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Modeling the effect of real-time crowding information (RTCI) on passenger distribution in trains

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A R T I C L E I N F O

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A B S T R A C T

Overcrowding has become a big challenge for public transport systems, affecting passengers' travel experience. At the same time, service supply is often underutilized due to large variations in crowding across services, vehicle trips on the same service and different compartments of the same vehicle. Real-time operational measures, such as information provision, can potentially reduce on-board crowding unevenness and its negative effects. In this study, we extend a dynamic public transport simulation model to provide passengers with predictive real-time crowding information (RTCI) concerning individual train cars. Passengers utilize this information when choosing a specific train car to board. It is demonstrated through a case study for the Stockholm metro network area that in the presence of car-specific crowding information, passengers alter their car boarding choices to avoid on-board crowding, leading to a more even passenger distribution inside trains. We find that passengers' travel experience improves with the provisioning of RTCI, which is a result of the lower on-board crowding unevenness. Moreover, this improvement increases with increased demand levels but only up to a certain point beyond which passengers do not gain from switching train cars.

1. Introduction

Overcrowding is a major issue in the management of public transport systems and is critically linked to passengers' on-board discomfort and the performance of the system (Tirachini et al., 2013). There are often large variations in passenger loads among individual cars of multi-car vehicles (e.g. metro trains) even during peak hours (TRB, 2014). Such an imbalance in passenger load distribution leads to even higher experienced discomfort and denied boarding incidents as well as inefficient capacity utilization and thus, larger fleet requirements to serve the demand. Public transport authorities and operators aim to reduce the crowding effects and improve capacity utilization through infrastructure or operational investments, e.g. real-time crowding information (RTCI) provision. This requires the development of models that can adequately capture the effects of crowding information provision systems on passengers' travel behavior and train-car boarding choices prior to field implementations.

Public transport users make travel decisions, e.g. which specific train car to board, considering factors such as travel time, walking distance, and expected on-board comfort. Passengers may adapt their travel choices to avoid crowding on-board the vehicle (Raveau et al., 2014; Pel et al., 2014). In particular, Kim et al. (2015) shows that some passengers choose alternative travel paths, while Pownall et al. (2008) and Peftitsi et al. (2020) find that passengers in high-demand conditions make trade-offs, choosing a less crowded train car, to avoid on-board crowding effects.

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Public transport assignment models, categorized into frequency-based and schedule-based, are widely used to model crowding at stations and on-board vehicles and evaluate its effects on passengers. Frequency-based models that account for passenger crowding-dependent travel cost and service capacity were presented by Lam et al. (1999) and Cepeda et al. (2006), respectively. Dynamic frequency-based approaches were introduced by Schmöcker et al. (2008) and Schmöcker et al. (2011), accounting for denied boardings and the probability of not getting a seat. Schedule-based approaches that take line schedules and vehicle capacity constraints into account were introduced by Nguyen et al. (2001), Papola et al. (2009), Khani et al. (2015) and Ranjbari et al. (2020). Seated capacity constraints were considered in Sumalee et al. (2009) and Hamdouch et al. (2011) to model how on-board discomfort is experienced by sitting and standing passengers. A dynamic transit assignment model, BusMezzo, which mimics the behavior and choices of individual passengers and introduces vehicle capacity constraints and seating priority rules for evaluating crowding effects was proposed by Cats et al. (2016). In a recent study, BusMezzo was extended for evaluating the effect of passengers' prior travel experience on their decision to board a specific train car (Peftitsi et al., 2021).

Some studies have focused on proposing crowding management measures for improving capacity utilization and reducing the unevenness of passenger distribution inside the train. Sohn (2013) developed a model to determine the optimal train stop location at the station platform, aiming for a more even passenger distribution. Muñoz et al. (2018) installed a gate on a crowded metro platform in Santiago, Chile, allowing only one direction of passenger flow that resulted in improved capacity utilization and service regularity.

Travel time information systems have been widely tested for alleviating congestion in the context of car traffic. Several studies have simulated rerouting phenomena in the presence of predictive travel time information (Ma et al., 2016; Cao et al., 2017; Kucharski and Gentile, 2019; Falek et al., 2022). In the case of transit, real-time information (RTI) systems are used for influencing passenger route choices and improving the travel experience (Fonzone and Schmöcker J.D, 2016). The effect of RTI on passengers' travel times was modeled in an agent-based public transport assignment model by Cats et al. (2011), resulting in passengers' route choices shifts and travel time gains in the metro network of Stockholm, Sweden. RTI concerning on-board crowding levels, i.e. real-time crowding information (RTCI), is a novel solution for reducing crowding effects and improving passengers' travel experience. RTCI has the potential to reduce the negative effects of crowding by influencing passengers' boarding choices (Preston et al., 2017). Until now, only a limited number of studies have examined the impact of RTCI. Kim et al. (2009) used survey data to model the effect of bus occupancy on passengers' choices in South Korea, showing that the probability of choosing a bus increases with the availability of empty seats. Based on stated preference studies in the UK, rail passengers were found to change their choices in response to crowding information, leading to benefits for both passengers and operators (Pritchard, 2017). The behavioral effect of RTCI was assessed in a pilot study in the Stockholm metro network, which showed that the provision of car-specific RTCI was successful in reducing the number of passengers boarding the most crowded metro car (Zhang et al., 2017).

Practical implementations of providing RTCI concerning the occupancy of individual train cars have been presented in London (Schmitt, 2017) and Sydney (Hendry, 2019). This information is communicated to the passengers through on-board displays or at station platforms and is calculated based on car weight data. Furthermore, a smartphone application is used in the Netherlands for providing train crowding information based on historical load observations (Nederlandse Spoorwegen, 2021).

There are only a few studies that proposed models for simulating the effects of RTCI. A transit assignment model was presented by Nuzzolo et al. (2016) for modeling the impact of real-time predictive information on path choices, travel times, and vehicle crowding in a day-to-day learning process. The prediction of on-board crowding of a single vehicle is based on a fixed-point solution. A simple crowding prediction scheme was used in Drabicki et al. (2020) to incorporate vehicle crowding information for evaluating the effects of crowding on passengers' within-day path choices in the transit-assignment model BusMezzo. Information is predicted based on the crowding on-board the latest vehicle trip and is provided through a four-level scale. The application of this model to the urban public transport network in Krakow, Poland shows improvements in passengers' travel experience. Using a fixed-point solution, Noursalehi et al. (2021) presented an on-line simulation-based decision support platform that provides predictive information on crowding on platforms and trains. The information is provided through a three-level descriptive scale based on the train boarding likelihood. The results from an application of this model show better train capacity utilization as a result of the predictive crowding information provision.

To the best of our knowledge, no study has proposed a public transport assignment model that incorporates passengers' access to real-time information on the crowding distribution inside trains in passengers' decision-making process. It remains therefore unknown how the provision of RTCI concerning individual train cars impacts vehicle capacity utilization and passengers' travel experience. The objective of this study, motivated by the aforementioned limitations, is to develop a quantitative approach for evaluating the effect of providing information on the crowding level in individual cars of the arriving train. The key contributions of the paper are:

- The development of a quantitative approach for simulating passengers' train car choices when crowding information is provided.
- Modeling the impacts of RTCI systems under alternative provision schemes, classified into app-based and platform-based RTCI.
- The impacts of crowding information at the car level and the vehicle level are modeled and compared.
- Application of the developed model for the metro network in Stockholm, Sweden demonstrates the potential changes in passengers' "local" train car choice and "global" route choice as well as overall travel experience.
- The effect of car-specific RTCI is investigated with respect to the information provision scheme and demand level using simulation scenarios.

In this study, we use the transit assignment model BusMezzo that was extended in Peftitsi et al. (2021) to simulate passenger's train car choices, and thus, it captures the distribution of passengers among individual cars of a train. In the previous paper, experienced passengers form expectations of on-board crowding based on their prior travel experience, while inexperienced passengers do not have any crowding expectations. In this paper, we further extend this model to incorporate passengers' access to crowding information concerning individual train cars. Thus, this model extension allows inexperienced passengers to form expectations regarding downstream on-board crowding distribution based on the available information, thereby affecting the decision-making process.

The remainder of the paper is structured as follows. Section 2 describes the proposed methodology. In Section 3, we present details of the Stockholm metro system and the scenarios tested. Results showing the effects of the RTCI provision are presented in Section 4. In Section 5 we discuss the findings and the limitations of the model and outline follow-up work.

2. Methodology

2.1. Modeling passenger choices

Modeling the effect of RTCI provision on the distribution of passengers along multi-car rail vehicles (e.g. metro trains) requires a passenger assignment model. Such a model needs to capture individual passengers' choices to board a specific car of a train. A dynamic agent-based public transit simulation model, BusMezzo, is used in this study for modeling individual passenger path decision-making (Cats, 2013). The model simulates the movements of individual transit vehicles, i.e. trains, and the decisions that individual passengers make. The capabilities of this model were extended in Peftitsi et al. (2021) to allow for modeling individual passengers' car-specific boarding choices, thereby capturing on-board crowding distribution among individual cars of the train. As a result, passengers' generalized travel cost is evaluated more accurately, considering that passenger loads are not evenly distributed inside the train. The simulated car-specific passenger loads were validated against an empirical passenger load dataset based on car-specific weights in Peftitsi et al. (2021).

In BusMezzo, each passenger makes sequential travel decisions, i.e. walking, boarding and alighting, that combined define the resulting path alternative. Each path alternative a, connects origin o to destination d and is included in path set A^{od}. The path alternative is defined as a combination of stops associated with a platform section, transit lines associated with a train car, and a set of walking links between stops as well as platform sections (Peftitsi et al., 2021). We associate each path alternative a with a utility; the deterministic part of the utility of a feasible path a for passenger y ($y \in Y$, where Y is the set of all passengers) is:

$$v_{y,a} = \beta_y^{inv} t_{y,a}^{inv} + \beta_y^{wait} t_{y,a}^{wait} + \beta_y^{walk} t_{y,a}^{walk} + \beta_y^{transfer} N_a^{transfer} \quad \forall y \in Y, a \in A^{od} \tag{1}$$

where $t_{y,a}^{inv}$ is the expected total perceived in-vehicle time, $t_{y,a}^{wait}$ is the expected total waiting time, $t_{y,a}^{walk}$ is the expected total walking time, including within-station walking time at the origin, transfer and destination station, $N_a^{transfer}$ is the number of transfers included in the path alternative and β's are the corresponding utility function coefficients.

Walking and waiting times are weighted with the corresponding user-specific parameters for walking β^{walk} and waiting time β^{wait}, respectively. Each transfer is penalized with the corresponding user-specific parameter for transfers $\beta^{transfer}$. The disutility of in-vehicle time, reflecting on-board passenger discomfort, is given as the nominal in-vehicle travel time weighted with the corresponding user-specific parameter for in-vehicle time β^{inv}, which reflects the value of uncrowded in-vehicle time, and a crowding factor. The latter depends on the ratio of car occupancy to the seated capacity and whether the passenger has a seat or not (Wardman and Whelan, 2011) and reflects the expectations of crowding that the passenger forms based either on experience or provided information. In BusMezzo on-board passengers have priority to get a seat and there are standing passengers only when all seats are occupied (Cats et al., 2016).

In the decision-making process, passenger y chooses at any decision point the next path element c, i.e. walking to a platform section, boarding a train car and alighting from a train car, that maximizes their expected utility. In other words, passengers choose the next path element that minimizes their total downstream expected travel cost. Passenger y associates a utility, denoted by $u_{y,c}$, with a path element c ($c \in C$). This utility is given as the joint utility of all path alternatives available upon choosing c, A^{cd}, using the logsum term:

$$u_{y,c} = ln \sum_{a \in A^{cd}} e^{v_{y,a}} \tag{2}$$

Passenger y chooses then the following path element c with probability $P_{y,c}$.

$$P_{y,c} = \frac{e^{u_{y,c}}}{\sum_{c' \in C} e^{u_{y,c'}}} \tag{3}$$

Transit route choice might violate the property of the multinomial logit (MNL) model that assumes the independence of irrelevant alternatives (IIA). The choice-set generation model applied in BusMezzo alleviates this shortcoming by merging the most correlated paths into single hyperpaths (Cats et al., 2011; Cats and West, 2020). Furthermore, passengers make travel action choices (e.g. boarding versus staying) in the decision-making process in BusMezzo rather than path choices, which reduces the unaccounted correlations.

Table 1
RTCI levels and the corresponding crowding factors.

RTCI level	Car capacity utilization		Crowding factor
●○○○	<= 80% seated capacity		1.0
●●○○	>80% seated capacity	<= 100% seated capacity	1.3
●●●○	>100% seated capacity	<= 50% total capacity	1.5
●●●●	>50% total capacity		1.8

2.2. Modeling real-time crowding information

Measurements of the crowding level in each train car i are assumed available upon train departure j from a stop s, i.e. for each trip segment between consecutive stops (e.g. through weighting train cars at stations). The objective crowding level is determined by the capacity utilization of the car (i.e. the ratio of car occupancy to capacity). We follow the approach proposed in Drabicki et al. (2020) for including passengers' access to RTCI in the decision-making process. Based on the measured crowding level, we define four descriptive levels of crowding information; each of them is associated with a crowding factor according to the crowding valuations reported in Wardman and Whelan (2011) as shown in Table 1. The crowding factor, showing the valuation of the objective crowding level, takes values between 1 for uncrowded conditions and 1.8 for highly crowded situations, i.e. the car occupancy is approaching the total capacity.

The measured car crowding information is used to predict the crowding of each trip segment, i.e. crowding in individual cars of the vehicle upon its departure from a stop, which is then provided to the passengers. In the following, a simple crowding prediction method is used, according to which, the crowding is predicted based on the measured car crowding of the most recent train trip j that has departed from the same stop s. More elaborate prediction methods are possible, but this simple one is likely to be used in practice.

The generated car-specific RTCI is then utilized by each passenger as a crowding factor, i.e. in-vehicle time multiplier, in the decision-making process when the passenger chooses the next path element c. Thus, the expected perceived in-vehicle time $t^{inv}_{y,a}$, included in Eq. (1), is weighted by both the expected car-specific crowding factor and the corresponding in-vehicle time valuation β^{inv}_{y}. As a result, the expected perceived in-vehicle time differs for each train car.

We model two different schemes for providing RTCI, *app-based* and *platform-based* (Fig. 1). The app-based RTCI system, available through smartphones or other devices, provides passengers with car crowding information upon train trip departure from each stop, i.e. for each trip segment between consecutive stops, along a path alternative, and hence, the nominal in-vehicle time of a trip segment is weighted with the corresponding crowding factor. Alternatively, the platform RTCI system, available through displays at station platforms, provides information on the expected car crowding level on-board the next train trip upon its departure from the respective platform. In this case, passengers are assumed to use this information as if it applies to downstream trip segments, and hence, the in-vehicle time of each trip segment along a path alternative is weighted with the same crowding factor.

The model can generate the RTCI at the individual car level and the vehicle level. Information at the vehicle level provides passengers with the expected crowding on-board the next arriving train according to the algorithm presented in Drabicki et al. (2020). The train crowding level is determined by a crowding factor that depends on the capacity utilization of the train as a whole, assuming that crowding is evenly distributed among individual train cars. In other words, when passengers utilize crowding information at the vehicle level, they expect that perceived in-vehicle time does not differ among individual cars.

The provisioned crowding information, which is predicted through the simple adopted method, may differ from passengers' experienced crowding due to uncertainty and variations in supply and demand. In addition, the accuracy of the predicted information depends on the number of passengers utilizing this information and adapting their choices, which then affects passengers' discomfort. This study evaluates the accuracy of the crowding information by testing the effect of passengers' response rate on their travel experience.

2.3. Performance evaluation

To evaluate the impact of RTCI on the performance of the system, we consider two measures; the average unevenness of passenger distribution inside the train and the generalized travel cost.

2.3.1. Crowding unevenness

Having a single metric of on-board crowding unevenness enables easy comparisons between different on-board passenger load distributions. In this study, we measure the unevenness of crowding δ_{js} among the cars $i \in I$ of a train trip j when it departs from stop s, considering the ratio of the difference in passenger load between the most and the least crowded cars to the total on-board passenger load in train trip j:

$$\delta_{js}(\%) = \frac{\max_{i=1}^{I} q_{ijs} - \min_{i=1}^{I} q_{ijs}}{\sum_{i=1}^{I} q_{ijs}} * 100 \tag{4}$$

where q_{ijs} denotes the passenger load in car i of a train trip j, departing from stop s.

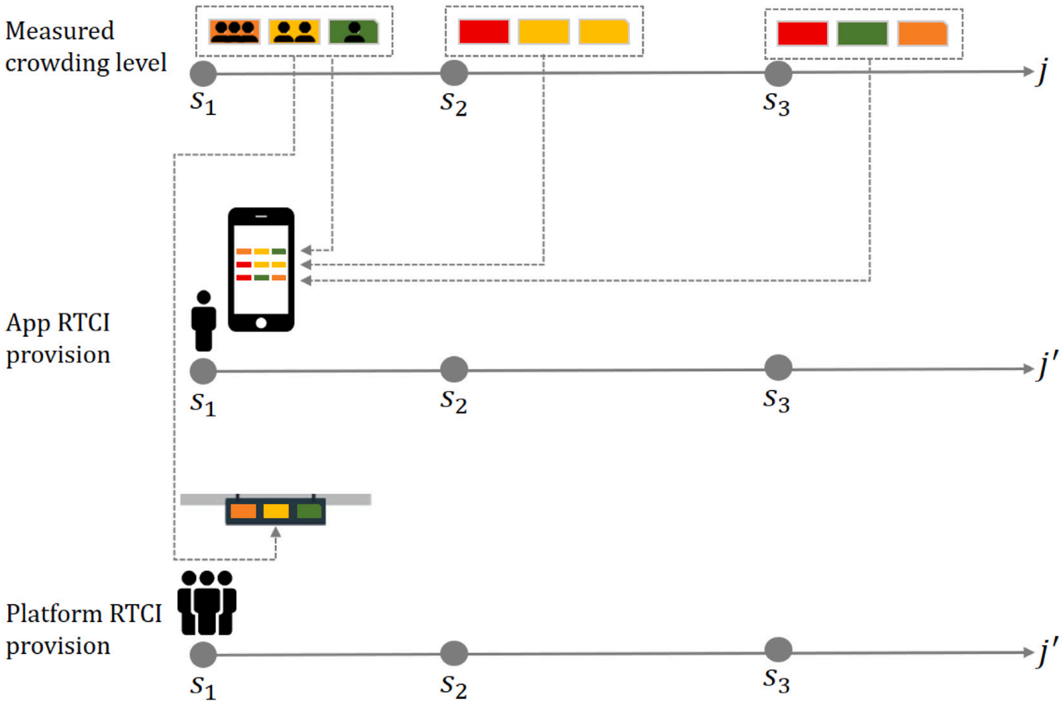


Fig. 1. RTCI provision schemes. Crowding level is measured upon train trip j departure from each stop s. The crowding information for trip j' is based on the measured crowding of the most recent trip j. The app-based scheme provides the RTCI for each stop along the passenger's path alternative. The platform-based scheme provides the RTCI on-board train trip j' at the passenger's boarding stop.

Larger values of this metric correspond to a greater unevenness of the on-board passenger load distribution. This metric is based on the total passenger load in the train and does not give any information about the mid-loaded cars of the train. For instance, a change in the unevenness by 1% point on-board a train with a total passenger load of 100 passengers, represents a change in the difference between the most and least crowded cars by 1 passenger. This does not imply that only one passenger adapts their car choice since the metric lacks information about how the passenger load in the mid-loaded cars changes.

2.3.2. Generalized travel cost

The generalized travel cost reflects passengers' overall travel experience. It is defined as the weighted sum of all the experienced travel path attributes, i.e. in-vehicle, walking and waiting times as well as the number of transfers. The same weights as used in the passenger choice model, as presented in Section 2.1, are used also for the performance evaluation. Based on the time valuations reported in the literature, walking and waiting times are valued as twice the value of in-vehicle time in uncrowded conditions, while the transfer penalty is valued five times the in-vehicle time and they are set to: $\beta^{inv} = -1$, $\beta^{walk} = \beta^{wait} = 2 \cdot \beta^{inv} = -2$, $\beta^{transfer} = 5 \cdot \beta^{inv} = -5$ (Wardman, 2004).

The nominal in-vehicle time is weighted with the valuation of in-vehicle time and the crowding factor to reflect the on-board discomfort. Crowding factors values for the seated passengers range from 0.95 to 1.71 when the ratio of car occupancy to the car seated capacity increases from 50% to 200%. Standing passengers are assigned with crowding factors between 1.78 and 2.69 that are only considered when all seats are occupied (Wardman and Whelan, 2011).

3. Application

3.1. Study area

To evaluate the effects of RTCI, we apply the proposed modeling framework to the case study of the metro network in Stockholm, Sweden, which consists of seven lines (Fig. 2). More than 1 million passengers use the Stockholm metro every day. Although passenger loads almost reach capacity during peak hours, passengers are often unevenly distributed among train cars and thus, trains are underutilized; on average, 40% of the metro train seats remain empty during morning peak hours (SL, 2019). The average share of empty seats upon train trip departure from a stop during the morning peak period in the absence of crowding information using the simulation approach presented in Section 2.1 is shown in Fig. 3. Even when passenger loads exceed the total seated capacity of 378 for the train as a whole, there are still seats that remain empty in individual cars. This demonstrates the consequences of an uneven distribution of the passenger load resulting in inefficient seated capacity utilization of the metro trains.

Fig. 2. Stockholm metro network. Encircled are the metro stations with the most uneven distribution of boarding passengers.

The case study application includes 210 stops (i.e. metro rail platforms) situated in 100 stations, timetables and walking links between platforms, as well as walking links between sections of the platform. The metro operations and the passenger demand are simulated for the morning rush hour (06:00–09:00 am), during which the metro trains operate with a high-frequency service and a planned headway of 5 min per line. In total, the stops are served by 504 vehicle trips in the morning rush hour. The trains that serve the stops are composed of three train cars; each car has a seated capacity of 126 seats and a total capacity of 414.

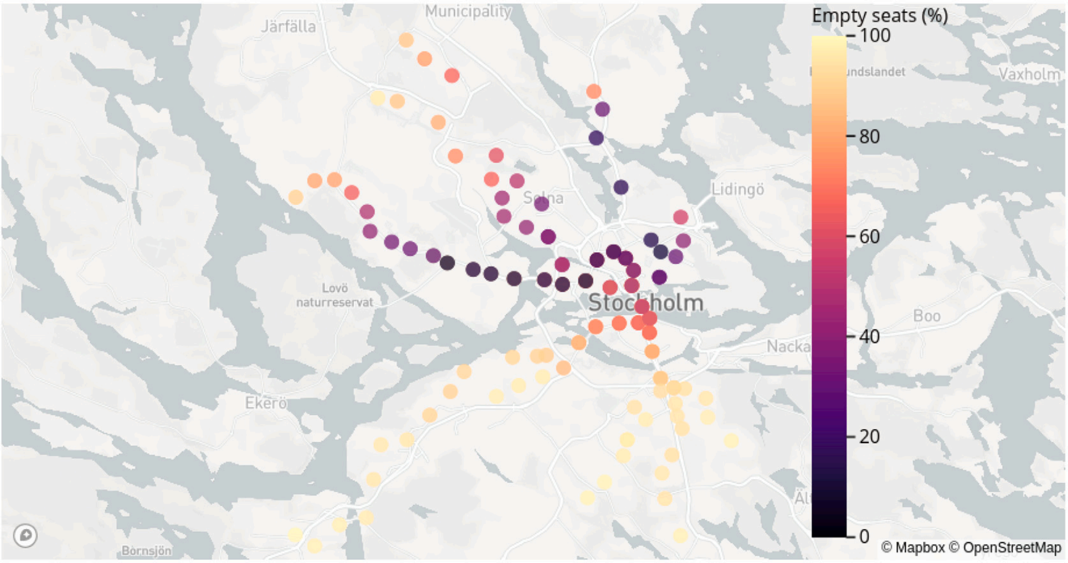
The transit network is simulated with the baseline average morning peak hour passenger demand of October 2016 which includes around 95 thousand passenger trips per hour. The station-to-station demand is estimated based on smartcard tap-in transactions (Kholodov et al., 2021). For each origin–destination pair, the probability that a passenger starts and ends the trip at a certain section of the platform at the origin and destination, respectively, is estimated based on observed entering and outgoing passenger flows at each station entrees.

3.2. Scenarios design

To evaluate the effect of providing RTCI on passengers' travel behavior, car boarding choices and passengers' generalized travel cost, the case study considers three schemes of RTCI provision:

(1) **No RTCI scenario**, where passengers have no access to car crowding information, making travel choices expecting uncrowded conditions in each train car.
(2) **App RTCI scenario**, where passengers have remote access to car crowding information along a path alternative through, for example, mobile apps or other devices.
(3) **Platform RTCI scenario**, where passengers are provided with car crowding information upon train departure from the boarding platform. The information is available through displays on the station platforms.

Previous studies have found limited passengers' attention to the available crowded information. In particular, only 25% of the passengers noticed and considered the provided RTCI in a pilot study in the Stockholm metro network (Zhang et al., 2017). For this reason, to explore the RTCI effects in relation to passengers' attention to the information, we consider sub-scenarios for the app-based RTCI provision, varying the share of passengers that utilize the available crowding information (i.e. 25%, 50%, 75%, and 100%) in their decision-making process.



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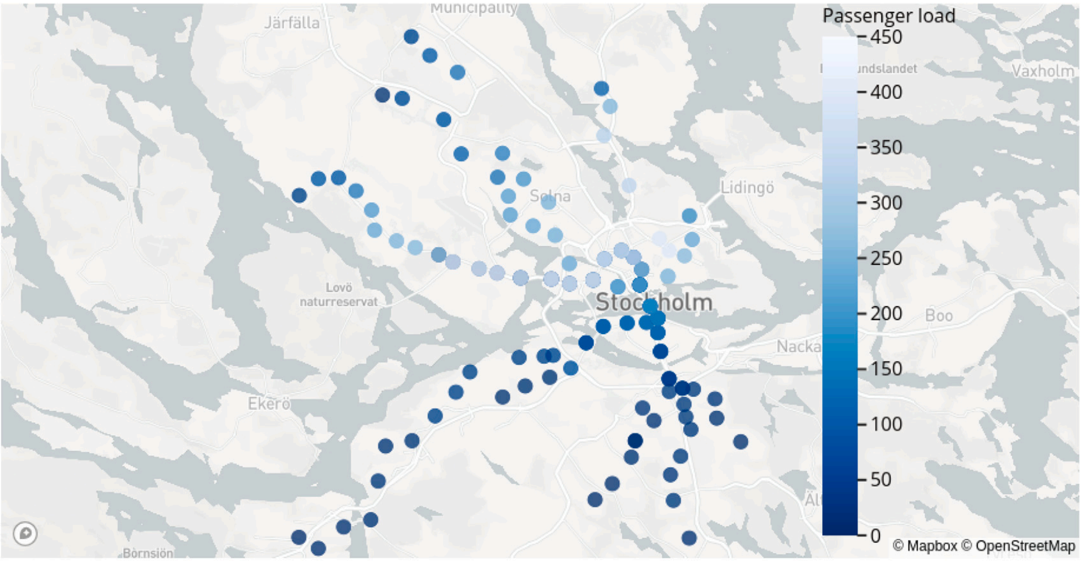


(b)

Fig. 3. (a) Average share of unoccupied seats (%); (b) Average on-board passenger load; in the southbound direction based on outputs of the train-car path choice modeling in BusMezzo.

For the platform RTCI provision, two scenarios are considered; in the first, the RTCI system is available at all metro platforms; in the second, only at platforms of the 10 most heavily loaded metro stations with the largest unevenness of boarding passengers distribution (Fig. 2). The latter is motivated by our expectations that the skewness of the distribution will result in a larger impact of the RTCI provision system. Thus, implementing the RTCI system at only 10 stations can potentially result in large benefits for the passengers at a lower total installation cost.

Passengers are assumed to expect relatively uncrowded conditions (i.e. no difference between perceived and nominal in-vehicle time) in the event that no RTCI is available.

For each scenario, 100 simulation runs were conducted for a one-hour period. Given significance level and allowed error of 5%, this number of replications was found to be sufficient for allowing statistically significant stability for the average generalized travel cost per passenger among the runs.

4. Results

4.1. RTCI effect on passenger crowding unevenness

Utilization of app-based car-specific RTCI by all passengers results in a more even passenger distribution, i.e. lower δ_{js}, inside metro trains in Stockholm in relation to the No RTCI scenario. Fig. 4 illustrates the average effect of RTCI on on-board crowding unevenness per metro stop. The availability of crowding information leads to lower crowding unevenness on-board trains departing from the most heavily loaded stops — those located upstream of the city center. This can be explained by the heavy passenger loads traveling towards central stops during the morning peak hour. On average, on-board crowding unevenness decreases by 0.4 and 1.6 percentage points on trains traveling southbound (Fig. 4(a)) and northbound (Fig. 4(b)), respectively. When RTCI is provided, passengers are informed about the expected crowded conditions along the path alternatives and this influences their car boarding choices. As a result, in anticipation of on-board crowding passengers choose to board less crowded train cars which leads to better train capacity utilization.

Importantly, RTCI affects not only the "local" car boarding choices but also influences under some circumstances the "global" path choices. Fig. 5(a) demonstrates an example of how passengers' transfer decisions are influenced by the availability of crowding information. With the availability of app-based RTCI, passengers incorporate the expected crowding on-board vehicles departing at alternative transfer stops. In the presence of app-based crowding information (assuming that 100% of the passengers comply with the information), passengers can make more informed decisions about where exactly to transfer between (possibly even alternative) lines. In particular, of those transferring to stops served by the northbound direction of the green line, 8% more passengers choose to alight at the T-centralen stop where departing trains are on average less crowded compared to the upstream transfer alternatives (Fig. 5(b)).

4.2. RTCI effect on passengers' generalized travel cost

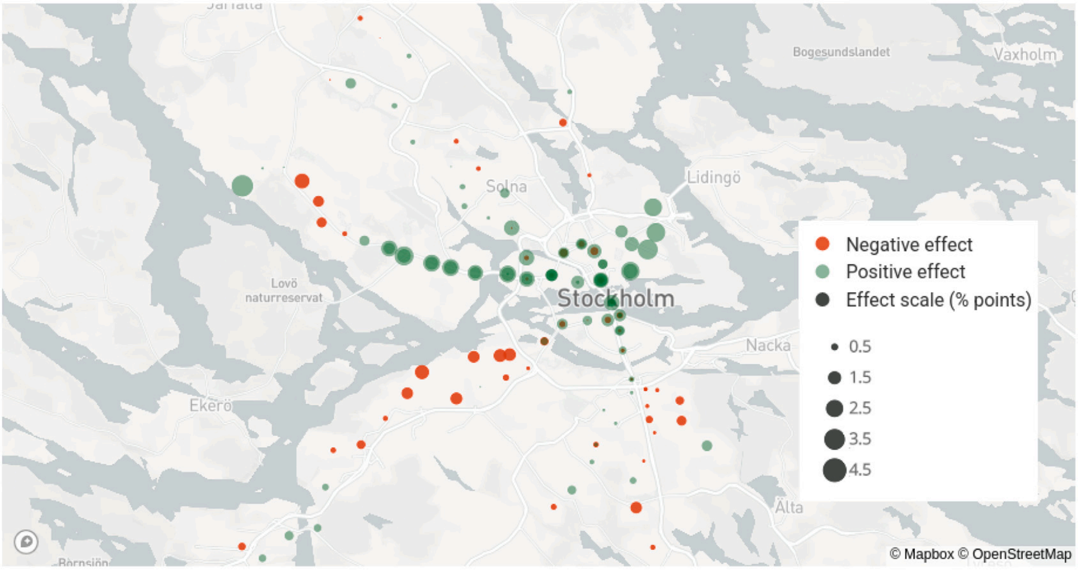
The effect of providing car crowding information on the savings in passengers' travel cost components is shown in Fig. 6(a). Compared to the No RTCI scenario, the provision of RTCI results in savings in total passenger perceived in-vehicle time. This stems from passengers' adjusted car boarding choices that lead to a more even passenger distribution on-board trains and hence, improvements in on-board travel comfort experienced by passengers. The benefits were observed to grow with the share of passengers responding to the available app-based RTCI. In particular, the total passenger perceived in-vehicle time drops by more than 185 pass-hrs over one simulation hour for 100% passenger compliance with the available app-based information. This translates into a decrease of the total passenger perceived in-vehicle time by 0.7%. A t-test showed that these in-vehicle time savings are statistically significant at the 5% significance level. This amounts to annual savings in perceived in-vehicle time of 52 min per passenger, considering a daily round-trip.

In the presence of app RTCI provision, passengers' adjusted car boarding choices translate into improved on-board comfort at the cost of increased walking times. The total walking time increases by 101 pass-hrs when all passengers incorporate the available app-based information in their decision-making process. This finding shows that passengers opt for walking more in anticipation of reduced on-board crowding and an overall reduction in their generalized travel cost. However, there is a discrepancy between passengers' anticipated and experienced travel cost due to the absence of demand-anticipatory capabilities of the RTCI provided. As a result, the utilization of app RTCI by 50% of the passengers results in the largest passengers' generalized travel time savings (Fig. 6(b)). We performed t-tests to investigate the statistical significance of the effect of RTCI provision on passengers' travel cost, finding that the effect of app RTCI is statistically significant at the 5% significance level.

Platform RTCI provision at all metro stops reduces total passenger perceived in-vehicle time by 0.4% which equals 110 pass-hrs over one simulation hour. This amounts to annual savings in perceived in-vehicle time of 34 min per passenger, considering a daily round-trip. Interestingly, providing the platform RTCI system only at the stops with the most uneven distribution of boarding passengers, as shown in Fig. 2, results in in-vehicle time savings that are on-par with those attained when equipping all stops with information displays (Fig. 6(a)). This shows that passengers, making boarding decisions at stops where departing trains are expected to be heavily loaded and on-board crowding is expected to be highly uneven, have larger motivation for adapting their boarding choices. As a result, more people adapt their choices on busy stations and thereby, more people on-board crowded trains are affected, leading to larger RTCI impacts. Although the RTCI impact on passenger discomfort is similar for the two platform RTCI provision scenarios, the total savings in generalized travel cost when providing the information at the 10 selected stations are twice the savings attained when all stops provide RTCI (Fig. 6(b)). The impact of the platform RTCI provision system at 10 stations on the total travel cost is statistically significant at the 10% significance level. Also in the case of platform displays, there is a potential discrepancy between what passengers anticipate and what they finally experience. This can be explained by the fact that the information provided through displays on platforms is not representative for all the downstream trip segments.

4.3. Crowding information at the car level vs train level

In contrast to the car-level information system, which provides information on the crowding level of individual train cars, a train-level RTCI system provides crowding information at the vehicle level, assuming even on-board crowding distribution among train cars. This assumption might underestimate passengers' expected experience of crowding, leading to lower motivation for passengers to alter their travel choices and thereby lower impact of RTCI on passengers' travel cost. Moreover, the train-level RTCI system gives



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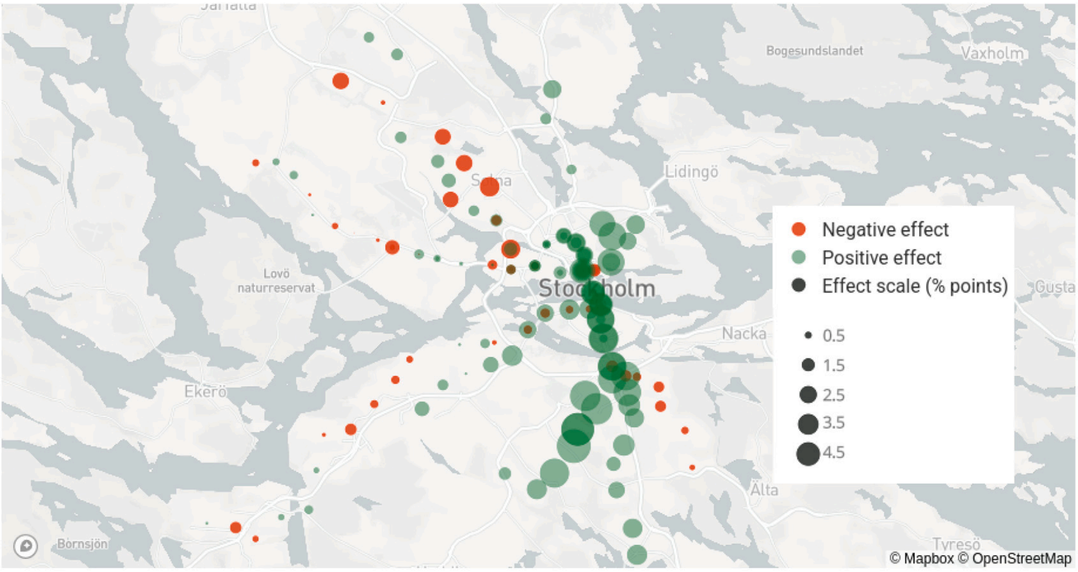


(b)

Fig. 4. Average app-based RTCI (100% passenger response rate) impact on crowding unevenness on-board trains heading: (a) southbound; (b) northbound; compared to the No RTCI scenario.

no motivation to passengers to walk to another train car, which is expected to result in lower impact of the information provision system regardless of the crowding level. Fig. 7 compares the impact of car-level and train-level RTCI on passengers' travel cost. On average, the total savings in generalized travel costs attained by the provision of RTCI drop by 76% when information is provided at the train level instead of the car level. T-tests show that the effect of train-specific crowding information provision is not statistically significant at the 5% significance level.

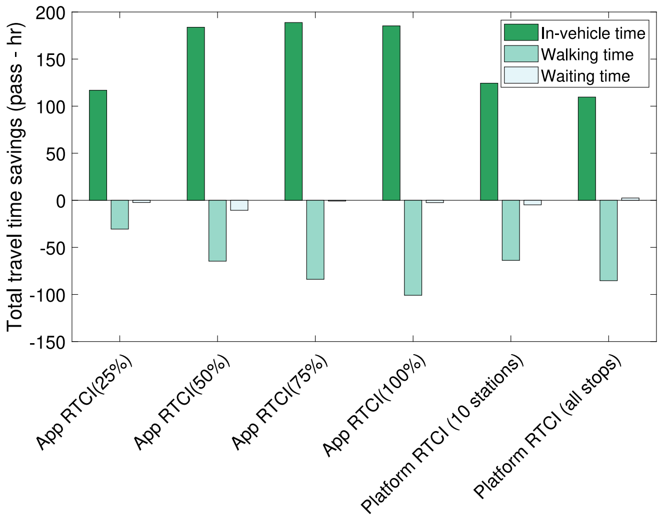
4.4. RTCI effect with respect to demand level

The adaptation of passengers' car choices and their effect on experienced discomfort are highly influenced by the on-board crowding conditions. Thus, the efficacy of RTCI systems is expected to be sensitive to the network demand level. In low crowding conditions, RTCI system is expected to have low impact on passengers' experienced crowding, since passengers make car choices

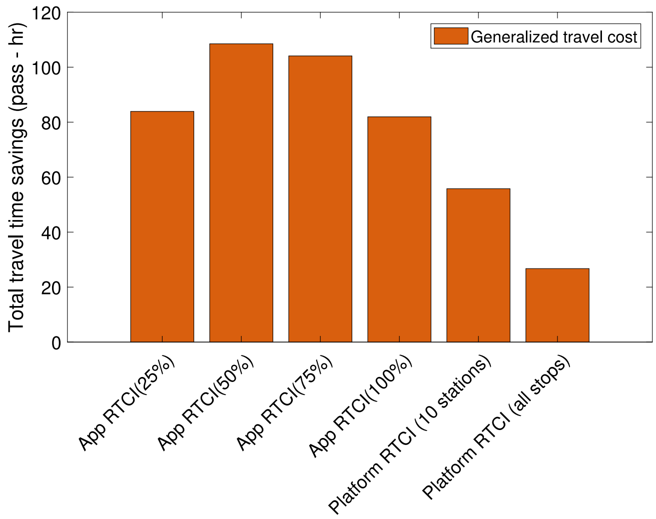
Fig. 5. (a) Impact of app-based RTCI (100% passenger response rate) on the frequency of transfer stop choices on the northbound green metro line segment, between Slussen and T-centralen stations, compared to the No RTCI scenario; (b) Average on-board passenger load upon train departure from a stop. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

not necessarily for avoiding crowding. In overcrowding conditions, all train cars are expected to be heavily loaded and thereby, passengers' adjusted car choices might result in little or even counter-productive effect. Thus, the RTCI provision effect can potentially be larger in moderately crowded conditions. For this reason, we investigate the impact of crowding information under various network demand levels.

Fig. 8 demonstrates how network demand level affects the impact of app-based RTCI on the average time savings per passenger, assuming that all passengers comply with the available information. We find that the walking time savings decrease with increasing demand level. Due to higher expected on-board crowding, passengers opt to alter their car choices and, hence, they choose to walk more. The savings resulting from RTCI peak for 120% of the current demand level in the case study network, where an average passenger perceives in-vehicle time as 15 s shorter. In this crowded situation, savings in waiting time are attributable to the trade-offs between walking and waiting time. For demand level larger than 120%, the RTCI impact drops since the network is already



(a)



(b)

Fig. 6. RTCI impact on average savings in: (a) total passenger generalized travel cost components; (b) total generalized travel cost; over one simulation hour compared to the No RTCI scenario.

oversaturated, and the majority of the line segments experience high crowding level, hence passengers cannot gain from changing their choices.

5. Discussion and conclusion

This study contributes to the assessment of car-specific real-time crowding information (RTCI) systems, providing a travel behavior model that represents the changes in passengers' travel choices in response to train-car crowding information. We proposed a modeling framework that includes passengers' access to RTCI in the decision-making process and evaluates the effects of information provision on passengers' car choices and travel cost. The crowding level in individual train cars is measured every time the train departs from a stop. This crowding information is then made available to passengers either through smartphones or displays at station platforms. Passengers incorporate the available information when making travel decisions. In other words, in the presence of crowding information, passengers consider the trade-offs between the expected walking and in-vehicle crowding, representing a behavioral trade-off, aiming to minimize their expected total travel cost.

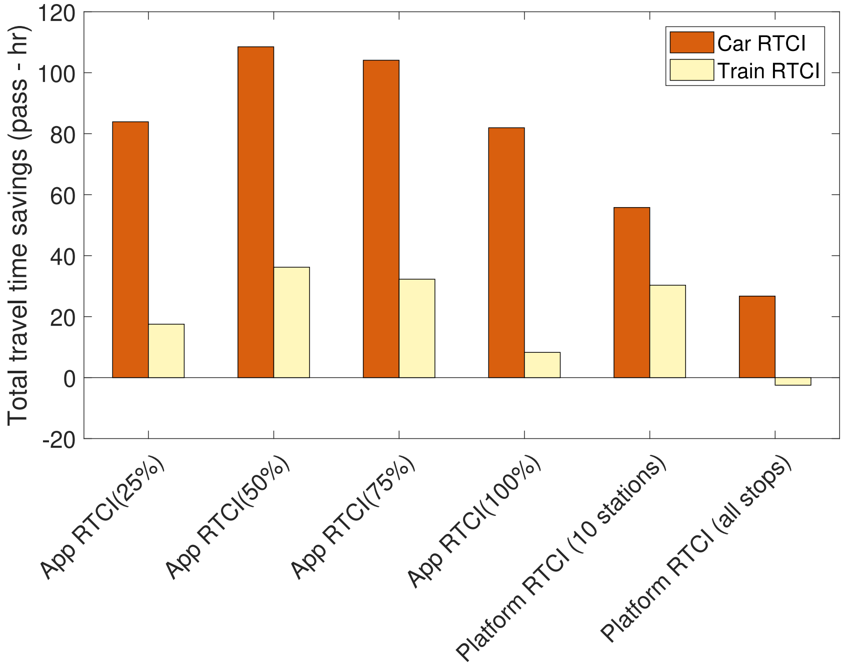


Fig. 7. RTCI impact on average savings in total generalized travel cost over one simulation hour with respect to the level of crowding information. No RTCI is the reference scenario.

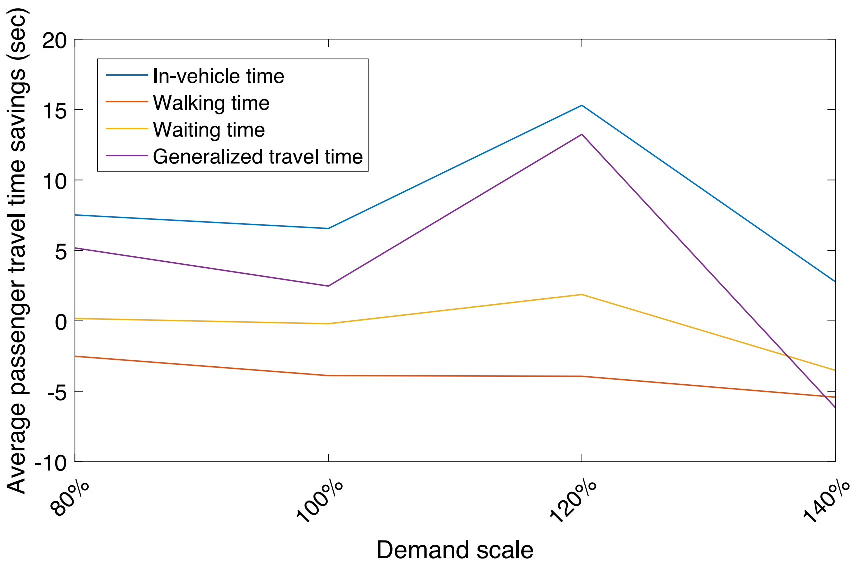


Fig. 8. Impact of app-based RTCI (100% passenger response rate) on average savings in generalized travel cost components per passenger over one simulation hour compared to the No RTCI scenario for different demand levels.

The model was used as an evaluation tool for the Stockholm metro network. The results indicate that in the presence of car-specific crowding information, passengers make car choices aiming to save crowding across and within Stockholm metro trains. These results are consistent with the findings of an empirical study by Zhang et al. (2017) who tested the effect of providing real-time car crowding information at a metro station in Stockholm, finding that the information provided has a statistically significant impact on passengers' car boarding choices. In particular, the simulated effect of the crowding information provision on the share of passengers choosing the most crowded train car is consistent in direction and magnitude with the results of the aforementioned empirical study, offering support for the validity of our model which can be applied to a large variety of scenarios. In other words, passengers alter their car boarding choices in anticipation of high on-board crowding, making trade-offs between walking and on-board comfort, aiming to improve their overall travel cost, in line with results reported by Pownall et al. (2008) and Kim et al.

(2015). Apart from shifts to less crowded cars, RTCI encourages flow shifts to less crowded routes. In particular, having access to RTCI, passengers make transfers at less crowded stops served by the same transit lines.

Moreover, the results indicate savings in the total passenger travel cost as a result of the more even crowding distribution. In particular, the simulated RTCI provision schemes result in annual savings in perceived travel cost that range between 10 and 33 min per passenger, considering a daily round-trip. However, the number of passengers complying with the information affects the accuracy of passengers' expectations. The RTCI system has the largest impact on passengers' travel experience when only half of the passengers utilize the available information provided through apps. This is explained by the discrepancy between expectations and experience when all passengers adapt their car choices since the model lacks demand-anticipatory capabilities.

According to Cantwell et al. (2009) and Batarce et al. (2016), passengers experience higher discomfort in high-density scenarios and when there are no available seats or there is a risk of failing to board the train. In line with this, the impact of RTCI on passengers' travel cost is found to depend on the crowding across the network. In oversaturated conditions, information provision can be counter-productive due to larger passenger volumes and a higher risk of denied boardings.

Adaptation of travel decisions in the presence of crowding information critically depends on how passengers value crowding. Valuation of crowding has been traditionally based on stated-preference studies (Wardman and Whelan, 2011). More recently, the availability of smart card data has enabled estimating crowding valuations based on revealed-preference data (Yap et al., 2018). The results of the latter suggest that choice experiments might overestimate the crowding valuations. The aforementioned revealed-preference study reflects the impact of crowding on passengers' actual choices and estimated in-vehicle time multipliers that are much lower than the ones reported by Wardman and Whelan (2011). Thus, the overall impact of crowding information provision systems is sensitive to passengers' tolerance of crowding. There are also indications that the perceptions of on-board crowding have significantly changed during the COVID-19 pandemic crisis (Shelat et al., 2022b,a) although it remains to be seen whether these changes in perceptions will persist.

The methodology presented and the results are of value for public transport agencies and operators in order to increase the attractiveness and capacity utilization of public transport. The developed simulation model facilitates the further design, analysis and assessment of novel RTCI systems, allowing for measuring the effectiveness of such implementation under various scenarios and what-ifs prior to field implementations. Particularly, the way crowding information is distributed, the added value of improved information accuracy due to different provision schemes, the share of users that should be exposed to RTCI as well as the different crowding level display schemes can be tested and evaluated in order to offer an overall assessment of RTCI as a crowding management measure. Pioneering deployments of real-time crowding information provision systems enable complementary future empirical research, allowing for measuring passengers' response to information and thereby supporting model calibration and validation.

In the following, we highlight potential applications of RTCI systems. Passengers' tolerance of crowding on-board public transport vehicles is much lower due to the COVID-19 pandemic, while this situation might be sustained even in the post-pandemic period. Thus, more passengers are expected to be willing to adjust their travel choices, seeking crowding information (Tirachini and Cats, 2020). However, the reliability of the crowding information might be hindered by passengers' over-response. The proposed model can be used to assess the RTCI system, based on passengers' response rate, as an investment for mitigating on-board crowding unevenness and reducing the contagion risk under various demand scenarios. Moreover, in-vehicle crowding and in particular the unevenness of crowding has negative effects on the reliability and performance of the public transport system. The proposed framework can be used as a support tool for applications that can improve incident management in public transport systems.

In the proposed framework, we assume that passengers are unfamiliar with the public transport system and do not have prior experience of on-board crowding conditions and thus, they form expectations of crowding based solely on the provided information. Inexperienced passengers are expected to be more willing to seek information and adapt their path choices in the absence of past experience to rely on. In contrast, experienced passengers add value to the provided information on a day-to-day basis based on the credibility of the information. Future behavioral research may examine how experienced passengers form expectations of on-board crowding conditions in the presence of real-time information. Furthermore, passengers may consider the reliability and demand-anticipatory aspects of such information as part of their decision-making process.

Another direction for future research pertains to the generation of real-time crowding information. Real-time information – in reality as well as the one generated by the simulation – is based on current and historical data. Consequently, crowding information provided to passengers in the simulation model is based on predictions that might be subject to errors as a result of uncertainty and variations in supply and demand. This results in inevitable deviations between the experienced crowding in the simulation and the previously provisioned information. This has been analyzed in detail in relation to vehicle arrival time information in Cats and Gkioulou (2017) and Cats and West (2020). For instance, even though passengers utilize the available crowding information for each trip segment every time they choose their following action, i.e. boarding, alighting or walking, this information might be outdated by the time the passenger traverses the downstream trip segments. However, this reflects reality in situations where the train configuration does not allow movements between the individual train cars while traveling. To improve the accuracy of the simple prediction scheme specified in this study, a future direction may enhance the RTCI algorithm used to generate information by integrating the crowding level of several previous train trips to potentially provide higher accuracy of the provided information or possibly even introduce demand-anticipatory capabilities using a fixed-point problem formulation.

CRediT authorship contribution statement

Soumela Peftitsi: Formal analysis, Conceptualization, Methodology, Data curation, Writing – original draft. **Erik Jenelius:** Formal analysis, Conceptualization, Methodology, Writing – review & editing, Supervision, Project administration. **Oded Cats:** Formal analysis, Conceptualization, Methodology, Supervision, Writing – review & editing.

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