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Integrating COVID-19 health risks into crowding costs for transit schedule planning

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ABSTRACT
The public transport sector worldwide experienced the worst impact in recent history, in terms of ridership loss, due to the COVID-19 pandemic. The pandemic negatively affected passengers’ perceptions of public transport and is likely to make a lasting impact on ridership, trip patterns, and modal share. Without any supportive changes to transit operations, ridership is likely to decline. This study explores the setting of frequencies in transit lines and proposes a two-part methodology that addresses the changing perceptions of users, especially in a health-related context. The first part develops a mathematical model that expresses the pre-COVID-19 cost of passenger crowding as an integral part of user costs to determine the optimal headway that considers the trade-offs between user and operator costs. A continuum approximation for the demand of the bus line has been used in the derivation. The second part extends the developed model to include both the costs of the health risks associated with the COVID-19 pandemic and crowding. The developed models will help transit planners and operators to plan and adapt operations to changing health risks during the pandemic and post-pandemic. Several numerical examples are provided to describe the uses and applications of the analytical models using information obtained from the literature.

1. Introduction

The rapid spread of COVID-19 had profound effects on the lives of people worldwide. The World Health Organization (WHO) declared COVID-19 a pandemic on 11th March 2020 (WHO 2020). Among the steps taken to curb the spread of COVID-19, social distancing measures and travel restrictions had a detrimental effect on the public transportation (PT) sector. Fear of contamination from exposure to other people, along with government restrictions, resulted in a plunge in PT demand of 70%-90% (UITP 2020). The loss of PT demand can mostly be attributed to reduced travel demand resulting from a combination of public health restrictions, working from home, online schooling, shift to online shopping, transit service cuts, and loss of employment. PT as a mode absorbed some of the most adverse effects (Tirachini and Cats 2020). The coronavirus pandemic may prove to be a catalyst for long-term changes in trip making behaviour. Many people might continue to work remotely, at least part time, which means travelling to work fewer days per week. In addition, because of passengers’ concerns about PT hygiene (Beck and Hensher 2020a) and their reluctance to use transit (Labonté-Lemoyne et al. 2020), there is a risk of significantly low PT ridership levels even in the aftermath of the pandemic.

The negative impacts of reduced PT demand are widespread. While it directly impacts transit agencies, it will have a ripple effect on several layers of society. Revenue loss due to lower ridership reduces a transit agency’s capability to provide the same service levels. This revenue loss therefore results in reduced frequency and time span of service, which are evident during and after lockdowns due to COVID-19 (Gkiotsalitis and Cats 2020). Cuts to service adversely affect the quality of service offered, leading to even lower demand. This downward spiral trend will crucially affect social equity and deprive parts of some communities of their accessibility and mobility needs that could not be otherwise met for seniors, school children, essential workers, and other segments of the population. The resulting shift away from transit also leads to increased passenger car use, which creates other problems, such as increased greenhouse gas (GHG) emissions, traffic accidents, fuel costs, and traffic congestion (Eboli and Mazzulla 2007). The importance of preventing transit demand and mode share degradation during the phased reopening of the economy and the aftermath of the pandemic is evident.

Transit agencies face many challenges in adapting their services while considering COVID-19 health risks and the changes in transit
demand levels. Although the economy will eventually reopen from lockdown, it will go through many hiccups because reopening will be affected by the penetration rate of COVID-19 vaccines and the variants of the virus that might cause further waves of spread. Therefore, for a given community, the state of the pandemic has been dynamic and uncertain. Because of the lack of useful decision support tools to help redesign services in times of dynamic uncertainty, transit agencies have resorted to ad-hoc measures (Gkiotsalitis and Cats 2020). To accommodate reduced demand due to COVID-19, most transit agencies have responded by cutting services and operating on reduced schedules and capacities. Such cuts in service cause a further downward spiral in transit demand (Tirachini and Cats 2020). While fare revenue is reduced, unit operating cost has increased because of the need to address varying health safety measures and social distancing guidelines.

The interest of this study is the science of qualitative interrelations between variables for frequency setting amidst COVID-19. This paper revisits the optimum headway problem and considers crowding in conjunction with the issues of public health, quality of service, capital, and operating costs of the system. In this approach, COVID-19 related issues are considered as part of passengers’ perceived health risks associated with crowding using a crowding penalty factor, i.e., the value of ride time multiplier under crowding. At a particular crowding level, the perceived risk of crowding is incorporated differently for various pandemic levels. The developed approach is numerically tested using a simple case of a single bus line with and without the constraint of bus size.

2. Literature review and background

This section is divided into five parts. First, it reviews the recent literature on the impact of the COVID-19 pandemic on transit operations. It then discusses the recent attempts to revise transit operations to cope with the challenges posed by the pandemic. The following section briefly explores the new generalized user and operator costs due to the pandemic, which is integral to minimizing the tradeoffs between user and operator costs. The last two parts of this section describe the basic principles used in the methodology to calculate crowding costs and measure crowding using the related literature.

2.1. COVID-19 impacts on transit

During different pandemic stages, the PT demand was significantly low due to travel and activity restrictions and fear of infection (Honey-Roses et al. 2020; De Vos 2020). Even in the aftermath of the pandemic, researchers anticipate a potential increase in teleworking and tele-shopping (Orro et al. 2020; Shamshiripour et al. 2020). While these new trends in trip making behaviour point towards a sustained reduction in PT demand, they do not necessarily mean a reduction in transit modal share. In contrast, a reduction in transit modal share during and post-COVID-19 expresses a preference for other modes. Studies show that there is a significant reduction in the modal share of transit in response to COVID-19 (Apple 2021; Orro et al. 2020). This shift can be attributed, at least in part, to negative passenger perceptions of the potential health risks of riding transit (Przybylowski, Stelmak, and Suchanek 2021). If these negative perceptions are not properly addressed during the transition stage, the reduction in the modal share of transit may be sustained for an extended period in the aftermath of the pandemic (Przybylowski et al. 2021; Tirachini and Cats 2020).

2.2. Attempts to alleviate pandemic induced issues in transit operations

Studies on addressing pandemic related issues in transit scheduling attempt to allocate transit agency resources optimally while introducing capacity reductions brought on by social distancing measures as constraints (Gkiotsalitis and Cats 2020; Tirachini and Cats 2020). This approach can be further explored through models that set frequencies for a single line (Furth and Wilson 1981) or for a network with limited resources as constraints (Yu et al. 2011); models that maximize resource allocation can also be used (Verbos and Mahmassani 2013; Verbos and Mahmassani, 2015). Gkiotsalitis and Cats (2021) extend the approach of Furth and Wilson (1981) to a network-wide problem of optimal frequency setting. Their approach considers the lost revenue from passengers left behind because of transit vehicles adhering to social distancing measures (restricting adjacent seats, etc.) with the objective of minimizing the tradeoffs between user and operator costs. These approaches, however, do not consider the new perceived discomfort cost, induced by COVID-19, in riding in a crowded vehicle.

Perceived risk is the primary factor that influences human decision-making behaviour (Bavel et al. 2020). The perceived health risk of being in an enclosed space with a crowd has reduced the use of public transport during the pandemic (Dandapati et al. 2020) and will continue to do so post-pandemic. In fact, crowding was found to be the most important factor in mode choice during the pandemic (Shin et al. 2021). Research has revealed that passengers’ willingness to return to transit significantly depends on perceived safety and comfort of using transit during the pandemic (Kopidas et al. 2021; Przybylowski et al. 2021). Tan and Ma (2020) found that people who perceived a higher risk of contracting the virus by taking transit had a lower probability of taking transit. Further, passenger perception of public transit being safe was found to have increased overall satisfaction with transit (Dong et al. 2021). Supporting these claims, studies report that negative perception of crowding was magnified by an amount of 1.04 – 1.23 due to the pandemic (Cho and Park 2021). Shin et al. (2021) reported that metro passengers in the city of New York showed ride time crowding multiplier values of 2.13 and 2.65 for sitting and standing passengers, respectively. Pollock et al., (2021) reported an implied cost increment of about $37 (CAD) due to the disutility of high pandemic severity compared to low pandemic severity as measured by the number of daily infections. Therefore, it is evident that transit mode choice during the re-opening stages and the aftermath of COVID-19 will continue to be significantly influenced by the perceived health risk/safety.

2.3. Pandemic induced generalized costs of transit

Although the evidence that reveals the significance of crowding induced health risks for transit riders in determining transit attractiveness post-COVID-19, there are no studies that investigate the effects of crowding induced health risks in transit scheduling. Consequently, some transit agencies have adopted the physical distancing measures recommended by health professionals to curb the spread; these measures mean that there is a specific maximum level of crowding allowed in transit vehicles (Kamga and Eckemeyer 2021). Nevertheless, different people can view this same level of crowding as having different levels of risk, which will affect transit demand. This situation can even propagate to the aftermath of a pandemic when transit systems may not require social distancing measures, but passengers may still have residual anxiety from COVID-19. To develop an analytical expression for the optimal headway of a transit line, we first briefly explore the generalized costs of users and operators.

The pandemic has had a multifaceted impact on generalized operator and user costs. Table 1 highlights some cost increments due to the pandemic. Of the operator and user-related cost increments, all except crowding discomfort due to COVID-19 health risk can be directly quantified. For example, the increased operator costs are reflected in the cost of dispatching a transit vehicle in a particular route as discussed later in the paper. Increased passenger costs are directly reflected by the increased values of ride and wait time of the passengers. The discomfort due to crowding on the other hand depends on passenger’s perceptions of COVID-19 health risks while riding transit and therefore becomes a challenging issue that requires considerable theoretical support.

This research is mainly to find a way to quantify the cost of crowding discomfort due to COVID-19 and to incorporate the cost into an
We are interested in calculating the user cost associated with the level of crowding depends on passengers' perceptions as in Whelan and Crockett (2009); the value of riding time (VoRT) is another person may view the same vehicle as not crowded. Therefore, one person may consider a transit vehicle crowded and another person may view the same vehicle as not crowded. Different individuals can view a transit vehicle that has a certain number of passengers as having different levels of crowding discomfort. In other words, one person may consider a transit vehicle crowded and another person may view the same vehicle as not crowded. Therefore, the level of crowding depends on passengers’ perceptions (Whelan and Crockett 2009). We are interested in calculating the user cost associated with crowding discomfort as a markup on the mean value of riding time inside a transit vehicle. The second approach calculates the cost of discomfort due to crowding as a portion of user costs. For example, in Qin (2014) and Whelan and Crockett (2009), the mean value of a unit of riding time spent by a passenger is multiplied by a crowding penalty factor to represent the disutility experienced by a passenger in a crowded situation inside a transit vehicle. The third approach calculates the cost of discomfort due to crowding as a markup on the mean value of riding time. For instance, in Qin (2014) and Whelan and Crockett (2009), the mean value of a unit of riding time spent by a passenger is multiplied by a crowding penalty factor to represent the disutility experienced by a passenger in a crowded situation inside a transit vehicle.

2.4. Cost of crowding on an urban bus route

There are three main approaches that capture the cost due to crowding: the time multiplier, the monetary value per unit time, and the monetary value per trip (Li and Hensher 2011). The first approach is to quantify the cost of disutility due to crowding as a markup on the mean value of riding time. For instance, in Qin (2014) and Whelan and Crockett (2009), the mean value of a unit of riding time spent by a passenger is multiplied by a crowding penalty factor to represent the disutility experienced by a passenger in a crowded situation inside a transit vehicle. The second approach calculates the cost of discomfort due to crowding as a portion of user costs. For example, in Klumperhouver and Wirasinghe (2016) and in Lu et al. (2008), a value of discomfort (measured in dollars per unit time per person) is multiplied by a discomfort factor (a function of crowding level/loading) to represent different levels of crowding. The third approach calculates the cost of crowding discomfort as a “per trip” value for a given level of crowding as in Polydoropoulou and Ben-Akiva (2001) and Hensher et al. (2011). This study expands the first approach because the approach has the advantage of transferring to different contexts.

2.5. Measuring crowding

Different individuals can view a transit vehicle that has a certain number of passengers as having different levels of crowding discomfort. In other words, one person may consider a transit vehicle crowded and another person may view the same vehicle as not crowded. Therefore, the level of crowding depends on passengers’ perceptions (Whelan and Crockett 2009). We are interested in calculating the user cost associated with crowding discomfort as a markup on the mean value of riding time as in Whelan and Crockett (2009); the value of riding time (VoRT) is multiplied by the crowding penalty factor (CPF), which is also called the VoRT multiplier. The CPF is a function of the level of crowding (LoC). The LoC is measured mainly using the loading factor (L), which is the ratio of the number of passengers on board a vehicle to the number of seats in that vehicle (Qin 2014). For a transport mode mostly designed for seated passengers, it is suitable to use “L.” as the measure of crowding, while for modes designed mostly for standees, the best measure is the number of passengers per square meter (TCRP Project A-15C 1999).

3. Methodology

Fig. 1 shows the outline of the methodology followed in this paper with related equation numbers. Optimizing the headway without crowding is combined with the crowding cost function developed using a relationship CPF and load factor to optimize the headway with crowding costs. The developed model is extended to incorporate the pandemic health risks. It is further shown how the developed approach can be adopted during operations under capacity.

This section first presents the well-known baseline model for optimizing the headway of a bus line (without the effects of crowding). Then, the relationship between the VoRT multiplier and the loading factor (L) is developed to account for crowding discomfort (CPF). An analytical model is developed in the next step which represents the cost of crowding of a bus line in the objective function followed by a methodology to optimize the headway in the presence of crowding. Next, a mechanism that incorporates the cost of crowding induced COVID-19 related health risks in the process of headway optimization is developed by modelling the CPF. The above steps are developed assuming a linear relationship between CPF and L for computational plausibility; if the relationship between CPF and L is exponential, limitations exist, and these are shown in the Appendix A.

3.1. Optimizing transit headway without considering crowding costs

As suggested in Section 2, the pandemic struck an imbalance between user and operator contributions to transit trips. An approach that rights the imbalance must incorporate the new costs of both users and operators. Accordingly, we intend to minimize the trade-off between user and operator contributions to reach a favourable ground – favourable headway in this case · for transit trips to happen. To this end, we utilize the optimal time dependent headway model proposed by Newell (1971) and extended by Wirasinghe (1990) to include many-to-many demand.

An urban public bus line with time varying many-to-many demand is considered. Let the passenger demand to board a bus at the station/stop i at time t given in passengers per hour be Pi(t) – the rate of passenger arrivals at station i. We assume the passengers that arrive at the stop i, board the first bus that arrives. If the travel time taken from the origin to the station i is given by ti , the total passenger demand in passengers per hour to board the entire route can be represented using an equivalent demand at the origin. Let the total passenger demand to board, hereafter referred to as “demand” of the bus line at time t be given by

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**Table 1**

| Cost of mandated safety measures | Increases in User Costs |
|---------------------------------|-------------------------|
| (cleaning vehicles and infrastructure) | Increased ride time cost due to adopted health precautions (passenger metering at stations and using specific doors to board and alight) |
| Cost due to increased operating time (higher round trip time due to cleaning activities and safety measures for passengers boarding alighting and in-vehicle circulation) | Increased wait time costs due to cuts in service (longer headways cause longer mean wait times) |
| Cost due to reduced capacity (more vehicles need to be dispatched per unit time) | Increased cost of crowding discomfort due to COVID-19 health risks |

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![Fig. 1. Outline of the methodology.](image-url)
\[ P(t) = \sum_{i=0}^{n-1} P_i(t + t_i) \quad (1) \]

where \( n \) is the number of stops in the transit line.

If we assume mean values and a uniform headway for the time period considered (e.g., peak period, off-peak period), the total cost in dollars per hour (summation of operator and user costs) given by \( Z \) can be represented as

\[ Z = \left( \frac{H}{2} \right) \gamma_w \rho + \lambda_0 / H \quad (2a) \]

where \( P \) is the mean demand of the bus line in passengers per hour, i.e., the mean value of \( P(t) \) over the considered time period, \( H \) is the uniform headway of the line given in hours, \( \gamma_w \) is the mean value of wait time (VoWT) of passengers given in dollars per passenger per hour, and \( \lambda_0 \) is the cost of dispatching a bus on the bus route and includes the operational, maintenance, and discounted capital costs of the buses given in dollars per dispatch. The first term of the model represents the passengers’ mean wait time cost per hour. The second term represents the mean cost of operating the transit line per hour.

The optimum headway that minimizes the trade-offs between the user and operator costs can be obtained by taking the derivative of Eq. (2a) with respect to headway \( H \) and equating it to zero as follows:

\[ \frac{\partial Z}{\partial H} = \frac{\gamma_w \rho}{2} - \lambda_0 / H^2 = 0 \quad (2b) \]

The optimum headway without the effect of crowding is given by Eq. (3a).

\[ H = \sqrt{2 \rho \lambda_0 / \gamma_w \rho} \quad (3a) \]

This model is capable of representing the new increased costs of the operator, such as increased roundtrip time due to safety measures (and hence, human resources) and cleaning costs through \( \lambda_0 \). If at any point, passengers experience anxiety while waiting for the bus at the transit stop due to pandemic health risks, this can be represented by \( \gamma_w \).

During higher-than-mean demand, e.g., peak periods, dispatching buses according to the optimal headway might not be enough to meet demand, which leads to some passengers not being able to board the bus. The dispatching policy introduced by Newell (1971) and Wirasinghe (1990) does not allow passengers to be left behind. According to Newell (1971), the time varying headway under capacity operations for a many-to-one time-varying demand can be presented as

\[ H_c(i) = \frac{C}{Q(t)} \quad (3b) \]

where \( C \) is the design capacity of the bus. In a many-to-one or one-to-many bus line, each passenger-space is used by one passenger only or not used at all. But, in a many-to-many bus line, a passenger-space can be used by several passengers in series. Therefore, to be used in a many-to-many bus line, Eq. (3b) can be modified by replacing \( P(t) \) with the demand in passenger-spaces per hour \( Q(t) \) for the bus line (Wirasinghe 1990).

\[ H_c(i) = \frac{C}{Q_c(t)} \quad (3c) \]

Wirasinghe (1990) shows how \( Q(t) \) can be derived for a bus line using boarding and alighting data. It is important to note here that \( Q(t) \) is different from the load of a bus at time \( t \). He further shows that, in the common case of a bus line having a fixed maximum load point, \( Q(t) \) is equal to the rate at which the passengers pass the maximum load point and can be measured by placing an observer at the maximum load point.

To obtain a uniform headway for a time period, e.g., peak period, we can use the mean value of the demand in passenger-spaces per unit time at the maximum load point \( Q \). Hence, we have

\[ H_c = \frac{C}{Q} \quad (3d) \]

where \( H_c \) is the uniform headway under capacity operations during peak-period.

Although \( Q \) is defined as a mean value, demand varies with time as \( Q(t) \), and capacity \( C \) must be able to deal with demand at the height of the peak. Thus, \( C \) must be chosen carefully as the sum of the seated capacity plus only a portion of the standing capacity. At the height of the peak, the bus is then still able to maintain the same uniform headway, but with a higher load, and does not leave passengers behind.

The normal industry practice is to use a “policy-headway,” \( h \), which is subjective to a transit agency, as an upper limit of the allowable headways. The intention is to limit the maximum waiting time of passengers in the transit system below a given threshold. That is, even though there is minimal demand, which makes the optimal headway significantly high, i.e., \( H > h \), the transit agency will run buses using \( h \). Having a policy headway ensures a quality of service provided by transit agencies because passengers are aware that the waiting time will not be longer than a given value under any circumstances, which creates trust.

Dispatching policy is to utilize the minimum of optimum headway [Eq. (3a)], capacity headway [Eq. (3d)], and policy headway. Accordingly, the dispatching policy \( H_p \) is presented as

\[ H_p = \min \left( H_c, \frac{H}{h} \right) \quad (3e) \]

The crowding cost function is inserted into Eq. (2a) as a user cost. This formulation is carried out for a single line of an urban public bus route with many-to-many demand where fleet size (number of buses available to be dispatched on the line) is not a constraint, passengers arrive randomly at bus stops, and passengers are served by the first arriving vehicle (i.e., passengers are not left behind).

### 3.2. Effect of COVID-19 on crowding discomfort

It is evident that the extent of discomfort corresponding to a given level of crowding is partly influenced by COVID-19 related health risks (Cho and Park, 2021; Shin et al., 2021). Before the pandemic, discomfort due to crowding was influenced by the sense of a lack of privacy (Fried and Defazio 2016) because of the standing passengers and the difficulty of boarding and alighting. Discomfort is further amplified by COVID-19 related health risks. Due to its integral role in terms of crowding, we consider the pandemic health risks as one of the two components that influence discomfort due to crowding. In other words, discomfort and the associated costs corresponding to a given level of crowding have increased because of the pandemic. If we assume that the resulting crowding discomfort varies linearly with the level of crowding (Jara-
Diaz and Gschwender 2003), the effects of the pandemic health risks can be expressed along with crowding discomfort in a form similar to Fig. 2.

The crowding discomfort of a passenger due to COVID-19 depends on the perception of the prevailing health risks associated with riding transit (Cho and Park, 2021). Perception of the overall health risks depend on cleaning strategies undertaken by the operator; safety measures onboard and at stations, such as mask policy and social distancing; rate of compliance to the safety measures (Beck and Hensher 2020b; Elias and Zattme-Kanj 2021); and the stage of the pandemic expressed in terms of measures such as daily infection rates and number of infected persons in the city/province per 10,000 persons (Shelat et al., 2020). The collective effect of the above factors can be represented as the perceived chance of getting infected while taking transit. Most of these factors can be controlled or remain unchanged over long periods, but the state of the pandemic cannot be easily predicted. Therefore, the factor “state of the pandemic” is selected to represent the perceived health risk of taking transit. Selecting the factor “state of the pandemic” helps the study achieve one of its primary intentions: to help estimate passenger perception towards crowding during different pandemic phases (including the aftermath).

3.3. Crowding penalty factor (VoRT multiplier) with loading factor

Crowding penalty factor (CPF) is the factor by which the VoRT of a passenger is multiplied to account for the discomfort caused by the level of crowding. VoRT can be obtained using a stated preference survey (Basu and Hunt 2012; Lam, Cheung, and Poon 1999; Ojeda-Cabrals, Batley, and Hess 2016; Rizzi, Limonado, and Steimetz 2012). Studies have proposed methods to obtain the CPF by modelling the marginal utility of travel time as a function of the level of crowding in a transit vehicle (Batarce et al., 2016; Haywood and Koning 2015). We introduce an approach to model CPF initially as a function of the level of crowding, and subsequently, perceived COVID-19 health risks at a given state of the pandemic are added to the model.

3.4. Modelling the crowding cost function

The mean cost due to crowding of a given bus line is first calculated. We assume a mean demand rate and a uniform headway for the time period considered.

Number of buses operating (running) on the route at any given moment

\[
\frac{T}{H} = \frac{C}{L}
\]

(4a)

where \( T \) is the trip time of a bus from start to end, and \( H \) is the uniform headway of the bus line.

Mean load of passengers per bus has been shown to be \( PH(\bar{D}/D) \) by Tirachini et al.,(2010) and Qin (2014)

where, \( \bar{D} \) = mean trip distance of passengers in the bus route

\( D = \) length of the bus route (round trip)

Therefore, the number of passenger hours spent riding in the bus route per hour

\[
PH \frac{T}{D} = PT \frac{\bar{D}}{D}
\]

(4b)

The mean loading factor \( L \) is defined as the mean number of passengers on a bus divided by the seat capacity of the bus:

\[
L = \frac{PH(\bar{D}/D)}{S}
\]

(4c)

where \( S \) is the number of available seats on the bus.

Let the mean CPF (the VoRT multiplier) for passengers in the route be

\[
\beta = 1 + \emptyset L
\]

(5a)

where \( \emptyset \) denotes the rate of change in mean CPF with the mean loading factor.

In the literature, CPF has been modelled using different functional forms, namely stepwise linear (de Palma, Kilani, and Proost 2015), exponential (Qin 2014), stepwise exponential (Qin 2014), and quadratic (Tirachini et al. 2010). Depending on the situation, it can be more appropriate to use an exponential form or a quadratic form to model the variation of CPF with the loading factor. We use a function in the linear form of CPF and explore the issue of using an exponential form in the Appendix 1.

The mean VoRT of passengers under crowding, as given by \( \gamma \), can be obtained by multiplying the mean VoRT of passengers without the effect of crowding, as given by \( \gamma' \), by CPF:

\[
\gamma - \gamma' = (1 + \emptyset L)\gamma'
\]

(5b)

CPF is always larger than one. That is, the VoRT with discomfort of crowding can take a minimum value of VoRT without crowding. Therefore, the ratio of the VoRT with crowding to VoRT without crowding is always greater than or equal to one. Hence, the intercept of Eq. (5a) is 1.

Therefore, using Eqs. (4c and 5b), we have

\[
\gamma = (1 + \emptyset \frac{PH}{DS})\gamma'
\]

(6)

It is important to note that in Eq. (5a), the possible different values of seated and standing passengers’ mean perceived VoRTs have been considered through the mean value of CPF that can be obtained through a stated preference survey.

Using Eqs. (4b and 6), we can calculate the user costs due to crowding by multiplying the mean number of passenger hours spent on the bus route per hour by the mean value of perceived ride time of passengers in a bus given by dollars per passenger per hour.

The average cost of riding in crowded conditions per hour is as follows:

\[
TC_c = PT IT \frac{1 + \emptyset \frac{PH}{DS}}{\bar{D}}\gamma'
\]

(7)

Eq. (7) denotes the total cost of both riding and crowding of bus line passengers per hour. However, headway only affects the level of crowding but not the riding time of a passenger. Therefore, to account only for the additional cost incurred by passengers due to crowding discomfort, Eq. (7) can be modified. Instead of the perceived value of riding time due to crowding, we use only the markup applied to the mean value of riding time:

\[
\gamma' - \gamma = (1 + \emptyset \frac{PH}{DS})\gamma' - \gamma = \left(1 + \emptyset \frac{PH}{DS}\right)\gamma'
\]

(8a)

Therefore, \( TC_{c\gamma} \), the cost of only crowding discomfort, can be obtained as follows:

\[
TC_{c\gamma} = PT IT \frac{1 + \emptyset \frac{PH}{DS}}{\bar{D}}\gamma'
\]

(8b)

Let the mean running speed of a bus on a bus route be

\[
V = \frac{D}{T}
\]

(9)

Using Eqs. (8b and 9),

\[
TC_{c\gamma} = \frac{PI}{V} \frac{PH}{DS}\gamma'
\]

(10)

The ratio of the mean trip distance (\( \bar{D} \)) to the mean running speed (\( V \)) is the mean trip time (\( T \)) of passengers in the transit line and can therefore be denoted as
\[
\frac{1}{\overline{P}} = 1
\]  

Therefore, Eq. (10) can be modified as follows:

\[
TC_{cr} = \frac{P^2H^*\gamma P}{DS} H
\]  

Eq. (12) represents the average cost of crowding per hour given in dollars per hour.

3.5. Optimum headway of operating with consideration of crowding costs

Using Eq. (2a) and Eq. (12), the cost of users, i.e., costs due to both crowding discomfort and waiting, and the cost of operators due to the headway of operating bus routes can be stated as

\[
Z = \left( \frac{H}{2} \right) \gamma P + \frac{P^2H^*\gamma P}{DS} + \lambda P / H
\]  

The optimum headway \((H^*)\) that minimizes the total cost of the bus route associated with headway can be obtained by taking the derivative of Eq. (13) with respect to \(H\) and setting the derivative equal to zero.

\[
H^* = \left[ \frac{2 \lambda P DS}{\gamma P} \right]^{1/2}
\]  

The second derivative of Eq. (13) with respect to \(H\) is positive. Hence, \(H^*\) provides the optimum headway that minimizes the trade-offs between user costs and operator costs.

Utilizing Eq. (7) instead of (12) in the objective function does not affect the result as the first term within the brackets of Eq. (7) disappears when taking the derivative. While the variation in headway affects the level of crowding and the cost due to crowding discomfort, it does not affect the cost of riding a bus without crowding. Therefore, the derivative that represents the rate of variation of different cost components with respect to headway variation is independent of the cost of riding even though it is included in the objective function. However, Eq. (12) must be used because it conveys the concept accurately.

Eq. (14) can be further rearranged as follows.

\[
H^* = \left[ \frac{2 \lambda P DS}{\gamma P} \right]^{1/2}
\]  

Since the denominator of the \(H^*\) is greater than 1 and the numerator of the Eq. (15) is the optimum headway without crowding costs \((H^*')\), the optimum headway with crowding cost \((H^*)\) is always smaller than \(H^*\). This finding is expected because user costs are higher when crowding is considered, and the operator has to balance this extra cost utilizing a higher frequency in the bus line, which increases operator costs.

The analytical model represented by Eq. (14) shows the interrelation between a bus line’s parameters and the optimum headway in the presence of crowding costs. As shown, \(H^*\) varies with passenger demand on a bus line, while \(H^*\) only varies with the square root of passenger demand because \(H^*\) is affected by crowding cost and passenger demand has a squared effect on crowding cost. It should also be noted that as values of mean trip distance, the basic VoRT, VoWT of passengers, and \(\phi\) increase, the optimum headway with crowding becomes smaller. Also, for longer bus lines and larger bus sizes, the optimum headway with crowding is greater. However, all these parameters, except a line’s passenger demand, have a square root effect on the optimum headway/frequency.

3.6. Incorporating pandemic health risks into the calculation of crowding costs

As the level of crowding (or loading factor) increases, passengers are willing to pay more to travel using a mode that is less crowded (Yap, Cats, and van Arem 2020). Therefore, a higher load factor indicates a higher disutility per unit time. At the onset of the COVID-19 pandemic, a particular crowding level posed different levels of disutility depending on the severity of the pandemic (Pollock et al. 2021; Shelat et al., 2020). For example, a person may be comfortable travelling on a given transit line at a given loading factor when a city’s daily infection rate is around a typical intermediate level of 300 (NAIT 2021). The same person might not be comfortable travelling on the same transit line at the same level of crowding when the daily infection rate in the city is around 800, which is near a lockdown state (NAIT 2021). Therefore, the disutility of travelling time (units per unit time), and hence, the VoRT, depend on both the loading factor and the health risks posed by the pandemic at that time. Accordingly, the resulting change to CPF can be expressed by adding another term to Eq. (5a) as follows:

\[
\beta = 1 + (\phi + \sigma R) \frac{PHI}{DS}
\]  

where \(R\) represents the level of pandemic severity (e.g., daily infection rate), and \(\sigma\) is a constant that indicates the rate of change in CPF for a unit change in RL. The term \(\sigma RL\) is the mean amount by which passengers might increase their CPF to trade off the health risks caused by a given level of pandemic severity and a given level of loading. Here, \(\sigma\) can be interpreted as the rate of change in \(\beta\) with the pandemic severity \((R)\), and \(\phi + \sigma R\) can be interpreted as the rate of change in \(\beta\) with loading factor \((L)\).

Studies have reported that the COVID-19 virus can live on different types of surfaces for different durations of time up to a few days (Moriyama, Hugentobler, and Iwasaki 2020; Nishiura, Linton, and Akhmetzhanov 2020). Thus, despite regular cleaning and safety measures, passengers could still perceive a health risk in travelling on a transit vehicle even when the bus has no other passengers, i.e., zero loading. This health risk can increase as the severity of the pandemic increases; more active cases in a community increase the chance of getting infected. This component of the health risk also causes the value of \(\beta\) to increase in a fashion that only depends on pandemic severity and not on the level of crowding. Accordingly, Eq. (16) can be modified by adding the term \(sR\), where \(s\) is a constant that represents the rate of change in the portion of CPF that depends only on \(R\), the pandemic severity.

Tirachini and Cats (2020) emphasize the possibility that there might be a residual health risk even in the aftermath of the pandemic. In other words, there is a portion of the health risk, independent of both the level of crowding and the severity of the pandemic, that will increase CPF and remain even when the pandemic is over. This portion of the health risk can be expressed by adding the term \(\omega\) to Eq. (16), where \(\omega\) is a constant that represents the residual health risk unique to the population considered.

Eq. (16) can be modified using the expression for \(L\) from Eq. (4c):

\[
\beta = 1 + (\phi + \sigma R) \frac{PHI}{DS}
\]  

Fig. 3 illustrates Eq. (17) and the terms \(sR\) and \(\omega\).

Fig. 3 shows the ways in which pandemic health risks can affect passenger’s perceptions of riding transit. However, \(s\) and \(\omega\) are eliminated in the process of obtaining the optimum headway, i.e., taking the derivative in terms of \(H\) to obtain the optimum headway eliminates these terms as they are not dependent on the headway. On the other hand, we expect \(s\) and \(\omega\) to be negligible because having no other users inside a transit vehicle does not pose a significant health risk to most users most of the time. The residual perceived health risk \((\omega)\) also does not affect most users and dissipates over time (and into the aftermath).

Substituting from Eq. (17) in Eq. (6) to develop the objective function as in Eq. (13) and taking the derivative in terms of \(H\), the optimum headway, considering both crowding and pandemic health risk related costs \((H^{**})\), can be obtained as follows:

\[
H^{**} = \left[ \frac{2 \lambda P DS}{\gamma P} \right]^{1/2}
\]
As shown in Eq. (18), in the presence of pandemic health risks, the optimum headway is further reduced as expected by the addition of $\sigma R$ to the value of $\emptyset$. As the severity of the pandemic increases, the cost of perceived health risks increases, which lowers the optimum headway.

The estimations for $\emptyset$ and $\sigma$ can be obtained using a stated preference survey of transit passengers. For example, Batarce et al. (2016) has shown that the marginal utility of transit travel time can be modelled as a linear function of the loading:

$$\delta_1(L) = \delta_0 + \delta_1 L$$

(19)

where $\delta_0$ (utils per hour) can be expressed as the basic marginal utility of travel time – without the effect of crowding and pandemic health risks, and $\delta_1$ (utils per hour per unit loading) can be expressed as the marginal utility of travel time with crowding. During a pandemic, the value of $\delta_1$ is further affected by the pandemic severity level ($R$). Therefore, taking a similar approach to Batarce et al. (2016) in Eq. (19), we propose that the value of $\delta_1$ can be modelled as a linear function of pandemic severity:

$$\delta_1 = \theta_0 + \theta_1 R$$

(20)

where $\theta_0$ (utils per hour per unit of loading) can be expressed as the basic marginal utility of travel time with crowding – without the effect of pandemic health risks, and $\theta_1$ (utils per hour per unit of loading and pandemic severity) can be expressed as the marginal utility of travel time with crowding under pandemic health risks.

Using this modelling approach, CPF can be obtained for different levels of loading and pandemic severity through a stated preference survey. The obtained values reflect the mean passenger perception of pandemic health risks under different crowding and pandemic severity conditions. Using these values, the function for CPF in the presence of crowding and pandemic severity, Eq. (17), can be developed, which provides the values for $\emptyset$ and $\sigma$. A practical example of deriving a function for CPF is presented in the section “Applications and discussion” using available CPF values from the literature for different loading conditions. Similarly, the method described herein supports the derivation of the CPF as a function of loading factor and health risk measure.

### 3.7. Operations under capacity during the pandemic

The norm in capacity operations is to dispatch buses when full. In a many-to-many demand bus line, the concept of “dispatching buses when full” entails meeting the demand of the rate of passengers passing through the maximum load point using the bus capacity (a bus full of passengers). Yet, the term “full” can be subjective, i.e., the person operating the transit vehicle and the passengers inside the transit vehicle may have different opinions on what “full” means; it can be even more subjective under the effect of COVID-19 health risks (Dai and Taylor 2020). There is a maximum number of passengers that can physically fit in a transit vehicle of given size, commonly known as the crush capacity, which is sometimes referred to as 1.5 times the number of seats available (TCRP Project A-15C 2003). The regular practice is to use a number that represents the number of passengers allowed in a bus that is lower than the crush capacity $C$. Therefore, $C$ is normally in the range of 1 to 1.5 times the seat capacity.

The load factor resulting from operation under optimum headway can rise above the crush capacity under extreme values of some parameters (e.g., $\lambda_\emptyset$), which significantly increases operator costs. Therefore, it is necessary to have an upper limit to the loading factor. This upper limit is normally the crush capacity (1.5 times the seat capacity). Under pandemic conditions, such a value indicates a significant health risk. Therefore, during a pandemic, transit agencies need to consult the health authorities to agree on an upper limit to the level of loading/crowding allowed to manage the health risks of the pandemic. If the health authorities request a minimum distance between passengers, this required distance can dictate a particular design capacity depending on the available space inside the bus. Likewise, if the upper limit for the design capacity is $C'\emptyset$, the capacity headway $H_\emptyset$ becomes the ratio of $C'\emptyset$ to $Q$:

$$H_\emptyset = \frac{C'}{Q}$$

(21)

Accordingly, the resulting dispatching policy is to use the minimum $H_\emptyset$ and $H''\emptyset$.

As discussed in Section 3.1, the policy headway is related to the quality of service and trust. Significant increases in operator costs and reduced demand due to a pandemic can make adhering to the same policy headway challenging for transit agencies. In a pandemic, essential workers, health care and front-line workers, depend on transit services. Reducing the policy headway will significantly affect essential workers’ travel.

Therefore, the dispatching policy is
4. Applications and discussion

4.1. A numerical example for a function of crowding penalty factor

An example function for the CPF is derived first. A 12 m long bus that has 44 seats (S = 44) is used for this example. According to the Transit Capacity and Quality of Service Manual (TCRP Project A-15C 2013), the design capacity is C = 1.25S = 55, and the crush capacity is C’ = 1.5S = 66.

Table 2 shows the factors by which passengers increase their riding time values under different passenger load conditions. The variable “n” represents the number of passengers on board the vehicle, and “S” represents the number of seats in the bus.

The mean VoRT multiplier for passengers on the bus (S = 44, C = 55, C’ = 66) can be calculated by adding passengers one-by-one to the bus and calculating the mean VoRT multiplier. Mean VoRT multipliers with corresponding loading factors (number of passengers on the bus divided by the number of seats in the bus) are shown in the Fig. 4.

Curves that have different functional forms can be fitted to this dataset:

Exponential:
\[
\text{Avg CPF} = 1 + ae^{BL} = 1 + 0.0114e^{2.864L} \quad (R^2 = 0.94)
\]  \hspace{1cm} (24)

Linear:
\[
\text{Avg CPF} = 1 + aL = 1 + 0.3015^*L \quad (R^2 = 0.64)
\]  \hspace{1cm} (25)

CPF's (VoRT multipliers) are normally acquired from stated preference surveys. Results from such surveys determine CPFs for the corresponding levels of crowding. The number of data points that can be obtained depends on the number of levels utilized in the survey on crowding. If more levels are used, more data points can be obtained, and hence, the derived functional form is more accurate. However, more levels require a larger number of survey responses to maintain a certain accuracy level for the data points.

4.2. Numerical example

In this section, we present a numerical example to determine the optimum headway with and without crowding costs. The parameters in Table 3 are assumed for an existing transit line.

For the parameters shown in Table 3, the optimum headway without crowding from Eq. (3a), \( H' = 18 \) minutes. Capacity headway, \( H_c = 20 \) minutes from Eq. (3d). In this example, passenger carrying capacity is assumed to be equal to bus size \( S \) to obtain a benchmark value, i.e., buses are dispatched when all seats are filled. Since \( H < H_c \), according to Eq. (3e) the bus line runs under optimum headway. Optimum headway with crowding is \( H' \approx 15 \) minutes from Eq. (15). Consequently, the effect of crowding costs reduces the optimum headway by nearly 3 min. Optimum headway is bound to reduce further in the presence of COVID-19 health risks.

4.3. Sensitivity analysis

To simplify the variation between \( \beta \) and \( L \) in Eq. (16), let us replace \( \varnothing + aR \) by \( \varnothing \) for a given level of pandemic severity:

\[
\beta = 1 + 8L
\]  \hspace{1cm} (26)

When there is no pandemic, \( R \) is zero and the value of \( \varnothing \) is equal to \( \varnothing \). As shown in Fig. 3, the value of \( \varnothing \) (rate of change in CPF with L and R - gradient) is higher in the presence of perceived health risks in taking transit. This value increases or decreases during different stages of a pandemic. For example, during a near lockdown (the stage when the infection rate is close to highest but not yet locked down and, hence, the health risks might be highest), the value of \( \varnothing \) might be highest, and during the aftermath of a pandemic, it might be lowest.

The sensitivity of \( H' \) (optimum headway with crowding costs) and \( H' \) (optimum headway without crowding costs) are assessed against some key operational parameters. The effects of perceived health risks during different imaginary stages of a pandemic (expressed using different \( \varnothing \) values) are explored. It should be noted that the effects of the perceived health risks during different imaginary stages of a pandemic (expressed using different \( \varnothing \) values) are explored.
health risks during a near lockdown stage can increase the value of $\theta$ to more than two times the value of $\varnothing$ (Shin et al. 2021). The value of $\theta$ can also be nearly as low as $\varnothing$ (the effect of the pandemic health risks is negligible), and this situation occurs in the aftermath when passengers are no longer affected by COVID-19. However, the variation of $\theta$ with the different stages of the pandemic, i.e., the variation of CPF with respect to the severity of the pandemic, is unique for a given community. Accordingly, the values of optimum headway with crowding ($H^*$ - Eq. (14)) and without crowding ($H'$ – Eq. (3a)) are allowed to change with changes in critical parameters, such as demand, bus size, and passengers’ mean trip time in Figs. 5-7 using data in Table 3. Mean trip distance has a similar effect to that of mean trip time, and the length of the bus route has a similar effect to that of bus size owing to the nature and positioning of these variables in Eq. (14). These sensitivity analyses are also extended to represent different potential severity levels of a pandemic by increasing the value $\theta$ by 50% ($H^* @ 50\%\theta$) and by 100% ($H^* @ 100\%\theta$) to be in line with the findings in the literature (Shin et al. 2021). The value of $\theta$ is assumed to represent no pandemic severity ($R = 0$) and is equal to 0.3, which is the value of $\varnothing$ in the example presented in Fig. 4. These results are compared with the optimum headway without crowding costs to show the significant impact of crowding costs on optimum headway.

Fig. 5 indicates that as demand increases, the values of both the optimal headways ($H^*$ and $H'$) decrease. Higher demand implies higher passenger costs for the same headway value, which also means the same operator cost. An optimized headway balances this difference between operator and user costs by reducing headway. Fig. 5 shows that as demand increases, the difference between $H^*$ and $H'$ increases. This difference is more significant for higher values of demand, and at such values, there is a higher chance of the bus line running under capacity headway and not at optimal headways. The increasing difference between $H^*$ and $H'$ indicates that as demand increases, crowding cost of passengers also increases, which decreases the value of optimum headway with crowding. Nevertheless, for all demand levels, the effect of crowding and health risks of COVID-19 on optimum headway are distinct as increasing COVID-19 severity has reduced the optimum headway for a given demand to account for the increased cost of crowding and health risks. This difference is sufficiently significant such that transit agencies should consider using a similar methodology to set frequencies for their transit lines because it will help retain and improve transit modal share while optimally allocating resources. However, according to the methodology suggested in this study, which balances the tradeoffs between increased operator and user costs, transit agencies will have to increase their resource contribution because $H^*$ will have to be reduced to match the increased user costs, which will in turn increase operator costs. Increased operator costs also mean that the transit agency needs increased funding/subsidy for their operations. During COVID-19, allocations of emergency funding have been made to promote and maintain sustainable transportation modes as public transit (Mallett 2020). On the other hand, given the COVID-19 situation where increased health risks lead to reduced transit ridership, the normal practice is to reduce the frequency of operation. However, the proposed dispatching policy take the increased generalized user costs, due to the raised cost of riding time, into account. Such an approach will result in less significant changes in the frequency of dispatch during the pandemic.

Fig. 6 shows that smaller bus sizes are related to lower optimum headway with crowding. The optimum headway without crowding ($H'$) stays constant as it does not depend on bus size. This result also demonstrates that smaller bus sizes are related to higher effects of crowding on $H^*$. If the same dispatching policy is adopted for small and big buses for a particular demand, passengers on small buses will find the bus
more crowded. Perceived health risks have been shown to amplify this effect: the difference between $H^* @100\%$ and $H^*$ increases as bus size decreases, which makes sense because as spaces become more confined, discomfort due to crowding and health risks grows.

As mean trip time on a given transit line increases, the difference between $H^*$ and $H^*$ increases as shown in Fig. 7. If the same frequency setting policy is adopted for different transit lines that have different mean trip times, service will not be equitable/favourable, especially for the bus lines that have higher mean trip times. This effect is amplified in the presence of COVID-19 health risks; as mean trip time increases, the effect of health risks on passenger costs also increases. An unfavourable transit service may cause a decrease in transit ridership. As such, according to the developed model, optimum headway is sensitive to the mean trip time. The degree of success of the methodology depends on accurately estimating the perceived health risks of different pandemic stages. The methodology presented in Section 3.6 in this study helps accurately estimate $\mathcal{O}$ values that consider discomfort due to both crowding and health risks during different stages of a pandemic.

The proposed methodology supports managing the significantly reduced demand during a pandemic, and it also applies to normal demand levels. It is presented in a way such that it can be easily translated to potential future pandemic situations by deriving CPF functions for different pandemic severity levels. It is important to note that this method is developed for public bus lines and not for private bus lines. As the paper focuses on the headway, a parameter that is based on the entire route, an approach concerning the average cost of the entire bus route has been taken. Although different sections along the bus route can have different costs for crowding, the rate of dispatch is mainly affected by the average cost - crowding and waiting - of the entire route. It can be shown, even in the case where the VoRT is fluctuating with the varying load factor along the route, the mean VoRT of the bus route can be obtained using the average load factor of the bus route.

### 4.4. An example of operations with capacity constraint

Consider a bus line that has the parameters presented in Table 4.

Optimum headway under crowding for this bus line can be obtained using Eq. (15) for the parameters presented in Table 4 ($H^* = 0.3\text{hrs} = 18\text{minutes}$). In this example, we assume there is no pandemic health risks involved (no additional cost due to health risks). At near lockdown stages of the pandemic, vehicle capacities were restricted sometimes to half the seating capacity - blocking adjacent seats - by some transit agencies to adhere to social distancing regulations. In this situation, the load factor is 0.5, and the corresponding vehicle capacity $C^*$ becomes bus size times the load factor, i.e., $44 \times 0.5 = 22$. Therefore, according to Eq. (21), the capacity headway $H_i$ is $(22/150) \times 60 \approx 9\text{ min}$. Therefore, according to the dispatching policy, Eq. (22), buses need to be dispatched with a headway of 9 min on this line. This process can be used to meet the guidelines of health authorities that limit vehicular capacity.

### 5. Conclusions

This study approaches the problem of estimating transit headways by considering perceived COVID-19 pandemic health risks as an integral part of crowding discomfort. This paper makes two important methodological contributions: it presents a new methodology to estimate the cost of crowding on a bus line, and it presents an approach that incorporates transit riders’ perceptions of COVID-19 health risks as part of headway optimization. The perceived health risks of crowding are modelled using a crowding penalty factor (CPF), which is the value of ride time multiplier under crowding. It is postulated that discomfort, and hence cost, for a given level of crowding is also affected by the perceived health risks of the severity of a pandemic. An analytical model is then developed to obtain the optimum headway that considers average passenger cost of crowding.

The cost of crowding for users, which is also influenced by pandemic health risks, can be reduced by decreasing the headway of a bus route that operates under normal conditions. However, if the headway is decreased, operation costs increase. A trade-off is achieved by finding an optimal headway. This revised optimal headway provides favourable conditions for both users and operators. With minor modifications, the developed methodology can be adopted for trains’ operation.

One of the main challenges transit agencies face during a pandemic is to schedule transit while managing crowding and increased operating costs. The presented methodology addresses this issue by deriving an optimum headway that balances increased passenger costs due to crowding and operator costs in meeting the existing demand. As reported in the literature, passengers’ perceptions of safety/health risks while riding transit and adapting to the changing perceptions during different pandemic stages must be addressed. Modelling the CPF with loading factor and pandemic stages helps transit agencies address this issue. Passenger’s changing perceptions of a particular pandemic severity level with time can affect the accuracy of predicted costs using the method suggested. Despite this limitation, the developed method facilitates capturing the current sensitivity of passengers to a given pandemic severity which is a crucial issue for transit planning and scheduling.

Transit agencies looking to adopt this methodology need to develop the functions for CPFs that depend on loading factors of different stages of a pandemic, or a function for crowding penalty factor that depends both on loading factor and pandemic stage. Combined revealed and stated preference surveys that ask about willingness to pay for various crowding levels can be conducted to develop CPFs. The approach presented in Section 3.6 can be utilized to derive values for CPFs at different pandemic stages.

### CRediT authorship contribution statement

Kaushan W. Devasurendra: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Visualization.

Saeid Saidi: Conceptualization, Writing – review & editing.

S.C. Wirasinghe: Methodology, Supervision, Conceptualization, Writing – review & editing, Resources.

Lina Kattan: Supervision, Writing – review & editing, Resources, Project administration, Funding acquisition.

### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

The total cost function for optimum headway when CPF varies exponentially with loading factor

The exponential form of CPF with respect to the loading factor is investigated because it has been shown to be a better fit in some cases (Qin 2014). The CPF can be expressed as

$$CPF = 1 + ae^{bL}$$ (A.1)

where ‘a’ and ‘b’ are route-specific constants.

Substituting for L from Eq. (4), we have

$$CPF = 1 + ae^{bPH_lDS}$$ (A.2)

Therefore, the total crowding cost (without riding cost) is

$$TC_{cr} = PT_l\gamma_orae^{bPH_lDS}$$ (A.3)

This equation shows the average crowding cost of passengers on a bus line per hour. The crowding cost now varies exponentially with headway. Hence, the total cost Z is

$$Z = \left(\frac{H}{2}\right)^{\gamma_or} + PT_l\gamma_orae^{bPH_lDS} + \frac{\lambda_D}{H}$$ (A.4)

Taking the partial derivative with respect to H gives

$$\frac{\gamma_orP}{2} - \frac{abPT_l\gamma_orae^{bPH_lDS}}{DS} = \frac{\lambda_D}{H^2}$$ (A.5)

This equation can be solved using numerical methods. Although an approximation of the analytical solution of this equation can be obtained using the Taylor series expansion for the exponential CPF, it does not provide any useful insights as the solution turns out to be complex.

Appendix B – List of Abbreviations

| Abbreviation | Explanation |
|--------------|-------------|
| C            | Design capacity of a bus (pass./bus) |
| C'           | Upper limit of the design capacity during a pandemic |
| D            | Length of a bus route (km) |
| H            | Uniform headway of a bus line (hr/bus) |
| H'           | Optimum headway without the effect of crowding (hr/bus) |
| H''          | Optimum headway with the effect of crowding |
| H_c(t)       | Capacity headway of a bus line at time t (hr/bus) |
| H_p          | Dispatching policy |
| h            | Policy headway (hrs) |
| l            | Mean loading factor |
| l            | Mean trip distance of passengers riding a bus route (km) |
| P            | Mean demand to board a bus line (pass./hr) |
| P(t)         | Demand of passengers to board a bus line at time t (pass./hr) |
| Q            | Mean value of Q(t) (pass.spaces/hr) |
| Q(t)         | Demand of passenger spaces per hour in the bus line (pass.spaces/hr) |
| R            | Level of pandemic severity – daily infection rate in a city |
| S            | Number of available seats on a bus (pass./bus) |
| T            | Mean trip time of a bus from start to end (hrs) |
| TC           | Average cost of riding a bus line ($/hr) |
| TC_c         | Average cost of crowding discomfort on a bus line ($/hr) |
| V            | Mean running speed of a bus on a bus line |
| $\beta$      | Mean CPF (crowding penalty factor) |
| $\gamma_or$  | Basic mean value of $\gamma_or$ without the effect of crowding nor pandemic health risks |
| $\gamma_or$  | Mean value of ride time of passengers ($/pass.hr) |
| $\gamma_w$   | Mean value of wait time of passengers on a bus line ($/pass.hr) |
| $\delta_0$   | Basic marginal utility of travel time (utils/hr) |
| $\delta_1$   | Marginal utility of travel time with crowding (utils/hr) |
| $\delta_2(L)$ | Marginal utility of travel time as a function of L (utils/hr) |
| $\eta$       | Rate of change in CPF with pandemic severity |
| $\theta_0$   | Basic marginal utility of travel time with crowding (utils/hr) |
| $\theta_1$   | Marginal utility of travel time with crowding under pandemic health risks (utils/hr) |
| $\lambda_D$  | Average cost of dispatching a bus on a bus line ($/bus) |
| $\sigma$     | Rate of change in CPF for a unit change in RL |
| $\varnothing$ | Rate of change in mean CPF with the mean loading factor |

(continued on next page)
References
Apple. 2021. COVID-19 - Mobility Trends Reports. Retrieved March 5, 2021 (https://
COVID19.apple.com/mobility).
Basu, D., Hunt, J.D., 2012. Valuing of Attributes Influencing the Attractiveness of
Suburban Train Service in Mumbai City: A Stated Preference Approach. Transporta-
 tion Research Part A: Policy and Practice 46 (9), 1465–1476. https://doi.
org/10.1016/j.tra.2012.05.010.
Batarce, M., Munoz, I.C., de Dios Oria
tzar, J., 2016. Valuing Crowding in Public Transport: Implications for Cost-Benefit
Analysis. Transportation Research Part A: Policy and Practice 91, 358–378. https://
doi.org/10.1016/j.tra.2016.06.025.
Bavel, Jay V., Katherine Baicker, Paulo S. Boggio, Valerio Capraro, Aleksandra
Cichocka, Mina Cikara, Molly J. Crockett, Alla J. Cram, Karen M. Douglas, James N.
Druckman, John Drury, Oeinidria Dude, Naomi Ellems, Eli J. Finkel, James H.
Fowler, Michele Gelfand, Shilbai Han, S. Alexander Haslam, Jolanda Jetten, Shinobu
Kitayama, Dean Mobbs, Lucy E. Napper, Dominic J. Parker, Gordon Pennycook, 
Ellen Peters, Richard E. Plo harvested, David G. Rand, Stephen D. Reicher, Simone Schnall, 
Zamir Saffiri, Linda J. Skitka, Sandra Susan Smith, Cass R. Sunstein, Nastin Tabri, 
Joshua A. Tucker, Sander van der Linden, Paul van Lange, Kim A. Weeden, Michael 
J. A. Wohl, Jamil Zaki, Sean R. Zion, and Robb Willer. 2020. “Using Social and
Behavioural Science to Support COVID-19 Pandemic Response.” Nature Human
Behaviour 4(5):460–471. https://doi.org/10.1038/s41562-020-0884-z.
Beck, M.J., Hensher, D.A., 2020a. Insights into the Impact of COVID-19 on House-
hold Travel and Activities in Australia – The Early Days of Easing Restrictions. 
Transport Policy 99, 95–119. https://doi.org/10.1016/j.transprot.2020.08.004.
Beck, M.J., Hensher, D.A., 2020b. Insights into the Impact of COVID-19 on Household
Travel and Activities in Australia – The Early Days under Restrictions. Transport
Policy 96 (May), 76–93. https://doi.org/10.1016/j.tranpol.2020.07.001.
Cho, S.H., Park, H.C., 2011. Exploring the Behaviour Change of Crowding Impedance 
on Public Transport due to COVID-19 Pandemic: Before and After Comparison.
Transportation Letters 1–8. https://doi.org/10.1080/23748834.2020.1899397.
Dai, Tianxing, and Brian D. Taylor. 2020. When Is Public Transit Too Crowded, and How
Has This Changed During the Pandemic? Publication Date. UC Office of the President
Policy Briefs, October.
Dandapat, S., Bhattacharyya, K., Annam, K.S., Sayskar
dar, K., Maitra, B., 2020. Impact of COVID-19 Outbreak on Travel Behaviour: Evidences
from Early Stages of the Pandemic in India. SSRN Electronic Journal. https://
doi.org/10.2139/ssrn.392923.
de Palma, A., Kilani, M., Proost, S., 2015. Discomfort in Mass Transit and Its Implication
Dai, Tianxing, and Brian D. Taylor. 2020. When Is Public Transit Too Crowded, and How
Has This Changed During the Pandemic? Publication Date. UC Office of the President
Policy Briefs, October.
Dandapat, S., Bhattacharyya, K., Annam, K.S., Saysk
dar, K., Maitra, B., 2020. Impact of COVID-19 Outbreak on Travel Behaviour: Evidences
from Early Stages of the Pandemic in India. SSRN Electronic Journal. https://
doi.org/10.2139/ssrn.392923.
de Palma, A., Kilani, M., Proost, S., 2015. Discomfort in Mass Transit and Its Implication
Dai, Tianxing, and Brian D. Taylor. 2020. When Is Public Transit Too Crowded, and How
Has This Changed During the Pandemic? Publication Date. UC Office of the President
Policy Briefs, October.
Dandapat, S., Bhattacharyya, K., Annam, K.S., Sayskar
dar, K., Maitra, B., 2020. Impact of COVID-19 Outbreak on Travel Behaviour: Evidences
from Early Stages of the Pandemic in India. SSRN Electronic Journal. https://
doi.org/10.2139/ssrn.392923.
de Palma, A., Kilani, M., Proost, S., 2015. Discomfort in Mass Transit and Its Implication
Dai, Tianxing, and Brian D. Taylor. 2020. When Is Public Transit Too Crowded, and How
Has This Changed During the Pandemic? Publication Date. UC Office of the President
Policy Briefs, October.
Dandapat, S., Bhattacharyya, K., Annam, K.S., Saysk
dar, K., Maitra, B., 2020. Impact of COVID-19 Outbreak on Travel Behaviour: Evidences
from Early Stages of the Pandemic in India. SSRN Electronic Journal. https://
doi.org/10.2139/ssrn.392923.
de Palma, A., Kilani, M., Proost, S., 2015. Discomfort in Mass Transit and Its Implication
Dai, Tianxing, and Brian D. Taylor. 2020. When Is Public Transit Too Crowded, and How
Has This Changed During the Pandemic? Publication Date. UC Office of the President
Policy Briefs, October.
Tan, L., Ma, C., 2020. Choice Behavior of Commuters’ Rail Transit Mode during the COVID-19 Pandemic Based on Logistic Model. Journal of Traffic and Transportation Engineering (English Edition).

TCRP Project A-15C. 1999. Transit Capacity and Quality of Service Manual 1st Edition. Washington, D.C.

TCRP Project A-15C. 2003. Bus Transit Capacity. In Transit Capacity and Quality of Service Manual, Third Edition. Washington, D.C.: Transportation Research Board.

TCRP Project A-15C. 2013. Transit Capacity and Quality of Service Manual - Chapter 5, Third Edition. Washington, D.C.: Transportation Research Board.

Tirachini, A., Cats, O., 2020. COVID-19 and Public Transportation: Current Assessment, Prospects, and Research Needs. Journal of Public Transportation 22 (1), 1–34. https://doi.org/10.5038/2375-0901.22.1.1.

Tirachini, A., Hensher, D.A., Jara-Díaz, S.R., 2010. Comparing Operator and Users Costs of Light Rail, Heavy Rail and Bus Rapid Transit over a Radial Public Transport Network. Research in Transportation Economics 29 (1), 231–242. https://doi.org/10.1016/j.retrec.2010.07.029.

UITP. 2020. Public Transport Authorities and COVID-19: Impact and Response to a Pandemic. Retrieved December 12, 2020 (https://www.lek.com/sites/default/files/PDFs/COVID19-public-transport-impacts.pdf).

Wirasinghe, S.C., 1990. Re-Examination of Newell’s Dispatching Policy and Extension to a Public Bus Route with Many to Many Time-Varying Demand. In: Koshi, M. (Ed.), Transportation and Traffic Theory. Elsevier, pp. 363–377.

Yap, M., Cats, O., van Arem, B., 2020. Crowding Valuation in Urban Tram and Bus Transportation Based on Smart Card Data. Transportmetrica A: Transport Science 16 (1), 23–42. https://doi.org/10.1080/23249935.2018.1537319.

Yu, B., Yang, Z., Sun, X., Yao, B., Zeng, Q., Jeppesen, E., 2011. Parallel Genetic Algorithm in Bus Route Headway Optimization. Applied Soft Computing Journal. https://doi.org/10.1016/j.asoc.2011.05.051.