically sound and which contain choice factors relevant for explaining passengers' preferences as stated in our experiment (outlined in Table 3). All models are estimated using a tailored script developed in the Python 3.7 software (van Rossum & Drake, 2009).

We begin with an extended mixed logit model as defined in the Eq. 3, reporting the results in Table 4. Coefficient values are evaluated against the baseline utility of choosing the first urban PT departure, which is fixed to zero. Positive values denote choice factors which increase the utility of the stated WTW.

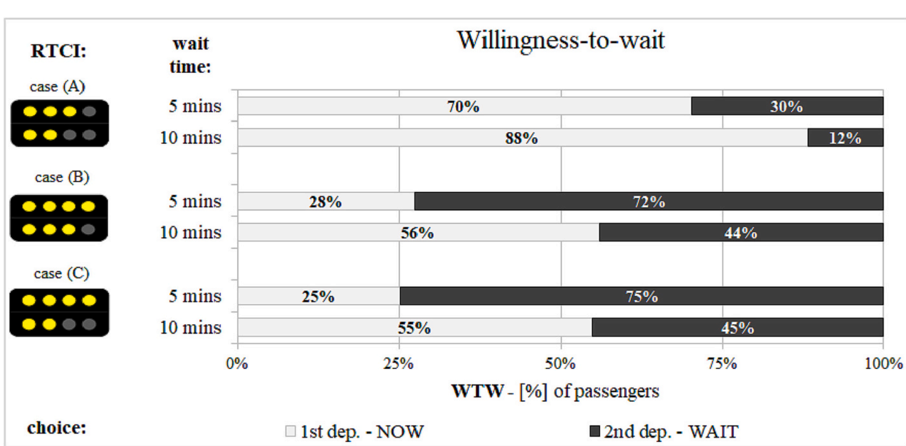
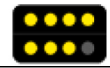


Fig. 2. Survey results – overall stated WTW in each scenario, depending on RTCI and wait time values.

Table 3
Survey results – descriptive statistics of WTW vs. main choice factors. Values denote the share of respondents' answers (sample size $n = 377$).

RTCI scenario:	case (A) 			case (B) 			*sample size (n = 377)*
Max. acceptable wait time:	0 - *depart now*	5 mins	10 mins	0 - *depart now*	5 mins	10 mins	
[mins]	WTW vs. **in-vehicle time**						
< 10	78%	16%	7%	47%	16%	37%	*76*
10 – 20	72%	18%	10%	22%	38%	41%	*139*
20 – 30	68%	20%	13%	21%	26%	53%	*111*
> 30	61%	18%	22%	28%	27%	45%	*51*
Need to arrive on-time?	WTW vs. trip **time-criticality**						
yes	84%	12%	4%	43%	33%	24%	*168*
no	60%	22%	18%	15%	25%	60%	*209*
origin *destination*	WTW vs. **trip purpose**						
home – work	79%	15%	6%	46%	27%	26%	*84*
home – education	90%	10%	0%	35%	32%	32%	*31*
home – leisure	52%	19%	29%	10%	5%	86%	*21*
work – home	74%	14%	12%	15%	38%	47%	*50*
education – home	64%	31%	5%	22%	26%	52%	*77*
leisure – home	31%	17%	51%	6%	17%	77%	*35*
non-home-based	80%	14%	6%	32%	36%	32%	*79*
[years old]	WTW vs. **age**						
< 25	77%	19%	4%	33%	26%	41%	*164*
26 – 40	76%	16%	8%	25%	44%	32%	*118*
41 – 50	73%	22%	5%	35%	19%	46%	*41*
51 – 65	50%	22%	28%	22%	17%	61%	*18*
> 65	28%	14%	58%	6%	6%	89%	*36*
using this PT route [days / week]	WTW vs. **trip frequency**						
5 – 7	72%	21%	7%	31%	26%	42%	*188*
2 – 4	77%	15%	7%	28%	34%	38%	*110*
1	55%	5%	39%	13%	30%	58%	*38*
< 1	58%	22%	20%	22%	24%	54%	*41*

As it can be seen in Table 4, the RTCI indicating reduced (over) crowding in the second urban PT departure increases the waiting utility in all three choice scenarios, albeit to a different extent. Marginal RTCI utility β^{s}_{RTCI} is already positive in case (A), i.e. when the first departure is moderately crowded (RTCI level 3). Moreover, it rises sharply (ca. 3.5 times) in cases (B) and (C), when RTCI allows to mitigate the high overcrowding conditions (RTCI level 4) expected on-board the first departure. Interestingly, there is barely any variation in utility coefficients between cases (B) and (C), despite the difference in RTCI level of the second departure. On the other side, the negative sign of wait time coefficient β_{wt} implies an additional disutility imposed by the required wait time, which contributes to a decreasing WTW utility.

In addition to the alternative-specific attributes, certain individual and trip attributes are also found to have an impact on the WTW. Age strongly influences the WTW utility among respondents: those between 50 and 65 years of age ($\beta_{age50-65}$) exhibit a higher WTW than younger respondents, rising further among elderly users above 65 years of age (β_{65plus}). An important factor but with an opposite influence upon WTW relates to the time-criticality of the trip ($\beta_{timecrit}$). As expected, the need to arrive on-time at the destination leads to substantially lower WTW utility, as waiting longer at the stop imposes much greater hindrance for passengers' trip itinerary. Also, in-vehicle time (β_{ivt}) has positive impact upon WTW utility, though rather negligible, as it is substantially (ca. 12 times) lower in magnitude compared to wait time utility. The final choice variable relates to the trip frequency ($\beta_{commute}$): WTW utility is lower if the current line (route) is used frequently, i.e. at least twice a

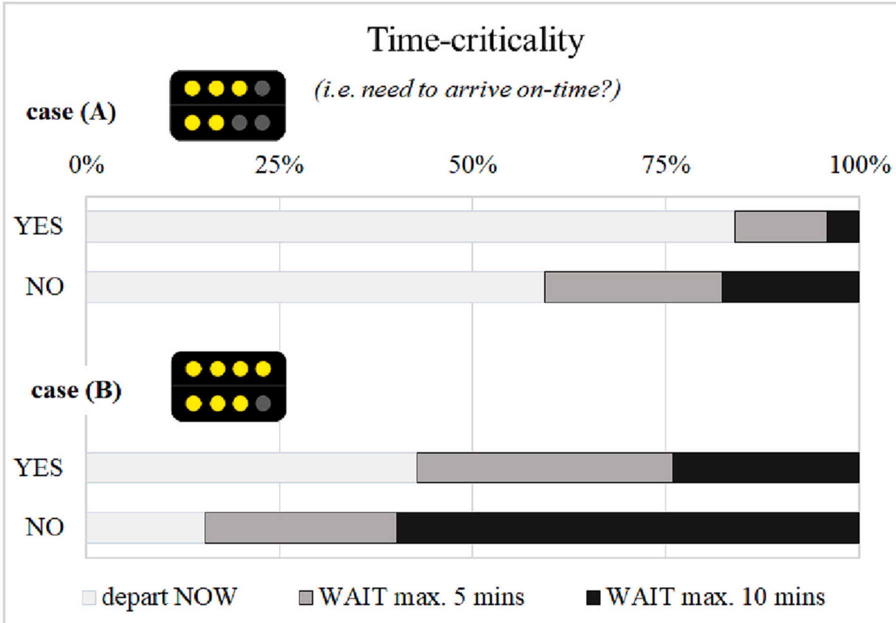


Fig. 3. Survey results – WTW vs. time-criticality.

Table 4
Choice modelling results – **extended binary mixed** logit model of the willingness-to-wait with RTCI. Mixing density applied to the wait time disutility (normally distributed).

		All trips			
Coefficients		Estimate	*Std. error*	*t-test*	*p-value*
$\beta^{3\text{-}2}_{RTCI}$		1.452	*0.359*	*4.04*	***
$\beta^{4\text{-}3}_{RTCI}$		4.812	*0.441*	*10.90*	***
$\beta^{4\text{-}2}_{RTCI}$		4.993	*0.515*	*9.70*	***
$\beta_{commute}$		- 0.482	*0.296*	*−1.63*	.
$\beta_{age50\text{–}65}$		0.624	*0.476*	*1.31*	.
$\beta_{age65plus}$		1.773	*0.443*	*4.00*	***
$\beta_{timecrit}$		- 1.565	*0.223*	*−7.03*	***
β_{wt}	μ	- 0.615	*0.051*	*−11.96*	***
	σ	0.162	*0.026*	*6.20*	***
β_{ivt}		0.04	*0.008*	*5.27*	***
initial log-likelihood (LL):		- 1380.7			
final log-likelihood (LL):		- 783.0			
LL ratio test:		1195.8			
adjusted rho-square:		0.405			
sample size:		377			

Significance codes (p-value): 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘’1.

week. However, the corresponding marginal disutility rate is rather low compared to other variables.

The second investigated model is the base mixed logit model as formulated in the (Eq. 4), confined to the two variables that define the trade-off embodied in our experiment. Applying such formulation yields a WTW model which is strictly a function of the trade-off between RTCI vs. wait time utilities.

In Table 5, we report base mixed logit model estimates for the whole sample (all trips), as well as for the sample subsets based on trip time-criticality. All the obtained estimates are statistically significant at the 95% confidence level and yield overall satisfactory goodness-of-fit results.

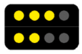
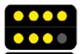
Results are analogous to the extended model (Table 4), reflecting the positive contribution of RTCI utility towards the WTW, offset by negative marginal disutility of wait time. Applying the mixed logit specification additionally reveals a considerable variation in the marginal wait time disutility value, β_{wt}. Its mean value is twice as high for time-critical trips when compared against the non-time-critical trip sample. The standard deviation of wait time disutility is equal to approx. 30–40% of its mean value. Comparison of mixed logit estimates implies that while the marginal utility of RTCI is (broadly) similar in all cases, inclusion of trip time-criticality imposes (on average) a twice higher penalty rate for each extra minute of waiting time.

Table 5
Choice modelling results – **base mixed binary** logit model of the willingness-to-wait with RTCI. Mixing density applied to the wait time disutility (normally distributed).

		All trips			Time-critical trips			Non-time critical trips		
Coefficients		Estimate	*Std err.*	*p-value*	Estimate	*Std err.*	*p-value*	Estimate	*Std err.*	*p-value*
$\beta^{3\text{-}2}_{RTCI}$		1.828	*0.226*	***	2.073	*0.350*	***	1.696	*0.340*	***
$\beta^{4\text{-}3}_{RTCI}$		5.294	*0.333*	***	5.545	*0.436*	***	5.105	*0.556*	***
$\beta^{4\text{-}2}_{RTCI}$		5.510	*0.481*	***	5.755	*0.663*	***	5.331	*0.776*	***
β_{wt}	μ	- 0.705	*0.060*	***	- 1.014	*0.099*	***	- 0.486	*0.007*	***
	σ	0.286	*0.045*	***	0.308	*0.081*	***	0.184	*0.043*	***
Initial LL:		- 1380.9			- 505.4			- 841.8		
Final LL:		- 816.5			- 319.3			- 463.6		
LL ratio test:		1128.4			372.2			756.4		
Adj. rho-square:		0.396			0.336			0.427		
Sample size:		377			168			209		

Significance codes (p-value): 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘’1.

Table 6
Simulation results – acceptable WTW thresholds according to base **mixed logit** model.

acceptable wait time [mins] - mean, *(90% CI)*		**All trips**	**Time-critical trips**	**Non-time-critical trips**
t_{WTW} $(\beta^{3\text{-}2}_{RTCI})$		3.2 *(−2.5 to 8.9)*	2.3 *(0.1 to 4.6)*	4.2 *(−1.5 to 9.9)*
t_{WTW} $(\beta^{4\text{-}3}_{RTCI})$		8.9 *(−0.6 to 18.4)*	6.2 *(1.2 to 11.1)*	12.1 *(1.8 to 22.4)*
t_{WTW} $(\beta^{4\text{-}2}_{RTCI})$		9.3 *(−0.4 to 19.0)*	6.4 *(1.3 to 11.5)*	12.6 *(2.1 to 23.1)*

3.3. Wait time thresholds and crowding multipliers

Choice modelling results allow us to estimate the acceptable wait time thresholds and the crowding multipliers. The ratio of marginal utilities of RTCI and wait time attributes, as formulated in (Eq. 6), yields the so-called WTW threshold t^{s}_{WTW}, i.e. waiting time acceptable as a trade-off for skipping the first departure, in the event that RTCI system indicates the possibility to reduce the exposure to overcrowding by waiting for the subsequent departure. Since the wait time disutility is parameterized with mixing density, we need first to compute the WTW distribution intervals. We perform this by means of Monte Carlo simulations (Sillano & de Dios Ortúzar, 2005) with 100,000 draws of wait time utility coefficients $\beta_{wt}(\mu,\sigma)$ and evaluate the corresponding wait time values (Eq. 6). In order to discard the outlier values, we filter out the unrealistic wait times $|t_{wt}| > 50$ [mins] which comprise approx. 1.5% of the sample. Next, we fit the simulated WTW values to different distribution functions. The best fit is obtained with the normal distribution which is finally assumed for our subsequent modelling objectives.

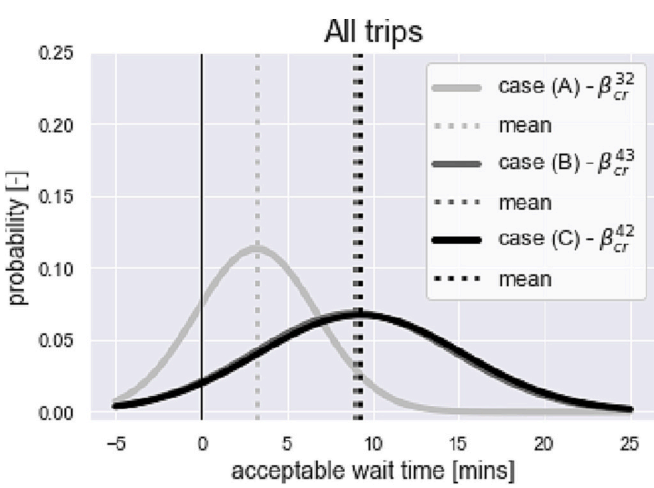


Fig. 4. Acceptable wait times, based on modelling estimates – for the whole trip sample.

Output acceptable wait times $t^{s}_{WTW}(\mu,\sigma)$ evaluated as normally distributed parameters are reported in (Table 6). Average wait time acceptance ranges between approx. 6–12 [mins] in the overcrowded scenario (RTCI level 4 of first departure): higher willingness to wait is observed if the trip is non-time-critical (and vice versa for a time-critical trip). In case of moderate crowding (RTCI level 3), the mean wait time threshold is ca. 4 [mins] for non-time-critical trips and just around 2 [mins] for time-critical trips. Hence, a much lower WTW acceptance range should be anticipated once the risk of overcrowding in the first departure is not indicated anymore by the RTCI system.

We plot the resultant WTW acceptance distributions (for cases (A) and (B)) in Fig. 4 for all trips, and in Fig. 5 for trips of distinct time-criticality. The presented confidence intervals should reflect taste variations in WTW acceptance among our respondents, thanks to the inclusion of panel and heterogeneity aspects in the mixed logit approach.

As shown for the aggregate trip sample (Fig. 4), the acceptable wait time reaches up to 11 [mins] (moderately crowded scenario (A)) and further up to 21 [mins] (overcrowded scenario (B)) in 95% of the cases. This dispersion in wait time is also evident for distinguished trip sample segments. For time-critical trips (Fig. 5, left), the distribution plots are relatively concentrated within a smaller range and do not exceed ca. 12 [mins], whereas the non-time-critical plots (Fig. 5, right) are much more widely distributed, reaching even as much as 20–25 [mins]. While these results might seem relatively large at first glance, these are only upper-bound values, and the wait time oscillates within the range of 2–15 [mins] in the majority (ca. 65%) of cases.

In the final step, we derive the WTW crowding multipliers CM^{s}_{WTW} (Table 7) for an average PT trip duration in Kraków of 20 [mins]. For example, a CM^{s}_{WTW} value of 1.3 implies that the traveller is willing to devote an additional 30% of his remaining (total) journey time to wait for the next, less-crowded departure. This illustrates that under the WTW regime, the perceived travel time of first departure is greater than that of second departure as long as the required wait time is shorter than 6 [mins], i.e. the acceptable threshold t^{s}_{WTW} in such instance. Results (Table 7) range from 1.1 (moderate crowding) to 1.5 (high overcrowding) for the whole trip sample. For time-critical trips, the corresponding rates are between ca. 1.0–1.1 to 1.3, and for non-time-critical trips they range from 1.2 to 1.6 respectively. This compares lower to rail-

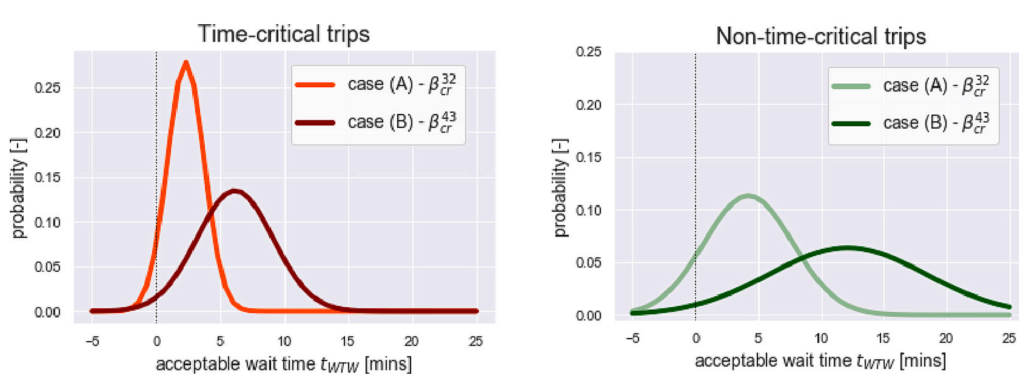
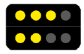
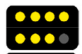


Fig. 5. Acceptable wait times, based on modelling estimates – distinguished for time-critical (left) vs. non-time-critical trips (right).

Table 7
Estimated WTW crowding multipliers for a 20-min journey time.

travel time multiplier mean, *(90% CI)* in-vehicle time t_{ivt} = 20 [mins]		**All trips**	**Time-critical trips**	**Non-time-critical trips**
CM_{WTW} $(\beta^{3\text{-}2}_{RTCI})$		1.13 *(1.06 to 1.20)*	1.10 *(1.07 to 1.13)*	1.17 *(1.09 to 1.25)*
CM_{WTW} $(\beta^{4\text{-}3}_{RTCI})$		1.38 *(1.20 to 1.56)*	1.27 *(1.17 to 1.37)*	1.53 *(1.30 to 1.76)*
CM_{WTW} $(\beta^{4\text{-}2}_{RTCI})$		1.39 *(1.21 to 1.57)*	1.28 *(1.17 to 1.39)*	1.55 *(1.30 to 1.80)*

based WTW valuations (Preston et al., 2017), where value-of-time multipliers for a 30-min regional rail trip range between 1.30 and 1.75.

Note that the interpretation of our WTW crowding multipliers is different from conventional state-of-the-art valuations of in-vehicle crowding (e.g. as in the works of Whelan and Crockett (2009); Wardman and Whelan (2011); Li and Hensher (2011); Tirachini et al. (2017)). Therein, crowding multipliers concern trade-offs between travel options of different journey times vs. their on-board crowding levels (which are experienced for the whole duration of the trip). Whereas, in the WTW context, both alternatives involve the same in-vehicle journey time (but different on-board crowding conditions), and passengers exercise trade-offs between the currently required waiting time at PT stop vs. *expected* later on-board crowding level.

3.4. Assessing the potential benefits of WTW with RTCI

To illustrate how our findings can help assist the appraisal of implications of the WTW with RTCI, we present the following numerical example. It relates to a fictitious urban bus stop *e*, where bus arrival times and crowding levels indicate an irregular pattern, resembling the well-known bus bunching problem. The RTCI disseminated among passengers q^r_{board} intending to board the first, overcrowded bus trip *r* allows a certain share of them to make an informed choice to wait instead for a less-crowded, later departure $r + 1$.

For the RTCI system to induce travel experience (and welfare) gains, the **WTW boarding volume** $q^{r+1}_{board,WTW}$ shall be essentially determined as the minimum of two variables:

- The *potential WTW volume*, i.e. the share of q^r_{board} willing to shift towards departure $r + 1$. This is obtainable as a probability function of: required waiting time t_{wt} and acceptable WTW threshold t^s_{WTW} in the specific scenario *s* (Table 6, Figs. 4 - 5).
- The max*imum WTW volume*, i.e. the max. Permissible volume shift, so that on-board crowding conditions of run $r + 1$ will not exceed the currently displayed RTCI level at any downstream stop *i*. This condition shall ensure that the prior RTCI advice will be fully consistent with passengers' subsequent crowding experience. In that vein, the max. WTW volume can be computed as a function of: critical on-board capacity for a given scenario *s,* and passenger in-vehicle and boarding flows at all downstream stops $i = e+1, e+2 \ldots \in r$.

Under these conditions, the prospective travel experience benefits can be evaluated in the form of perceived journey time (PJT) savings due to the WTW with RTCI. These can stem from the two following sources:

- *PJT savings incurred by the WTW boarding volume* $q^{r+1}_{board,WTW}$. Assuming the max. acceptable waiting time for passengers willing to wait for the run $r + 1$ equal to t^s_{WTW} [mins], the unit PJT reduction ΔPJT^s_{WTW} is essentially the difference between the WTW threshold and the actual (required) waiting time t_{wt}.
- *PJT savings additionally incurred by the remaining boarding volume of run r* (q^r_{board} - $q^{r+1}_{board,WTW}$). These are the extra travel benefits experienced by remaining passengers who boarded run *r* and experienced less-crowded conditions than originally indicated by the RTCI. This might arise e.g. as a consequence of the WTW volume outflux $q^{r+1}_{board,WTW}$. Such PJT savings will hold true only if the RTCI level anticipated whilst boarding run *r* arriving at stop *e* is eventually higher than the RTCI level experienced whilst on-board the same run *r* at all downstream arrivals at stops *e*+*1, e*+*2,* … The unit PJT reduction ΔPJT^s_{WTW} is then equal to the t^s_{WTW} rate, i.e. corresponding to the equivalent amount of time that passengers would need to spend otherwise in order to achieve the same reduction in on-board RTCI level.

For illustration purposes, we assume fixed inputs in our simplified example. Calculation results are presented in Table 8. These show how the favourable effects of boarding flows' migration within trip departure pairs *{r, r + 1}* can be quantified to deduce the WTW benefits at the specific stop. Estimated PJT savings are then projected into equivalent welfare rate *w*, assuming monetary valuations of travel time equal to 6 [EUR/h] (ca. 28 [PLN/h]). This numerical example indicates that tangible WTW benefits might be already attainable under (relatively) minor rates of passenger numbers and waiting times. Notably, the middle example highlights the potential of WTW behaviour to yield a substantial increase in welfare gains once on-board comfort improvements become valid simultaneously for both runs *r* and $r + 1$.

The purpose of this simplified example is to demonstrate how our

Table 8
Projected perceived journey time (PJT) savings $\mathbf{\Delta PJT^s_{WTW}}$ due to WTW induced by RTCI – numerical example for a fictitious bus stop.

input – fixed assumptions								output – WTW impact		
run	t^r_{dep} [gg:mm]	**[RTCI]** - before	q^r_{board} [pax.]	**time-crit?**	t^s_{WTW} [mins]	$q^r_{board}(RTCI)$ [pax.]	**[RTCI]** - after	ΔPJT^s_{WTW} [mins]	**PJT savings** [pass-mins]	**welfare gains *w*** [EUR]
r *r* + 1	7:00 7:03	**** ***	30 10	yes	**6**	20 10 + **10**	**** ***	 6–3 = **3**	 10 * 3 = **30**	**3**
r *r* + 1	7:10 7:13	**** ***	30 10	no	**12**	10 10 + **20**	*** ***	(**12**) 12–3 = **9**	10 * 12 = **120** 20 * 9 = **180**	**30**
r *r* + 1	7:20 7:28	**** ***	30 10	no	**12**	20 10 + **10**	**** ***	 12–8 = **4**	 10 * 4 = **40**	**4**

behavioural findings can support the quantitative assessment of the prospective benefits of RTCI-induced WTW phenomenon. It should be emphasized that a thorough appraisal of WTW effects requires a detailed analytical underpinning, in the form of PT simulation models and/or real-world observations. Only under such detailed setting the input and context variables, as well as attainable equalization of passenger volume distribution and travel welfare benefits, can be determined in a reliable manner.

4. Discussion

In this study, we investigate the stated willingness to wait (WTW) to travel inside a less-crowded vehicle in urban public transport (PT) systems in the presence of real-time crowding information (RTCI). While WTW can emerge with future implementation of RTCI on vehicle departures at PT stops and stations, its potential scale and implications are not fully examined in current state-of-the-art. To this end, we conduct a stated-preference experiment and quantify the phenomenon of WTW with RTCI through a set of discrete choice models, acceptable wait time thresholds and value-of-time crowding multipliers.

Our study reveals the prospective utility of RTCI in passengers' boarding decisions. Hence, it extends the classical findings on travel time and crowding valuations since the *certainty* value associated with the provided RTCI on next departure loads, and how it trades-off against (additional) waiting time in an *instantaneous* contextual setting, is internalized in model estimates (Shelat, Cats, & van Lint, 2021). Consequently, this reveals the potential of WTW to become a valid travel behaviour phenomenon in urban PT trips, especially in overcrowded conditions. Ca. 75% of our survey respondents would consider waiting 5 min for a second, less-crowded departure, and still 45% of them would do so when this induces the wait time of 10 min. This is the case when the first departure reaches maximum crowding level on the RTCI scale (level 4), i.e. conditions on-board imply severe overcrowding and even denial-of-boarding risk. For moderately crowded scenario (RTCI level 3 for the first departure), which refers to 'comfortable' standing conditions, the corresponding figures are substantially lower, reaching 30% (for a 5-min wait) and 12% (10-min wait), respectively. Interestingly, in case when first departure is overcrowded (RTCI level 4), despite further reduction in crowding conditions of the second departure (from RTCI level 3 down to level 2, i.e. so that seats become available), no significant changes in stated choices are observable, with a mere 2–3% rise in stated WTW.

Our study findings reaffirm the state-of-the-art observations on the non-linearity of crowding penalties upon travel time and travel experience valuations (see e.g. references in Section 1.). However, they differ from those reported in the relevant state-of-the-art in several important regards. Yu et al. (2015) found a greater influence of information on crowding level of second departure upon stated WTW (which may reach up to 90%) and relatively higher WTW rate emerging already at the *slightly-crowded* conditions of first departure. Firstly, negative impacts of bus overcrowding are much more prominent in their case-study area. Secondly, comparison of both studies underscores the relevance of semantic and communication aspects in the projected effects of RTCI (Saedi & Khademi, 2019). Seemingly, major variations in passengers' preferences can be obtained when RTCI is communicated either on a lexical scale (*not-, slightly- or very-crowded*) or a 4-level rating scale, as in our study. This forms one of (numerous) interesting paths for follow-up research.

Based on the SP survey results, we estimate a series of mixed logit models. Representing the WTW with RTCI as a binary choice problem (i.e. depart now vs. depart later). These models show that RTCI utility is 3–5 times higher in case when first departure is overcrowded (RTCI level 4) than when it its moderately crowded (RTCI level 3). Furthermore, wait time disutility for time-critical trips is twice higher than for non-time-critical trips. Depending on the crowding level of the first departure, acceptable wait times in urban PT trips range on average between 2 and 4 [mins] (moderate crowding) and 6–12 [mins] (high overcrowding), with higher values attainable for non-time-critical trips. This is lower than SP estimates for regional, longer-distance rail trips (Preston et al., 2017), which range on average between 8 and 23 [mins]. Applying the mixed logit modelling approach, moreover, allows us to additionally account for heterogeneity aspects and taste variations in the perceived wait time (dis)utility. Maximum wait times may thus reach up to even 12 [mins] (moderate crowding) and 25 [mins] (high overcrowding). Resultant WTW crowding multipliers for a 20-min urban PT trip range between ca. 1.0–1.3 for time-critical trips and 1.2–1.6 for non-time-critical trips.

These numerical outputs in form of WTW thresholds and crowding multipliers are applicable for the assessment of RTCI effects in cost-benefit analysis. In a simplified, numerical example, we demonstrate how the appraisal of prospective WTW benefits can be supported by our estimation results. In the future, these findings can be embedded in full-scale simulation and real-world studies to quantify the RTCI impacts upon travel experience. PT assignment models can be particularly instrumental in assessing the ramifications of RTCI provision in context of real-time PT performance and demand-supply dynamics. First research works based on simulation experiments point to the potentially promising advantages of the WTW with RTCI in the event of PT service disturbances (Drabicki, Kucharski, & Cats, 2022; Wang et al., 2021) and network-wide benefits of RTCI inclusion in route or departure choice decisions (Nuzzolo et al., 2016; Noursalehi, Koutsopoulos and Zhao, 2021; Drabicki et al., 2020; Peftitsi, Jenelius, & Cats, 2022). Alas, they also observe certain drawbacks such as inaccuracy risks of instantaneous crowding information.

Our findings underline how WTW probability is influenced by current trip properties and selected individual characteristics. Aside from the RTCI and waiting time variables, it is evident that WTW decreases for trips involving propensity to arrive on-time. Age is an influential choice factor, as we observe a substantial increase in waiting acceptance for respondents above 50 years of age, rising even further among those aged 65 and over. On the other hand, in-vehicle time (spent on-board) has only a limited impact on stated WTW. This seems to reaffirm other literature findings, e.g. Preston et al. (2017), and is arguably the case especially for urban PT trips with relatively short journey time. Also, trip frequency has a negative impact, though limited in magnitude, upon the stated WTW.

It should be stressed that the presented results are strictly characteristic for our survey sample, without any claims regarding their generalisability and transferability (Table 2). We refrained from weighting the survey results, since our principal objective was the research examination of novel WTW phenomenon on a randomly selected PT user sample. Arguably, the resulting WTW time thresholds and crowding multipliers might be actually greater, once adjusted for a higher share of middle- and old-age travellers and trips featuring arrival time flexibility.

4.1. Outlook and policy implications

With this study, our objective was to deliver an enriching contribution to the state-of-the-art research on development of RTCI systems. In the following, we discuss wider, behavioural and practical implications for the emerging passenger information solutions.

Firstly, in terms of designing and conveying the RTCI, distinguishing the information on high crowding conditions - i.e. excessive overcrowding vs. moderate standing crowding - seems to be of primary importance in case of high-frequency, urban PT networks, which are dominated by short-range trips and prone to episodes of serious overcrowding (e.g. denial-of-boarding risk). In contrast, quantitative information on the available seat capacity might not be as relevant as for regional and/or rail transport, especially when vehicle layout arrangement implies greater standing capacity, like for the bus and tram network in our case study. Insights from focus-group discussions presented in this paper also shed more light onto these attitudes and interpretations of descriptive RTCI classification schemes in urban PT networks.

Secondly, the prevalence of WTW phenomenon revealed in our stated-preference survey suggests that reliable and timely RTCI provision can facilitate substantial shifts between different services of the same line in congested urban PT networks. These can be beneficial both for passengers (reduced overcrowding experience, more informed travel choices) and operators (improved service capacity utilization). By raising the passengers' awareness of available on-board capacity, RTCI can be particularly advantageous in case of passenger load fluctuations. Further research attention needs to be devoted, though, to examine the achievable effectiveness of WTW with RTCI not just depending on the magnitude but also on the variability of passenger flows.

Finally, this underpins the potential of future RTCI system to become a useful travel demand management feature in counteracting service disturbances. For example, by encouraging passengers to *spread themselves out* over the next, less-crowded PT departures arriving later, the willingness to wait facilitated by RTCI can become a certain *soft holding strategy* that will effectively counteract the notorious bus bunching feedback loop (Drabicki et al., 2022). This positive effect will arise voluntarily, i.e. in accordance with travellers' objective of maximizing travel utility, without resorting to classical, supply-side holding and/or control strategies. Hence, the WTW with RTCI might establish a synergic interplay between the individual and collective effectiveness, narrowing the gap between user-equilibrium and system-optimum conditions. Notwithstanding, for such measures to be effective, efforts need to be devoted to ensure the trustworthiness of the provisioned RTCI, including the consideration of demand-anticipatory techniques.

Moreover, our findings offer insights relevant in context of the (yet on-going) COVID-19 pandemic and its negative impacts upon PT systems across the world. The necessity of physical distancing policies drastically reduces the system capacity, by even as much as 80% (Gkiotsalitis & Cats, 2021), while inducing a major problem of unsatisfied (and denied) passenger demand. This points to an ever greater, prospective role of RTCI in maximizing the awareness of available system capacity and mitigating the problem of uneven vehicle utilization. On top of that, there are major concerns that negative perceptions of PT sector as being unsafe and poorly adapted will persist in the post-pandemic times (Tirachini & Cats, 2020). In that vein, future RTCI provision can serve as a vital countermeasure, fostering the image of PT travel safety by informing and reassuring passengers in real-time about reduced (or non-existent) crowding conditions in PT services.

Our study is subject to several methodological limitations. The generality of WTW estimates may be somewhat limited (for longer waiting times) due to the setup of our stated-choice experiment, where waiting time alternatives were confined to values of 5 and 10 [mins] only. This constrain was imposed by the feasibility of our at-stop survey, where meaningful answers had to be obtained in a short amount of time. Future WTW evaluations could account for additional (and higher) waiting time values in stated-choice scenarios. Otherwise, passengers' own experience of PT (over)crowding, their perceptions of at-stop crowding levels and/or expectations of downstream crowding conditions can also be potentially impactful factors behind the WTW probability. Though survey respondents were told to assume the validity of presented RTCI for the remainder of their journey, the *uncertainty* attached to crowding levels at downstream journey stages may be already *internalized* in their choice preference, yielding potentially lower WTW rates. These notions should be investigated in follow-up research.

Furthermore, the caveats of the surveying methodology should be highlighted. There is evidence to suggest that the stated-preference approach is prone to overestimation of (over)crowding valuations (e.g. Tirachini et al. (2013); Kroes et al. (2014); Hörcher et al. (2017); Yap et al. (2018)). Only future, practical advancements with RTCI deployments will allow to validate the WTW results with revealed-preferences data and the choices actually made by PT users. On the other hand, the emerging research evidence suggests that passengers' sensitivity to PT (over)crowding increased by 25% (or even more) as a consequence of the COVID-19 pandemic, also among frequent PT users (Shelat et al. (2022a, b); Cho & Park, 2021; Aghabayk et al., 2021; Flügel & Hulleberg, 2022). Against this new evidence, we reckon that the stated-preference WTW time tolerance reported in our study might become higher in the aftermath of the COVID-19 pandemic crisis in PT sector.

The prospective research topics also relate to exploring how different RTCI representation schemes might influence passengers' choices and attitudes, and what is their effectiveness under various circumstances, such as for different PT sub-mode, vehicle type (including internal layout arrangement, share of seating vs. standing capacity), RTCI utilization rate, local conditions and network congestion levels. A vital follow-up notion pertains to investigating how RTCI can influence the WTW behaviour already in the pre-trip planning stage and to shape the day-to-day adjustments in travel strategies. This will also help to understand whether the WTW behaviour might contribute towards *flattening* of the peak-demand curve or defining more cost-effective demand pricing policies in the longer perspective. Finally, detailed simulation and empirical studies will help quantify the overall, prospective welfare benefits of the WTW with RTCI.

CRediT authorship contribution statement

Arkadiusz Drabicki: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization, Funding acquisition. **Oded Cats:** Methodology, Investigation, Resources, Validation, Writing – original draft, Writing – review & editing, Supervision. **Rafał Kucharski:** Methodology, Software, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Achille Fonzone:** Conceptualization, Methodology, Investigation, Validation, Writing – original draft. **Andrzej Szarata:** Resources, Writing – review & editing, Project administration, Funding acquisition.

Declaration of Competing Interest

Authors hereby declare **no known conflict of interest** associated with this publication. We also confirm that there was no significant financial support for this work that could have influenced its outcome. This manuscript has not been submitted to, nor is under review at, another journal or other publishing venue.

Acknowledgements

This study has been support by research grant received from the Iwanowska Programme, organized by the Polish National Agency for Academic Exchange (NAWA) (agreement no. PPN/IWA/2018/1/00084) and the STSM Grant from EU COST Action TU1305: Social Networks and Travel Behaviour. Authors would also like to express their gratitude towards two anonymous reviewers, whose insights and comments contributed to the final version of this paper.

References

Abenoza, R. F., Cats, O., & Susilo, Y. O. (2017). Travel satisfaction with public transport: Determinants, user classes, regional disparities and their evolution. *Transportation Research Part A: Policy and Practice, 95*, 64–84.
Aghabayk, K., Esmailpour, J., & Shiwakoti, N. (2021). Effects of COVID-19 on rail passengers' crowding perceptions. *Transportation Research Part A: Policy and Practice, 154*, 186–202.
Bansal, P., Hurtubia, R., Tirachini, A., & Daziano, R. A. (2019). Flexible estimates of heterogeneity in crowding valuation in the New York City subway. *Journal of Choice Modelling, 31*, 124–140.
Basnak, P., Giesen, R., & Muñoz, J. C. (2022). Estimation of crowding factors for public transport during the COVID-19 pandemic in Santiago, Chile. *Transportation Research Part A: Policy and Practice, 159*, 140–156.

Batarce, M., Muñoz, J. C., & de Dios Ortúzar, J. (2016). Valuing crowding in public transport: Implications for cost-benefit analysis. *Transportation Research Part A: Policy and Practice, 91*, 358–378.

Batarce, M., Muñoz, J. C., de Dios Ortúzar, J., Raveau, S., Mojica, C., & Ríos, R. A. (2015). Use of mixed stated and revealed preference data for crowding valuation on public transport in Santiago, Chile. *Transportation Research Record, 2535*(1), 73–78.

Börjesson, M., & Rubensson, I. (2019). Satisfaction with crowding and other attributes in public transport. *Transport Policy, 79*, 213–222.

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

Ceder, A. (2015). *Public Transit Planning and Operation: Modeling, Practice and Behavior* (Second Edition (2nd ed.). CRC Press.

Cho, S. H., & Park, H. C. (2021). Exploring the behaviour change of crowding impedance on public transit due to COVID-19 pandemic: Before and after comparison. *Transportation Letters*, 1–8.

City-Nav LLC. (2021). JakDojade.pl app. [Mobile application software]. http://www.jakdojade.pl.

De Palma, A., Lindsey, R., & Monchambert, G. (2017). The economics of crowding in rail transit. *Journal of Urban Economics, 101*, 106–122.

Drabicki, A., Kucharski, R., & Cats, O. (2022). Mitigating bus bunching with real-time crowding information. *Transportation*, 1–28.

Drabicki, A., Kucharski, R., Cats, O., & Szarata, A. (2020). Modelling the effects of real-time crowding information in urban public transport systems. *Transportmetrica A: Transport Science*, 1–39.

East Japan Railway Company. (2021). JR-EAST Train Info. [Mobile application software]. http://www.jreast-app.jp/en/.

van Essen, M., Thomas, T., van Berkum, E., & Chorus, C. (2016). From user equilibrium to system optimum: A literature review on the role of travel information, bounded rationality and non-selfish behaviour at the network and individual levels. *Transport Reviews, 36*(4), 527–548.

Flügel, S., & Hulleberg, N. (2022). Aversion to in-vehicle crowding before, during and after the COVID-19 pandemic. Findings, August. Retrieved January 10th, 2023: https://findingspress.org/article/37641.

Fonzone, A., & Schmöcker, J. D. (2014). Effects of transit real-time information usage strategies. *Transportation Research Record, 2417*(1), 121–129.

Gavriilidou, A., & Cats, O. (2019). Reconciling transfer synchronization and service regularity: real-time control strategies using passenger data. *Transportmetrica A: Transport Science, 15*(2), 215–243.

Gentile, G., & Noekel, K. (2016). *Modelling public transport passenger flows in the era of intelligent transport systems*. New York: Springer International Publishing.

Gkiotsalitis, K., & Cats, O. (2021). Public transport planning adaption under the COVID-19 pandemic crisis: literature review of research needs and directions. *Transport Reviews, 41*(3), 374–392.

Google LLC. (2021). Google Maps – Transit & Food [Mobile application software]. https://apps.apple.com/us/app/google-maps-transit-food/id585027354.

Haywood, L., & Koning, M. (2015). The distribution of crowding costs in public transport: New evidence from Paris. *Transportation Research Part A: Policy and Practice, 77*, 182–201.

Hörcher, D., Graham, D. J., & Anderson, R. J. (2017). Crowding cost estimation with large scale smart card and vehicle location data. *Transportation Research Part B: Methodological, 95*, 105–125.

Islam, M. F., & Fonzone, A. (2021). Bus passenger path choices after consulting ubiquitous real-time information. *Travel Behaviour and Society, 23*, 226–239.

Jenelius, E. (2018). Car-specific metro train crowding prediction based on real-time load data. In *2018 21st IEEE International Conference on Intelligent Transportation Systems (ITSC)* (pp. 78–83).

Jenelius, E. (2019). Data-driven bus crowding prediction based on real-time passenger counts and vehicle locations. In *2019 6th IEEE International Conference on Models and Technologies for Intelligent Transport Systems (MT-ITS 2019)*.

Jenelius, E. (2020). Data-driven metro train crowding prediction based on real-time load data. *IEEE Transactions on Intelligent Transportation Systems, 21*(6), 2254–2265.

Kattan, L., & Bai, Y. (2018). LRT passengers' responses to advanced passenger information system (APIS) in case of information inconsistency and train crowding. *Canadian Journal of Civil Engineering, 45*(7), 583–593.

Kim, J. K., Lee, B., & Oh, S. (2009). Passenger choice models for analysis of impacts of real-time bus information on crowdedness. *Transportation Research Record, 2112*(1), 119–126.

Kim, K. M., Hong, S. P., Ko, S. J., & Kim, D. (2015). Does crowding affect the path choice of metro passengers? *Transportation Research Part A: Policy and Practice, 77*, 292–304.

Kroes, E., Kouwenhoven, M., Debrincat, L., & Pauget, N. (2014). Value of crowding on public transport in île-de-France, France. *Transportation Research Record, 2417*(1), 37–45.

Li, H., Gao, K., & Tu, H. (2017). Variations in mode-specific valuations of travel time reliability and in-vehicle crowding: Implications for demand estimation. *Transportation Research Part A: Policy and Practice, 103*, 250–263.

Li, Z., & Hensher, D. A. (2011). Crowding and public transport: A review of willingness to pay evidence and its relevance in project appraisal. *Transport Policy, 18*(6), 880–887.

MBTA (Massachusetts Bay Transportation Authority) (2021). Crowding information for riders. Retrieved January 10th, 2023: https://www.mbta.com/projects/crowding-information-riders.

Moovit Inc. (2021). Moovit app [Mobile application software]. https://moovitapp.com/.

MPK Krakow (2022). (in Polish: Miejskie Przedsiębiorstwo Komunikacyjne) Main public transport operator in Greater Krakow area. Retrieved January 10th, 2023: https://www.mpk.krakow.pl/en/.

Nederlandse Spoorwegen. (2021). NS Reisplanner Xtra. [Mobile application software]. https://www.ns.nl/en/travel-information/ns-on-your-mobile/ns-app.html.

Noursalehi, P. (2017). *Decision support platform for urban rail systems: Real-time crowding prediction and information generation. Doctoral dissertation*. Boston: Northeastern University.

Noursalehi, P., Koutsopoulos, H. N., & Zhao, J. (2021). Predictive decision support platform and its application in crowding prediction and passenger information generation. *Transportation Research Part C: Emerging Technologies, 129*, Article 103139.

Nuzzolo, A., Crisalli, U., Comi, A., & Rosati, L. (2016). A mesoscopic transit assignment model including real-time predictive information on crowding. *Journal of Intelligent Transportation Systems, 20*(4), 316–333.

Peftitsi, S., Jenelius, E., & Cats, O. (2022). Modeling the effect of real-time crowding information (RTCI) on passenger distribution in trains. *Transportation Research Part A: Policy and Practice, 166*, 354–368.

Preston, J., Pritchard, J., & Waterson, B. (2017). Train overcrowding: Investigation of the provision of better information to mitigate the issues. *Transportation Research Rrecord, 2649*(1), 1–8.

van Rossum, G., & Drake, F. L. (2009). *Python 3 reference manual*. Scotts Valley, CA: CreateSpace.

Rudnicki, A. (1999). *[in Polish] Jakość komunikacji miejskiej [Quality of urban public transport]*. Krakow: SITK RP.

Saedi, R., & Khademi, N. (2019). Travel time cognition: Exploring the impacts of travel information provision strategies. *Travel Behaviour and Society, 14*, 92–106.

Schmitt, A. (2017, Aug 3). These london trains have real-time displays to reduce crowding. StreetsBlog USA https://usa.streetsblog.org/2017/08/03/these-london-trains-have-real-time-displays-to-reduce-crowding/.

Seoul Metropolitan Government (2017, May 24). New service allows passengers to check congestion level of buses in Seoul. Retrieved January 10th, 2023: http://english.seoul.go.kr/avoid-congested-buses-take-vacant-buses/?cat=29.

Shelat, S., Cats, O., & van Cranenburgh, S. (2022a). Traveller behaviour in public transport in the early stages of the COVID-19 pandemic in the Netherlands. *Transportation Research Part A: Policy and Practice, 159*, 357–371.

Shelat, S., Cats, O., & van Lint, J. W. C. (2021). Quantifying travellers' evaluation of waiting time uncertainty in public transport networks. *Travel Behaviour and Society, 25*, 209–222.

Shelat, S., Van De Wiel, T., Molin, E., van Lint, J. W. C., & Cats, O. (2022b). Analysing the impact of COVID-19 risk perceptions on route choice behaviour in train networks. *PLoS One, 17*(3), Article e0264805.

Sillano, M., & de Dios Ortúzar, J. (2005). Willingness-to-pay estimation with mixed logit models: some new evidence. *Environment and Planning A, 37*(3), 525–550.

Singapore LTA (Land Transport Authority). (2021). MyTransportSG. [Mobile application software]. https://www.mytransport.sg/content/mytransport/home.html.

Susan. (2018, May 17). *Sydney provides real-time info on train crowding.* The Transit Wire. http://www.thetransitwire.com/2018/05/17/sydney-provides-real-time-info-on-train-crowding/. Retrieved January 10th, 2023.

Szarata, A. (2015). [in Polish] Wyniki badań podróży w Krakowie – KBR 2013 [2013 comprehensive travel survey results in Krakow]. *Transport Miejski i Regionalny, 2015*(5), 4–8.

Tirachini, A., & Cats, O. (2020). COVID-19 and public transportation: Current assessment, prospects, and research needs. *Journal of Public Transportation, 22*(1), 1.

Tirachini, A., Hensher, D. A., & Rose, J. M. (2013). Crowding in public transport systems: Effects on users, operation and implications for the estimation of demand. *Transportation Research Part A: Policy and Practice, 53*, 36–52.

Tirachini, A., Hurtubia, R., Dekker, T., & Daziano, R. A. (2017). Estimation of crowding discomfort in public transport: Results from Santiago de Chile. *Transportation Research Part A: Policy and Practice, 103*, 311–326.

Tirachini, A., Sun, L., Erath, A., & Chakirov, A. (2016). Valuation of sitting and standing in metro trains using revealed preferences. *Transport Policy, 47*, 94–104.

VTA (Valley Transportation Authority). (2021). How do I find real-time crowding information?. https://www.vta.org/faq/how-do-i-find-real-time-crowding-information.

Wang, P., Chen, X., Zheng, Y., Cheng, L., Wang, Y., & Lei, D. (2021). Providing real-time bus crowding information for passengers: A novel policy to promote high-frequency transit performance. *Transportation Research Part A: Policy and Practice, 148*, 316–329.

Wardman, M., & Whelan, G. (2011). Twenty years of rail crowding valuation studies: Evidence and lessons from British experience. *Transport Reviews, 31*(3), 379–398.

Whelan, G., & Crockett, J. (2009, April). An investigation of the willingness to pay to reduce rail overcrowding. In *, Vol. 30. Proceedings of the first international conference on choice modelling, Harrogate, England*.

Więcek, P., Kubek, D., Aleksandrowicz, J. H., & Stróżek, A. (2019). Framework for onboard bus comfort level predictions using the markov chain concept. *Symmetry, 11*(6), 755.

WMATA (Washington Metropolitan Area Transit Authority). (2021). Know before you go: Real time crowding information now available for Metrobus and Metrorail. https://www.wmata.com/about/news/Real-Time-Crowding.cfm.

Yap, M., Cats, O., & van Arem, B. (2018). Crowding valuation in urban tram and bus transportation based on smart card data. *Transportmetrica A: Transport Science*, 1–20.

Yu, B., Li, T., Kong, L., Wang, K., & Wu, Y. (2015). Passenger boarding choice prediction at a bus hub with real-time information. *Transportmetrica B: Transport Dynamics, 3*(3), 192–221.

Zhang, Y., Jenelius, E., & Kottenhoff, K. (2017). Impact of real-time crowding information: A Stockholm metro pilot study. *Public Transport, 9*(3), 483–499.