MODELLING THE EFFECT OF REAL-TIME CROWDING INFORMATION (RTCI) ON PASSENGER DISTRIBUTION IN TRAINS

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ABSTRACT
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 experience 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 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.

Keywords: Public transport, Real time crowding information, Passenger distribution
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 (1). There are often large variations in passenger loads among individual cars of multi-car vehicles (e.g. metro trains) even during peak hours TRB (2). Such an imbalance in passenger load distribution leads to even higher experienced discomfort and denied boarding incidents as well as larger fleet requirements to serve the demand. Public transport authorities and operators aim to reduce the crowding effects 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 providing information on crowding in individual train cars on passengers’ travel behaviour and their car boarding choices.

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 (3, 4). In particular, some passengers may choose alternative travel paths (5), while in high demand conditions they make trade-offs, choosing a less crowded train car (6, 7), to avoid on-board crowding effects.

Public transport assignment models, categorized into frequency-based and schedule-based, are widely used to model crowding at stations and on-board vehicles as well as its effects on passengers. Frequency-based models that account for passenger crowding-dependent travel cost and service capacity were presented in (8) and (9), respectively. Dynamic frequency-based approaches were introduced in (10) and (11), 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 presented in (12–15). Seat capacity constraints were considered in (16, 17) 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 in (18). In a recent study, we extended BusMezzo for evaluating the effect of passengers’ prior travel experience on their decision to board a specific train car (19).

Some studies have focused on proposing crowding management measures for improving capacity utilization and reducing the unevenness of passenger distribution inside the train. A model to determine the optimal train stop location at the station, aiming for a more even passenger distribution was presented in (20). Installing a gate on a crowded metro platform in Santiago, Chile, allowing only for one direction of passenger flows resulted in improved capacity utilization and service regularity (21).

Real-time information (RTI) systems are widely used for influencing route choices and improving the travel experience (22). The effect of RTI on passengers’ travel times was modelled in an agent-based public transport assignment model in (23), 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 (24). Until now, only a limited number of studies have examined the impact of RTCI. Survey data was used to model the effect of bus occupancy on passengers’ choices, showing that the probability of choosing a bus increases with the availability of empty seats (25). 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 (26). Using smartcard data, a transit assignment model that produces platform density and train occupancy and can provide on-board crowding information in real-time was proposed (27). 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 (28). Practical implementation of providing RTCI concerning the occupancy of individual train cars have been presented in London (29) and Sydney (30). This information is communicated to the passengers through on-board displays or at station platforms and is calculated by car weight data. Furthermore, a smartphone application is used in the Netherlands for providing train crowding information based on historical load observations (31).

There are only a few studies that proposed models for simulating the effects of RTCI. A transit assignment model for modeling the impact of real-time predictive information on path choices, travel times and vehicle crowding in a day-to-day learning process was presented in (32). 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 (33) to incorporate vehicle crowding information for evaluating its effects on passengers’ within-day path choices. Information is predicted based on the crowding of the latest vehicle trip and is provided through a four-level scale. The application of this model in BusMezzo to the urban public transport network in Krakow, Poland shows improvements in passengers’ travel experience. Using a fixed-point solution, an on-line simulation-based decision support platform that provides predictive information on crowding on platforms and trains was presented in (34). The information is provided through a three-level descriptive scale based on the train boarding likelihood. The results from an application of the model show a 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 does the provision of RTCI concerning on-board conditions on individual train cars impacts the level-of-service and passenger load distributions. 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 they have access to crowding information.
- Modelling 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 at the vehicle level are modelled 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.

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 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

3 Modelling passenger choices

Modelling 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 modelling individual passenger path decision making (35). The model simulates movements of individual transit vehicles, i.e. trains, and the decisions that individual passengers make. The capabilities of this model were extended in (19) to allow for modelling individual passengers’ car 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 passengers are not evenly loaded inside the train.

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 (19). We associate each path alternative \( a \) with a utility; the deterministic part of the utility of a feasible path \( a \) for passenger \( y \) \((y \in Y)\) is:

\[
v_{y,a} = \beta_{inv}^{y,a} t_{inv}^{y,a} + \beta_{wait}^{y,a} t_{wait}^{y,a} + \beta_{walk}^{y,a} t_{walk}^{y,a} + \beta_{transfer}^{y,a} N_{transfer}^{y,a} \quad \forall y \in Y, a \in A^{od}
\]

where \( t_{inv}^{y,a} \) is the expected total perceived in-vehicle time, \( t_{wait}^{y,a} \) is the expected total waiting time, \( t_{walk}^{y,a} \) is the expected total walking time, including within-station walking time at the origin, transfer and destination station, \( N_{transfer}^{y,a} \) is the number of transfers included in the path alternative, \( \beta \)'s are the corresponding utility function coefficients and \( Y \) is the set of all passengers. Walking and waiting times are weighted with the corresponding user-specific parameters for walking \( \beta_{walk} \) and waiting time \( \beta_{wait} \), 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 \( \beta_{inv} \), which reflects the value of uncrowded in-vehicle time, and a crowding factor, depending on the ratio of car occupancy to the seated capacity and whether this passenger has a seat or not (36). In BusMezzo on-board passengers have priority to get a seat and there are standing passengers only when all seats are occupied (18).

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, i.e. passengers aim to minimize 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:

\[
u_{y,c} = \ln \sum_{a \in A^{cd}} e^{v_{y,a}}
\]

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

\[
P_{y,c} = \frac{e^{u_{y,c}}}{\sum_{c' \in C} e^{u_{y,c'}}}
\]
Transit route choice might violate the property of the multinomial logit (MNL) model which 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 (23, 38). 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.

Modelling 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 the capacity). We follow the approach proposed in (33) for including access to RTCI in passengers’ 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 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 each time the passenger chooses the next path element $c$, i.e. walking to a platform section, boarding a specific car of the train or alighting from a train car. Thus, the expected in-vehicle travel time $t_{y, a}^{inv}$, included in Equation 1, is weighted by both the expected car crowding factor and the corresponding in-vehicle time valuation $\beta_y^{inv}$. As a result, the expected in-vehicle time differs for each car of the train.

We model two different schemes for providing RTCI, app-based and platform-based (Figure 1). The app-based RTCI system, available through smartphones or other devices, provides passengers with 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

<table>
<thead>
<tr>
<th>RTCI level</th>
<th>Car capacity utilization</th>
<th>Crowding factor</th>
</tr>
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<tbody>
<tr>
<td>&lt;= 80% seated capacity</td>
<td>&lt;= 80% seated capacity</td>
<td>1.0</td>
</tr>
<tr>
<td>&gt;80% seated capacity</td>
<td>&lt;= 100% seated capacity</td>
<td>1.3</td>
</tr>
<tr>
<td>&gt;100% seated capacity</td>
<td>&lt;= 50% total capacity</td>
<td>1.5</td>
</tr>
<tr>
<td>&gt;50% total capacity</td>
<td>&gt;50% total capacity</td>
<td>1.8</td>
</tr>
</tbody>
</table>
FIGURE 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.

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.
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 distribution of passenger load among the cars \( i \in I \) of a train trip \( j \) when it departs from stop \( s \), using the ratio of the difference in on-board passenger load between the most and the least crowded cars \( \delta_{js} \) to the total on-board passenger load in train trip \( j \).

\[
\delta_{js}(\%) = \frac{\max_{i=1}^{I} q_{ij} - \min_{i=1}^{I} q_{ij}}{\sum_{i=1}^{I} q_{ij}} \times 100 \quad (4)
\]

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

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 3.1, 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: \( \beta_{\text{inv}} = -1, \beta_{\text{walk}} = \beta_{\text{wait}} = 2 \cdot \beta_{\text{inv}} = -2, \beta_{\text{transfer}} = 5 \cdot \beta_{\text{inv}} = -5 \quad (37) \).

The nominal in-vehicle time is weighted with the valuation of in-vehicle time and the crowding factor to reflect the on-board experienced 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 (36).

APPLICATION

Study area

To evaluate the effects of RTCI, we apply the proposed modeling framework to the case study of the metro network in Stockholm, which consists of seven lines (Figure 2). More than 1 million passengers use the Stockholm metro every day. Although passenger loads are close to capacity during peak hours, passengers are often unevenly distributed among train cars; on average, 20% of the seats remain unoccupied during the morning rush hour (39). 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 3.1 is shown in Figure 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 an inefficient seated capacity utilization of the metro trains.

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 it operates with a high frequency service and a planned headway of 5 minutes 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 sitting 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
FIGURE 2 Stockholm metro network. Encircled are the metro stations with the most uneven distribution of boarding passengers.

passenger trips per hour. The station-to-station demand is estimated based on smartcard tap-in transactions (40). 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.

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
FIGURE 3 (a) Average share of unoccupied seats (%); (b) Average on-board passenger load; on the southbound direction based on output of the car modelling simulation model.

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 (Figure 2). The latter is motivated by our expectations that the skewness of the distribution will result in a larger impact of the RTCI system. Thus, implementing RTCI system at only 10 stops can potentially result in large benefits for the passengers at a lower total installation cost.

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 generalized travel cost per passenger among the runs.

RESULTS

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 $\delta_{js}$, inside metro trains in Stockholm in relation to the No RTCI scenario. Figure 4 illustrates the average effect of RTCI on on-board crowding unevenness per metro stop. The availability of crowding information leads to a positive effect on 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 travelling 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 travelling 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 crowded conditions passengers choose to board less crowded train cars which leads to a better train capacity utilization.

Importantly, RTCI affects not only the “local” car boarding choices but also influences under some circumstances their “global” path choices. Figure 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 100% of the passengers complying 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 (Figure 5(b)).

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 Figure 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 as a result, improvements of 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.

In the presence of app RTCI provision, passengers’ adjusted car boarding choices translate into improved on-board experience at the cost of increased walking times. The total walking time
FIGURE 4 Average app-based RTCI impact on crowding unevenness on-board trains heading: (a) southbound; (b) northbound; with 100% passenger response rate compared to the No RTCI scenario.

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 lowest passengers’ travel cost (Figure 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%
Platform RTCI provision at all metro stops reduces total passenger perceived in-vehicle travel time by 110 pass-hrs. Interestingly, providing platform RTCI system only at the stops with the most uneven distribution of boarding passengers, as shown in Figure 2, results in in-vehicle time savings that are on-par with those attained when equipping all stops with information displays (Figure 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,
FIGURE 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.

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 experienced 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 when all stops provide RTCI (Figure 6(b)). The impact of platform RTCI provision system at 10 stations on total travel cost is statistically significant at the 10% significance level. Also in the case of platform displays, there is...
FIGURE 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.

...
FIGURE 8 App-based RTCI impact on average savings in generalized travel cost components per passenger over one simulation hour compared to the No RTCI scenario for different demand levels. A 100% passenger response rate is assumed in these scenarios.

**RTCI effect with respect to demand level**

Passengers’ adapting car choices and their effect on experienced crowding are highly influenced by the on-board crowding conditions and as a result, 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 not necessary 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. Figure 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 cost decreases with the demand level. Due to higher expected on-board crowding, passengers opt to alter their car choice 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 15 seconds 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 oversaturated, and the majority of the line segments experience high crowding level, hence passengers can not gain from changing their choices.
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.

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 in an empirical study at a metro station in Stockholm that tested the effect of providing real-time car crowding information, finding that the information provision has a statistically significant impact on passengers’ car boarding choices (28). 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 (6) and (5). Apart from shifts to less crowded cars, RTCI is found to encourage flow shifts to less crowded routes. In particular, having access to RTCI, passengers were found to make transfers at less crowded stops served by the same transit lines. Moreover, the results indicate savings in 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 total passenger travel cost that range between 6.5 and 26 thousand passengers hours. 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 (41, 42). Access to RTCI at the train level results in lower improvements in passengers’ generalized travel cost, compared to the car-specific RTCI. Finally, the impact of RTCI on passengers’ travel cost depends on the crowding across the network. In oversaturated conditions, information provision can be counter-productive due to larger passenger volumes and higher risk of denied boardings.

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 tool can support the further development of RTCI systems, allowing for measuring the effectiveness of such implementation under various provision strategies. 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. In the following, we highlight potential applications of RTCI systems. Passengers’ tolerance to 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 (43). 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 public transport. 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 knowledge of on-board crowding conditions and thus expect an even distribution of passengers across train cars. Future behavioral research may examine how experienced passengers form expectations about 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. The simulation model implementation is currently limited to providing crowding information that is based on the most recent train trip. This might lead to low accuracy of crowding predictions and, as a result, passenger’s crowding expectations might deviate from the crowding they eventually experience. Another future direction should include an extension of the RTCI algorithm to generate the information considering the crowding level in several previous train trips to provide higher accuracy of the provided information or possibly even introduce demand-anticipatory capabilities using a fixed-point problem formulation.

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