# Avoiding the Crowd: Traveller Behaviour in Public Transport in the Age of COVID-19

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## ABSTRACT

With a few exceptions, public transport ridership around the world has been hit hard by the COVID-19 pandemic. Travellers are now likely to adapt their behaviour with a focus on factors that contribute to the risk of COVID-19 transmission. Given the unprecedented spatial and temporal scale of this crisis, these changes in behaviour may even be sustained after the pandemic. To evaluate travellers' behaviour in public transport networks during these times and assess how they will respond to future changes in the pandemic, we conduct a stated choice experiment with train travellers in the Netherlands at the end of the first infection wave. We specifically assess behaviour related to three criteria affecting the risk of COVID-19 transmission: (i) crowding, (ii) exposure duration, and (iii) prevalent infection rate. Observed choices are analysed using a latent class choice model which reveals two, nearly equally sized traveller segments: 'COVID Conscious' and 'Infection Indifferent'. The former has a significantly higher valuation of crowding, accepting, on average 8.75 minutes extra waiting time to reduce one person on-board. Moreover, they demonstrate a strong desire to sit without anybody in their neighbouring seat and are quite sensitive to changes in the prevalent infection rate. By contrast, Infection Indifferent travellers' value of crowding (1.04 waiting time minutes/person) is only slightly higher than pre-pandemic estimates and they are relatively unaffected by infection rates. We find that older and female travellers are more likely to be COVD Conscious while those reporting to use the trains more frequently during the pandemic tend to be Infection Indifferent. Further analysis also reveals differences between the two segments in attitudes towards the pandemic and self-reported rule-following behaviour. We believe that the behavioural insights from this study will not only contribute to better demand forecasting for service planning but will also inform public transport policy decisions aimed at curbing the shift to private modes.

# 1.    INTRODUCTION

The COVID-19 pandemic has led to unprecedented restrictions on public life globally. Some of the first restrictions in many places were on public transport which, by its very nature of moving people in dense, enclosed spaces, could be a major transmission risk for this highly contagious virus[1]. While some public authorities completely stopped service (e.g., India (Union Home Secretary, 2020)), others restricted or discouraged use other than by essential workers or for urgent needs (e.g., Netherlands, United Kingdom (Department for Transport; Openbaar Vervoer Nederland, 2020a)). Then, at the end of the first infection wave, many authorities, pressed with a need to restart economies and provide essential transportation, eased restrictions and cautiously resumed public transport. Demand levels, however, did not return to pre-pandemic levels (Citymapper, 2021; Google LLC, 2021), at least partly, due to heightened (awareness of the) risk of infection (Beck and Hensher, 2020).

The effect of on-board crowding on travel behaviour has received much attention in literature and has been widely accepted to be a significant influence on various choice dimensions (Li and Hensher, 2011; Tirachini et al., 2013; Wardman and Whelan, 2011). Using choice observations, mainly from stated choice experiments (e.g., (Kroes et al., 2013; Sahu et al., 2018)) but also from revealed preferences (e.g., (Hörcher et al., 2017; Yap et al., 2018)), a number of studies have estimated the value of crowding in terms of the willingness to pay to reduce it or its impact on the value of travel time. The disutility of crowding in these studies arises primarily from physical and psychological discomfort and exhaustion. However, given the wide and sustained impact of the COVID-19 pandemic, travellers are now likely to want to avoid crowds even more so than under normal circumstances as a measure towards minimizing their exposure to the virus (Tirachini and Cats, 2020).

Travellers may now focus on factors contributing to COVID-19 transmission and for service planners to be able to respond to these changes in behaviour it is essential to have an empirical underpinning of those. The question is then: given the COVID-19 pandemic, how will travellers respond to crowdedness on public transport vehicles and future changes in infection rates? Studies on the COVID-19 pandemic as well as those on previous epidemics resulting from viruses spread through similar means (such as SARS, MERS, swine flu) have shown that people perceive avoiding public transport as a preventive measure (Gerhold, 2020; Kim et al., 2017; Lau et al., 2003; Rubin et al., 2009). A number of COVID-19 related analyses also indicate a significant mode shift to private modes such as bicycles and automobiles demand (e.g., Bucsky (2020)). While these studies focus on perceptions and aggregate statistics, a detailed analysis of public transport travellers' choice behaviour is largely missing.

A Scopus search[2] and other modes of literature collection found only two studies conducting choice analysis in the context of public transport and epidemics. Scorrano and Danielis (2021) conduct a mode choice analysis for before and during COVID-19 in Trieste, Italy. The impact of the pandemic on mode choice is parametrised as mode-specific penalties which they find to be negative (and even more so for COVID-19 risk averse travellers) for public transport. Cho and Park (2021) also conduct a before-after experiment and estimate mode-specific crowding multipliers using stated choice data from Seoul. They find that crowding impedance is 1.04–1.23 times higher during the pandemic, confirming expectations that travellers would be more wary of crowds. While this latter study focuses on crowding, Scorrano and Danielis (2021) do not address specific changes in public transport attributes (e.g., crowding) relevant to the risk of COVID-19 infection. Moreover, since they compare before and after situations directly, neither of these studies assess the impact of different stages of the pandemic on traveller behaviour.

To this end, we contribute to the growing literature on COVID-19 and public transport by analysing how travellers have adapted their behaviour under these exigent circumstances. A stated choice experiment is conducted to analyse traveller behaviour specifically related to three criteria affecting the risk of COVID-19 transmission (Hu et al., 2020; Prather et al., 2020): (i) distance to other people, (ii) duration of exposure, and (iii) prevalent infection rate. In the context of public transport travel, the first two correspond to on-board crowding and in-vehicle time, respectively. With the choice experiment, we measure travellers' crowding valuation in the backdrop of the ongoing pandemic and how these valuations are affected by factors that might affect the perception of related risk. These model estimates will not only be useful for demand forecasting but could also provide insights that may be valuable for policy designs aimed at managing demand (Gkiotsalitis and Cats, 2020). In this study, we report findings from the stated choice experiment conducted with train travellers in the Netherlands towards the end of the first infection wave, just as the first restrictions were being lifted.

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[1] However, there is no conclusive evidence to this end and indeed some suggest that if recommended mitigation measures are implemented, the risk of contracting COVID-19 in public transport could be low (Gkiotsalitis and Cats, 2020; Goldbaum, 2020)

[2] Scopus search term (on 25 March 2021):
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( TITLE-ABS-KEY ( pandemic OR epidemic OR sars OR mers OR "swine flu" OR h1n1 OR ebola OR covid ) AND
TITLE-ABS-KEY ( "public transport*" OR transit OR bus OR tram OR train OR metro ) AND TITLE-ABS-KEY ( ( choice
OR logit OR probit ) W/2 ( model* OR analys* ) ) )
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In the next section, we describe the survey design, data collection, and choice analysis methodology. This is followed by the results and discussions in section 3. Finally, a summary of the results, potential policy implications, limitations of the study, and future avenues of research are outlined in section 4.

## 2.      DATA AND ANALYSIS

To understand traveller behaviour under the new circumstances presented by the pandemic, a stated choice experiment was conducted with Dutch train travellers. The experiment was part of a larger survey that collected, among other things, travellers' socio-demographics, mobility choices, and pandemic-related qualitative measures. Discrete choice analysis is applied on observations from the experiment to measure crowding valuation while the personal characteristics are used to explain heterogeneity in behaviour either *a posteriori* or as part of the choice model.

### 2.1      Survey design

### 2.1.1      Stated choice experiment

The experiment consists of a series of choice situations in which respondents were asked to assume that they had arrived at a train station from which two trains were available for their destination. They were informed that they were travelling with the same purpose for which they had indicated they most frequently used the train before the pandemic-related restrictions. The train alternatives varied only in terms of on-board crowdedness (distance to other people) and waiting time. We note that this means that crowding valuation will be obtained in terms of waiting time savings instead of the usual money amounts. We did not use different travel costs directly to avoid interactions with respondent income and expectations from a higher travel class. Implying that a more costly train would be less crowded (and therefore safer) could also lead to protest answers. Contextual information about factors potentially affecting the perception of contracting the disease, namely travel time (exposure duration) in either train and prevalent infection rate, was also given. The latter was provided in terms of the proportion of Dutch population that is infectious and capable of transmitting the virus to others. To ensure that only in-vehicle time was considered as the duration of exposure, we noted that it was possible to maintain social distance while waiting. Furthermore, respondents were reminded of the mandatory face mask regulations on-board public transport vehicles (Openbaar Vervoer Nederland, 2020b). Respondents were asked to rank the two train alternatives and the option of not travelling by train for each choice situation. We asked for a ranking rather than a single best choice to enable us to obtain trade-off estimates in the case that the majority of respondents chose to opt-out altogether.

On-board crowding was presented graphically as the seated section in a single coach of a commuter train (known as *Sprinter* in the Netherlands). Five levels of crowdedness were used: 5, 18, 23, 28, and 36 seats occupied (out of 40), colloquially corresponding to the following labels: 'almost empty', 'able to sit alone', 'unable to sit alone but not too crowded', 'quite crowded', and 'packed' (Figure 1). Three levels of waiting times were used: 3, 12, and 25 minutes. A wide range was deliberately used to ensure that we would observe trade-offs between on-board crowding and waiting time savings.

It is likely that respondents would find it difficult to respond to infection rate numbers without any real-world references on which to anchor their evaluation of this variable. To help respondents interpret the infection rate numbers, we sought to provide them a best estimate of the infection levels (i) at the time of the survey when restrictions had begun to be lifted (0.1%) and (ii) at the peak of the pandemic (in terms of daily reported cases and hospitalizations) in mid-April (0.43%). The proportion of infectious people in the population is innately unknowable due to the presence of asymptomatic and pre-symptomatic cases, limited testing capacity, and reluctance to get tested. Therefore, in the absence of official estimates (at the time of the survey[3]), we obtained the above numbers from back-of-the-envelope calculations using daily reported infections. In the experiment, five levels around these reference infection rates were used: 0.01% (pre-restriction levels), 0.1% (at the time of the survey), 0.5% (mid-April level), 2% 10% (extremely high). For the other contextual variable, in-vehicle time, three levels were used: 10, 25, and 40 minutes.

We used a semi-random experiment design: weakly dominated and symmetrical choice situations were removed from the full factorial of the above described attribute levels; and from these, 4 subsets of 15 choice situations were randomly picked. Respondents then faced one of these subsets at random. Walker et al. (2018) argue that semi-random designs,

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[3] Since then, the Dutch government has published these figures (also retroactively) (Rijksoverheid, 2021). Their estimates for April 15 and May 20 (at the time of the survey) are 0.34% and 0.08%, respectively. Although these values are fairly close to ours, they estimate the peak of the infection rate to be around the end of March rather than mid-April.

where dominated choice tasks are eliminated, perform as well as efficient designs, particularly because they are robust against a large range of parameter estimates and model specifications. A screenshot of the experiment is shown in Figure 2.
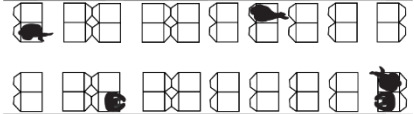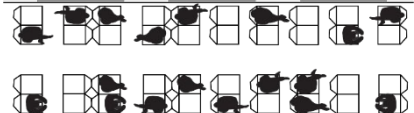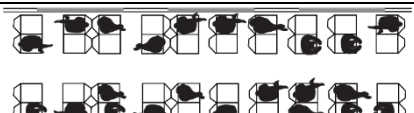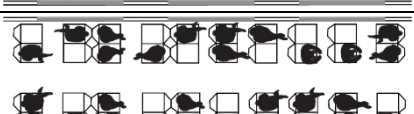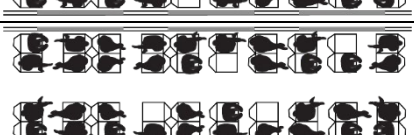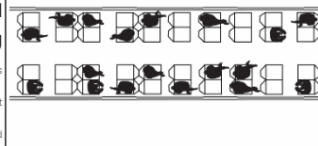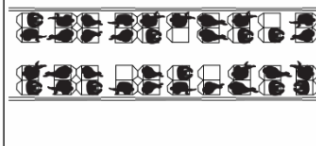
| Crowding Level | Graphic |
|---|---|
| Almost empty |  |
| Able to sit alone |  |
| Unable to sit alone but not too crowded |  |
| Quite crowded |  |
| Packed |  |

Figure 1: Graphical presentation of crowding levels



Figure 2: Screenshot of the choice experiment (translated to English)

### 2.1.2 Personal characteristics

Three categories of personal characteristics were collected to explain potential differences in behaviour: (i) mobility factors, (ii) socio-demographic factors, and (iii) COVID-19-related qualitative measures. In the first category, we asked travellers how often they travelled with the train before and during the pandemic-related restrictions, the crowding level

they usually experienced, their most frequent purpose of travel, and which alternative modes were available for these trips. In the second category, common socio-demographic questions (age, gender, income, employment status, zip code, highest education attained, and household size) were asked. In addition, some variables more specific to the current context were also collected; in particular, ages of household members and past, current, and expected future status of working or studying from home. The final category consists of questions regarding the perceived likelihood of the respondent or someone in their household getting infected and the severity of the disease if they do. Respondents were also asked about the degree to which they think they, themselves, and others follow pandemic related advice and regulations such as frequent hand sanitization and social distancing in public places. Finally, this category also includes questions about institutional trust and frequency of information seeking in relation to the pandemic. Note that all variables in this category except the last one noted here are qualitative Likert scale measures.

## 2.2    Data collection

The survey was distributed to Dutch train travellers who travelled by this mode at least once per month before March 2020 when the first pandemic-related restrictions were imposed. In March 2020, the Dutch government urged travellers to use public transport only 'if it is really needed'. By May 2020, having achieved a reduction in the daily reported cases, Dutch authorities announced that certain professions, services, and educational activities could resume by the end of that month (Rijksoverheid, 2020). Furthermore, public transport could be used once again by mid-June 2020 but with new regulations such as mandatory face masks and  seat blocking to maintain distance (the latter was stopped in July 2020) (Openbaar Vervoer Nederland, 2020b). Data collection took place from 20 to 25 May, after announcements concerning these measures had been made. A total of 513 valid responses[4] were collected via an online panel. The survey was offered in Dutch and we expected a completion time of 12–15 minutes. In addition to pre-COVID-19 train use requirements, we sought to collect a sample representative of the overall Dutch population in terms of age, gender, and education level (Table 1).

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[4] About 40 responses completed in less than 6 minutes were removed as this was considered to be too fast to have been properly answered. Response time was not a significant indicator in a simple linear-additive multinomial logit model and a model with just these responses returned many insignificant ($p < 0.05$) parameters indicating randomness in the responses given.

Table 1: Sample characteristics

| Total respondents | | 513 | |
|---|---|---|---|
| | | **Distribution (%)** | |
| **Attribute** | **Value** | **Actual** | **Required[5]** |
| | Female | 49% | ~50% |
| Gender | Male | 50% | ~50% |
| | Other | 0% | |
| | | | |
| | 18-24 | 15% | 11% |
| | 25-34 | 18% | 16% |
| | 35-44 | 17% | 15% |
| Age | 45-54 | 17% | 18% |
| | 55-64 | 19% | 17% |
| | 65-74 | 13% | 14% |
| | >74 | 2%[6] | 10% |
| | | | |
| | Elementary school (*basisonderwijs*) | 1% | ~29% |
| | Secondary school (*HAVO/VWO/VMBO*) | 27% | |
| Education[7] | Vocational diploma (*MBO*) | 34% | ~37% |
| | Higher professional education (*HBO*) | 25% | ~33% |
| | University education incl. bachelor, master, PhD (*WO*) | 13% | |

## 2.3    Choice analysis

Observations are analysed under the conventional random utility maximization framework where the utility of an alternative *i* for individual *n*, $U_{in}$, consists of a systematic ($V_{in}$) component, capturing the utility associated with factors observed by the analyst, and a random ($\varepsilon_{in}$) component. We assume that the systematic component is linear-additive and is computed by taking the sum of the alternate specific constant ($\beta_i$) and the product of taste preferences ($\beta_{ij}$) and the values of attributes, j ($x_{ijn}$) (Equation [1]). As respondents provide a ranking of train alternatives and the opt-out option, we can either use a linear-additive multinomial logit (MNL) or rank-ordered multinomial logit (R-MNL) model in each class. While the former only uses the top choice, the latter takes advantage of the information available in the complete ranking. We note that, since ranking is not something respondents do in real life, they are not always able to perform it efficiently which may lead to bias in the R-MNL model (Fok et al., 2012). The probability of choosing alternative *i* from *I* alternatives, that is the MNL model, is given by Equation [2]. The R-MNL model is a sequential application of this formula. The probability of subsequent choices is obtained by applying the same formula and removing the choices ranked higher from the choice set. The likelihood of observing a ranking is given by the product of the predicted probability of the top choice, the next choice, and so on.

$$U_{in} = V_{in} + \varepsilon_{in}$$
$$V_{in} = \beta_i + \sum_j \beta_{ij} \cdot x_{ijn} \qquad [1]$$

$$P_{in} = \frac{e^{V_{in}}}{\sum_{i'=1}^{I} e^{V_{i'n}}} \qquad [2]$$

To assess heterogeneity in traveller behaviour we use a latent class choice model (LCCM) which is a discrete mixture of choice models to which individuals are probabilistically allocated. Although the choice models can have different

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[5] Source: Centraal Bureau voor de Statistiek (2020)
[6] The under-sampling here is potentially due to the minimum train trip frequency requirement
[7] Translated to international equivalents

attributes, structures, or even belong to a completely different framework, we use the same model in each class. The probability of an individual $n$, belonging to class $s$ (amongst S classes) with probability $\pi_{ns}$, choosing alternative $i$ is the product-sum of the class membership probabilities and the probability of selecting that alternative for each class (given the vector of taste parameters in that class, $\boldsymbol{\beta_s}$) (Equation [3]). Panel effects are accounted for by assuming that a particular individual is allocated to each class with the same probability for all their choices. The likelihood of observing an individual's sequence of choices $i:i_1,...,i_T$ by individual $n$ over $T$ situations is given by Equation [4].

$$P_{in} = \sum_{s=1}^{S} \pi_{ns} \cdot P_{in}(\boldsymbol{\beta_s}) \qquad [3]$$

$$L_{in} = \sum_{s=1}^{S} \pi_{ns} \prod_{t=1}^{T} P_{in_t}(\boldsymbol{\beta_s}) \qquad [4]$$

An important aspect of LCCM is the ability to explain behavioural heterogeneity though class membership probabilities using values of individual characteristics, $k$ ($z_{kn}$) (Equation [5]). We use socio-demographic and mobility characteristics to explain class membership. For other, generally unobservable variables (such as, worrying about transmitting the infection to someone in the household), we conduct a posterior analysis to find the distributions of these variables in the classes of the estimated model.

$$\pi_{ns} = \frac{e^{\delta_s + \sum_k \gamma_{ks} \cdot z_{kn}}}{\sum_{s'=1}^{S} e^{\delta_{s'} + \sum_{k'} \gamma_{k's'} \cdot z_{k'n}}} \qquad [5]$$

The class-specific taste parameters ($\beta_s$) and membership coefficients ($\gamma_{ks}$, $\delta_s$) are simultaneously estimated using PythonBiogeme (Bierlaire, 2016).

## 3.     RESULTS

Since the experiment was conducted in the context of the COVID-19 pandemic, one fear was that a large number of respondents would simply opt-out of using trains altogether. Ultimately, this was not the case and only about 4% of the respondents always opted-out while 13% never opted-out in the 15 situations they faced. However, a substantial number of non-traders between the train alternatives were present: 13% of the respondents always preferred to wait for the less crowded train while 3% always took the more crowded option. As expected the proportion of observations where the respondent takes the crowded train rises with the extra waiting time required to reduce one person on-board (Figure 3).
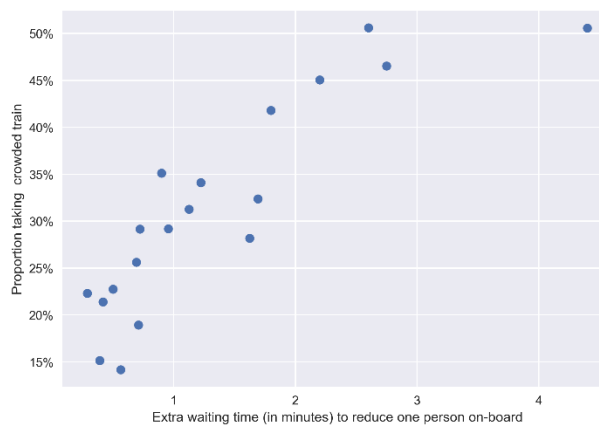


Figure 3: Proportion of observations choosing crowded train versus extra waiting time to reduce one person on-board

We tried a number of utility specifications, in particular varying whether attributes were modelled as having a linear or non-linear effect. This was done with both MNL and R-MNL models. Ultimately, the utility specification in Equation [6] within MNL was found to provide the most informative model parameters; that is, the estimated non-linear terms were meaningful and all parameters generally had the expected signs. Crowding and infection rate are included as non-linear variables. Since, perceived infection risk (and, therefore, disutility of a train alternative) may be higher when two contributing factors are higher together, we include interaction effects of crowding with infection rate and in-vehicle times in the utility specification.

$$V_{\text{train 1}} = \beta^{\text{crowd: can sit alone}} \cdot crowd_{18,\,\text{train 1}} + \beta^{\text{crowd: not crowded}} \cdot crowd_{23,\,\text{train 1}}$$
$$+ \beta^{\text{crowd: quite crowded}} \cdot crowd_{28,\,\text{train 1}} + \beta^{\text{crowd: almost full}} \cdot crowd_{36,\,\text{train 1}}$$
$$+ \beta^{\text{WT}} \cdot WT_{\text{train 1}} + \beta^{\text{crowd×infect}} \cdot crowd_{\text{train 1}} \cdot infect + \beta^{\text{crowd×IVT}} \cdot crowd_{\text{train 1}} \cdot IVT$$
$$V_{\text{train 2}} = \beta^{\text{crowd: can sit alone}} \cdot crowd_{18,\,\text{train 2}} + \beta^{\text{crowd: not crowded}} \cdot crowd_{23,\,\text{train 2}}$$
$$+ \beta^{\text{crowd: quite crowded}} \cdot crowd_{28,\,\text{train 2}} + \beta^{\text{crowd: almost full}} \cdot crowd_{36,\,\text{train 2}} \qquad [6]$$
$$+ \beta^{\text{WT}} \cdot WT_{\text{train 2}} + \beta^{\text{crowd×infect}} \cdot crowd_{\text{train 2}} \cdot infect + \beta^{\text{crowd×IVT}} \cdot crowd_{\text{train 2}} \cdot IVT$$
$$V_{\text{opt-out}} = \beta^{\text{opt-out}} + \beta^{\text{IVT}} \cdot IVT$$
$$+ \beta^{\text{infect: 0.01}} \cdot infect_{0.01} + \beta^{\text{infect: 0.5}} \cdot infect_{0.5} + \beta^{\text{infect: 2}} \cdot infect_{2} + \beta^{\text{infect: 10}} \cdot infect_{10}$$

Next, we find the optimal number of classes for the LCCM using an intercept-only class membership function. Typically, this is done using the model fit indicators, such as Bayesian information criterion (BIC), which explicitly penalize the number of parameters in the model. In our case, model fit indicators continued to improve as we increased the number of classes (we checked up to 6 classes). Therefore, we chose the 2-class model as it, in our opinion, best described heterogeneity in behaviour. While the 2-class model clearly delineated two behavioural types, adding more classes yielded intermediate groups without adding more insights. Moreover, adding more groups resulted in higher standard errors of estimated parameters and for higher number of classes, even led to unexpected parameter signs. A 2-class LCCM with R-MNL choice models using the same utility specification did not lead to a better model overall. The choice models in each class are finalized by removing insignificant ($p > 0.10$) parameters one-by-one. Finally, all non-correlated observable individual characteristics are included in the class membership function and eliminated one-by-one if they are insignificant to arrive at the final model shown in Table 3. Table 2 gives an overview of the attributes included in this final model.

The choice parameters in both classes have signs and magnitudes in line with expectations. Results show that, in general, higher levels of crowdedness, waiting times, and infection rates all reduce travellers' willingness to board a particular train alternative and increase the probability of opting out. Surprisingly, in-vehicle time—time to be spent in an enclosed train coach—does not affect travellers' decisions indicating that they might be underestimating the importance of duration of exposure on the risk of infection.

Table 2: Overview of attributes included in the final choice model

| Attributes | Symbol | Explanation | Range |
|---|---|---|---|
| **Choice coefficients** | | | |
| Crowding (level $i$) | $\beta^{\text{crowd: }i}$ | Categorical (effect coded) | |
| Waiting time | $\beta^{\text{WT}}$ | All time attributes are in minutes | 3-25 |
| In-vehicle time | $\beta^{\text{IVT}}$ | | 10-40 |
| Infection rate (level $i$) | $\beta^{\text{infect: }i}$ | Categorical (effect coded) | |
| Opt-out constant | $\beta^{\text{opt-out}}$ | | |
| | | | |
| **Personal characteristics** | | | |
| Age | $\beta^{\text{age}}$ | Ordinal in ascending order: 18-24, 25-34, 35-44, 45-54, 55-64, 65-74, 75-84 | 1-7 |
| Gender | $\beta^{\text{female}}$ | Categorical (effect coded): female, male | |
| Train use frequency during COVID | $\beta^{\text{train freq. covid}}$ | Ordinal in ascending order: never, once per month, 1-3 times per month, more than 4 times per week | 1-4 |

Table 3: Estimation results of the 2-class LCCM

| Model | LCCM 2-Class | | | | | |
|---|---|---|---|---|---|---|
| # Parameters | 23 | | | | | |
| Initial LL | −8054.030 | | | | | |
| Final LL | −6498.217 | | | | | |
| Adjusted $\rho^2$ | 0.190 | | | | | |
| BIC | 13202.246 | | | | | |
| | *Class-specific choice models* | | | | | |
| | **Class 1: COVID Conscious Travellers** | | | **Class 2: Infection Indifferent Travellers** | | |
| Class Size | 53.73% | | | 46.27% | | |
| | | | | | | |
| | Coeff. | p-val | Scaled | Coeff. | p-val | Scaled |
| $\beta^{\text{crowd: almost empty}}$ | 2.230 | − | −159.29 | 0.690 | − | −18.16 |
| $\beta^{\text{crowd: can sit alone}}$ | 0.792 | 0.00 | −56.74 | 0 | − | − |
| $\beta^{\text{crowd: not crowded}}$ | −0.531 | 0.00 | 37.93 | 0.110 | 0.01 | −2.89 |
| $\beta^{\text{crowd: quite crowded}}$ | −0.921 | 0.00 | 65.79 | −0.262 | 0.00 | 6.89 |
| $\beta^{\text{crowd: almost full}}$ | −1.570 | 0.00 | 112.14 | −0.538 | 0.00 | 14.16 |
| $\beta^{\text{WT}}$ | −0.014 | 0.02 | 1 | −0.038 | 0.00 | 1 |
| $\beta^{\text{crowd×infect}}$ | −0.0046 | 0.00 | 0.33 | −0.0026 | 0.00 | 0.07 |
| $\beta^{\text{crowd×IVT}}$ | − | − | − | − | − | − |
| $\beta^{\text{infect: 0.01}}$ | −0.720 | 0.00 | 51.43 | 0 | − | − |
| $\beta^{\text{infect: 0.1}}$ | −0.213 | − | 15.21 | −0.488 | − | 12.84 |
| $\beta^{\text{infect: 0.5}}$ | 0.133 | 0.08 | −9.5 | 0 | − | − |
| $\beta^{\text{infect: 2}}$ | 0.521 | 0.00 | −37.21 | 0.254 | 0.00 | −6.68 |
| $\beta^{\text{infect: 10}}$ | 0.279 | 0.05 | −19.93 | 0.234 | 0.00 | −6.16 |
| $\beta^{\text{IVT}}$ | − | − | − | − | − | − |
| $\beta^{\text{opt-out}}$ | 0.927 | 0.00 | −66.21 | −2.02 | 0.00 | 53.16 |
| | *Class membership model* | | | | | |
| | **Class 1: COVID Conscious Travellers** | | | **Class 2: Infection Indifferent Travellers** | | |
| | Coeff. | p-val | Scaled | Coeff. | p-val | Scaled |
| $\beta^{\text{intercept}}$ | 0 | − | − | −1.160 | 0.00 | 1 |
| $\beta^{\text{age}}$ | − | − | − | −0.107 | 0.08 | 0.09 |
| $\beta^{\text{female}}$ | − | − | − | −0.275 | 0.01 | 0.24 |
| $\beta^{\text{train freq. covid}}$ | − | − | − | 0.820 | 0.00 | −0.71 |

As can be seen from the scaled values in Table 3, the two estimated classes differ strongly on the relative impact of level of crowdedness and infection rates. Moreover, the general propensity to opt-out has a very large effect in both classes but is in opposite directions. We call travellers in the first class 'COVID Conscious'. For these travellers, decisions are more strongly driven by the level of crowdedness, infection rates, and the expected number of infected persons on-board (approximated by the interaction effect of crowdedness and infection rate). In contrast, travellers in the second class, who we call 'Infection Indifferent', are affected by these factors to a lesser degree and are also less likely to opt-out on average.

Typically, the effect of crowding has been modelled as an in-vehicle time multiplier (Li and Hensher, 2011; Wardman and Whelan, 2011). The idea being that the disutility of crowdedness should be larger for longer trips because passengers have to be in a crowded vehicle for a longer time. We included crowding in our model both as a constant penalty as well as an interaction effect with in-vehicle time (i.e., as a multiplier). As shown in Table 3, the time multiplier parameters were not significant. When constant penalties are excluded, the time multiplier parameters are significant but, similar to Kroes et al. (2014), the model has a significantly lower goodness of fit. We note that constant penalties may only be performing better for the range of in-vehicle times that were tested in this survey or because in-vehicle times were only included as context effects in the experiment.

Equation [7] shows how the values of crowding are calculated. Since we estimate parameters for each crowding level ($i$), the coefficient for change in crowding between two levels ($\beta^{\text{crowd:}i \rightarrow i+1}$) is given by the difference in the utility

contributions divided by the difference in the number of persons on-board ($x^i$). This crowding coefficient divided by the coefficient for waiting time gives the value of crowding in terms of waiting time between those levels ($\Upsilon^{i \to i+1}$). The average value of crowding ($\Upsilon$) is given by the weighted average of these individual values of crowding.

$$\beta^{\text{crowd: } i \to i+1} = \frac{\beta^{\text{crowd: } i} - \beta^{\text{crowd: } i+1}}{x^i - x^{i+1}}$$

$$\Upsilon^{i \to i+1} = \frac{\beta^{\text{crowd: } i \to i+1}}{\beta^{\text{WT}}} \qquad [7]$$

$$\Upsilon = \frac{\Upsilon^{1 \to 2} \cdot (x^2 - x^1) + \Upsilon^{2 \to 3} \cdot (x^3 - x^2) + \Upsilon^{3 \to 4} \cdot (x^4 - x^3) + \Upsilon^{4 \to 5} \cdot (x^5 - x^4)}{(x^2 - x^1) + (x^3 - x^2) + (x^4 - x^3) + (x^5 - x^4)}$$

Travellers in the COVID Conscious class, are willing to wait an extra 8.75 minutes, on average, to reduce just one person on-board. As shown in Figure 4, travellers in this class are willing to wait the most when there is a possibility to sit alone. This is indicative of the aversion towards infection risk in this class as well as the general framing of the choice situations in the context of the pandemic. Note that this is in contrast to previous studies which typically report that the impact of crowding increases with the number of persons on-board, especially after 60–80% load factor (Hörcher et al., 2017; Wardman and Whelan, 2011; Yap et al., 2018). The value of crowding for Infection Indifferent travellers seems to be more in line with values from previous studies (albeit on the higher end) with an average willingness to wait of 1.04 minutes to reduce one person on-board.
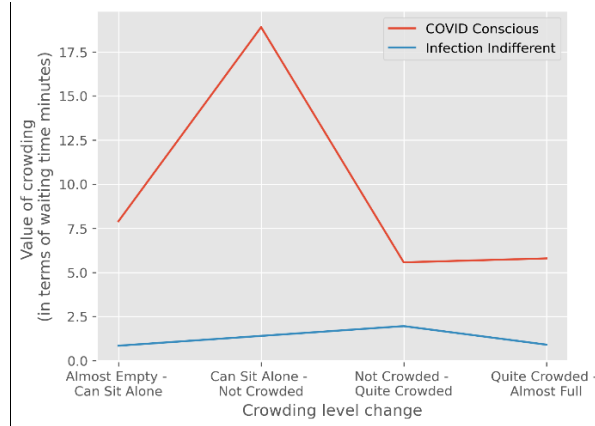


Figure 4: Value of crowding (in terms of waiting time minutes per person on-board) between levels in the two traveller classes[8].

Previous studies that evaluate the effect of seating occupancies — either as constant penalties or in-vehicle time multipliers — and waiting times can be compared with our results. To convert coefficients from such studies to units comparable to ours, where required, we assume a total seat capacity of 40 and an in-vehicle time range of 10–40 minutes. Preston et al. (2017) observed stated choices in an experiment where respondents chose between two trains: the first which was due but with no possibility to sit and the second with a given expected waiting time and one of two lower crowding levels. They report constant crowding penalties that lead to values of crowding in the range of 0.52–0.96 minutes per person. From an experiment similar to ours, Kroes et al. (2013) find a willingness to wait of 0.15 and 0.33 minutes per person to reduce crowdedness from 75% to 50% and from 100% to 75%, respectively. Assuming expected waiting times to be half of headways, Tirachini et al. (2013) find similar values of 0.15–0.6 minutes per person from a mode choice experiment. For comparison, note that we found the COVID Conscious and Infection Indifferent classes willing to wait 8.75 and 1.04 minutes per person, respectively. Douglas and Karpouzis (2006) and Sahu et al. (2018) use similar stated choice experiments for Sydney and Mumbai. They find that travellers are willing to wait 1.88–7.52 minutes and 3.58–14.32 minutes, respectively, for an uncrowded seat over a crowded seat alternative. Assuming 'not crowded' and 'almost full' to be the corresponding categories in our model, we find an extremely high value of 74 minutes and a more moderate 17 minutes in the COVID Conscious and Infection Indifferent classes, respectively. Using revealed preferences from smart card data in The Hague, however, Yap et al. (2018) found significantly lower values between 0.015 and 0.06 minutes per person (depending on in-vehicle times) for trams. Thus, while both the COVID Conscious and Infection Indifferent classes show higher values of crowding, the latter is much closer to pre-pandemic estimates from stated choice experiments.

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[8] The value of crowding interpolated between can sit alone and not crowded in the Infection Indifferent class

As shown in Figure 5, for both classes of travellers, the tendency to opt-out increases as a concave function of the prevalent infection rate. The effect plateaus at extreme infection rates (2% and 10%) indicating that travellers may be considering a threshold level beyond which the infection rate itself no longer contributes to perceived risk. The graph for COVID Conscious travellers demonstrates again the strong preference to sit in an almost empty coach or to sit alone. Furthermore, note that the opt-out rates for crowded vehicles in the COVID Conscious class are fairly inelastic in relation to infection rates. This might indicate that travellers in this group would not feel safe travelling in crowded vehicles even when infection rates are back to pre-pandemic levels.
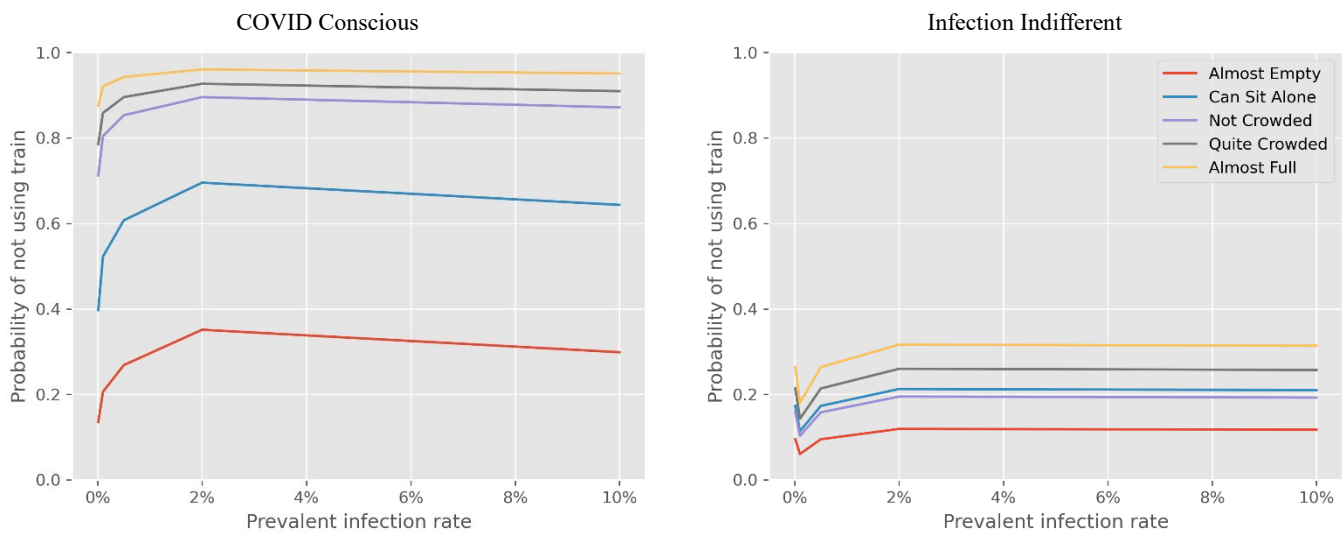


Figure 5: Probability of not using trains versus infection levels for different crowding levels in the two groups (wait time for trains is 12 minutes)

Amongst the individual characteristics collected, three variables contributed to explaining the differences in behaviour between the two classes. Older and female respondents were over-represented amongst COVID Conscious travellers whereas those reporting higher train use during the COVID-19 restrictions were likely to be Infection Indifferent. Presumably, older people, are more risk averse due to a higher vulnerability to the disease. While the disease does not seem to affect women more severely than men, female respondents have often been shown to be more risk averse in their decisions (e.g., de Palma and Picard (2005)). Kluwe-Schiavon et al. (2021) also find that older and female respondents had a lower COVID-19 risk tolerance for economic opportunity. The relationship between higher train use during the pandemic and lower risk aversion may be in either direction. Travellers classified as Infection Indifferent may have used the train more frequently because they are not particularly averse to the COVID-19 risk. Conversely, lower risk aversion amongst those who use the train more frequently during the pandemic might be explained by the existence of the description-experience gap when evaluating risky choices. When judging the likelihood of contracting COVID-19 on public transport, these travellers may be depending more on their experience rather than the risk described by authorities (Barron and Erev, 2003). When people make decisions based on experience, they do not account for rare events as much as the objective probabilities of such events suggest they should (Hertwig and Erev, 2009). A little surprisingly, having the possibility to conduct the trip with a private mode (e.g., car, bicycle, walk) was not related to the propensity to opt-out of the train alternatives.

Figure 6 shows the results of the posterior distributions of unobserved COVID-19-related qualitative measures in the final model. Although the two classes of travellers do not differ too strongly on these factors, small differences can be noted. COVID Conscious travellers tend to be more worried about the pandemic, specifically, about being hospitalized and spreading the infection to someone in their household. A moderate correlation exists between age and worrying about being hospitalized but not with other factors (older travellers are over-represented in this class). Additionally, COVID Conscious travellers reported themselves to be more rule-following, indicating that they followed advice such as frequently sanitizing hands and maintaining 1.5 m distances in public places. Moreover, they also had a more negative opinion about the degree to which others followed these rules. Indicative of the long drawn national debate over it (DutchNews.nl, 2020), face mask use seemingly does not follow this pattern and while rule following on other aspects are strongly correlated, face mask use is not.
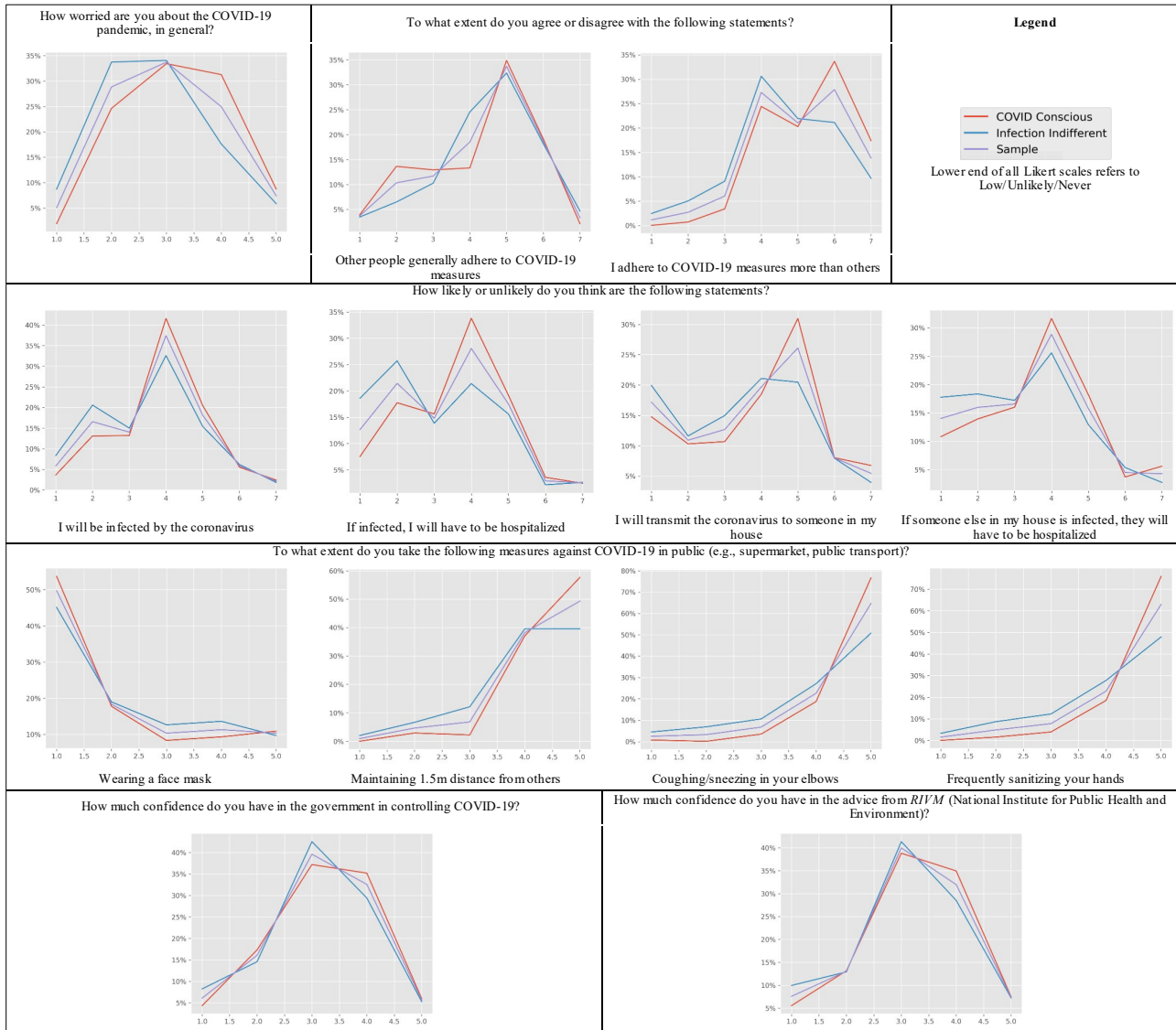
Figure 6: Class profiles of personal, unobserved, qualitative measures related to the COVID-19 pandemic

## 4. CONCLUSION

The COVID-19 pandemic has had an extensive impact on public transport. As a result of actions and advisories aimed at containing the disease, public transport ridership has declined sharply, perceptions regarding this mode have become more negative, and there has been a shift to personal transport modes. Consequently, changes in traveller behaviour in order to minimize exposure to the virus are expected. Moreover, these changes may be sustained through different stages of the pandemic and even have a significant effect on public transport demand after the pandemic. While a number of studies examine current ridership patterns and anticipated transport preferences, detailed investigation of trade-offs in the age of COVID-19 via choice analysis is missing.

In this study, we analysed traveller behaviour related to factors affecting the risk of COVID-19 transmission in public transport with a stated choice experiment. Since one of the most important ways to avoid exposure is to reduce contact with other people, we measured travellers' (potentially updated) valuation for on-board crowding. To do this, we obtained respondents' preferences between a crowded-but-low-wait-time and a less-crowded-but-higher-wait-time (and an opt-out) alternative. Choices were presented in the context of exposure duration (operationalised as the in-vehicle time of the alternatives) and infection rate to examine the effects of these risk-contributing factors on choice behaviour. Responses were collected from train travellers in the Netherlands at the end of the first infection wave (May 20-25, 2020), just as the first restrictions were being lifted and new regulations were setup for travel in public transport. We believe that behavioural insights from this study will not only contribute to better demand forecasting but will also be valuable in informing public transport policy decisions.

Applying a latent class choice model, we found two, nearly equal-sized traveller segments: COVID Conscious and Infection Indifferent. While higher crowding levels and infection rates reduce the willingness to board a train in both, the effect of these factors is much larger in the COVID Conscious segment. Value of crowding, measured as the number

of minutes travellers are willing to wait to reduce one person on-board, is also significantly higher in this class (on average 8.75 minutes/person) and increases sharply with the possibility to sit alone. In contrast, Infection Indifferent travellers' value of crowding (on average 1.04 minutes) is comparable to, although slightly on the higher end of, pre-pandemic evaluations. Moreover, unlike their counterparts, COVID Conscious travellers are highly affected by the prevalent infection rate, particularly at low crowding levels, and are more likely to opt-out in general. Surprisingly, neither group took the exposure duration into account. Older and female respondents are over-represented in the COVID Conscious class while those who report higher train use during the pandemic are more likely to belong to the Infection Indifferent class. Finally, distributions of COVID-19-related indicators showed that COVID Conscious travellers were more worried about the pandemic, considered themselves and household members more likely to be hospitalised if infected, and reported themselves to be following related measures to a higher degree.

A variety of direct and indirect effects of the pandemic have led public transport ridership to plummet. Given the importance of public transport in economic recovery and sustainable mobility, authorities and operators need to work to improve travellers' perception about public transport and slow down the shift to non-sustainable modes. Ridership levels have typically returned to normal at the end of previous localized catastrophic events, such as epidemics and security threats (Gkiotsalitis and Cats, 2020). However, the COVID-19 pandemic is unprecedented in its spatial and temporal scale with regions around the world going in and out of lockdowns over an extended period of time. Thus, authorities cannot depend on ridership to improve by itself but must actively work towards increasing public transport demand while providing this essential service safely.

The apprehension of the COVID Conscious segment seemingly follows calls from authorities to avoid public transport. While such calls are compatible with the intuition that sharing confined spaces may be unsafe, there is little to no hard evidence of outbreaks linked to public transport. This might suggest that public transport travel could be safe if recommended measures are implemented (Gkiotsalitis and Cats, 2020; Goldbaum, 2020; Schive, 2020; UITP, 2020). Yet, the fact that over two-thirds of COVID Conscious travellers in our sample are unwilling to travel if they cannot find an empty row, regardless of infection level, is an indication of how difficult it will be to restore travellers' confidence and foreshadows lingering behavioural adaptations from the pandemic in the future. Where trips cannot be replaced by telecommuting or active modes, providing crowding information for public transport can be the key. For low infection rates (0.1%), when there is a possibility to sit in an almost empty coach or with the adjacent seat empty, 50-80% of COVID Conscious travellers in our sample indicated that they will use the train. By highlighting which trains and coaches will be less crowded, these travellers can adjust their departure times, routes, and even the choice of which coach to board. Assuming that these travellers overestimate the likelihood of contracting COVID-19 on-board public transport, more experience with travelling (even in less crowded vehicles) could bring their assessments in line with reality.

While public transport may be safe with recommended measures, their overall lower concern regarding the virus and absence of substantial behavioural change, indicates that Infection Indifferent travellers may not be motivated to follow them carefully. Poor compliance from these travellers could increase the real as well as perceived risk for everyone and further drive the apprehension of other travellers. Therefore, we must continue to emphasize the need for simple measures such as face masks and recognize that returning to pre-pandemic levels of crowding while the prevalent infection levels are still significant would be reckless.

Although the stated choice experiment provides important behavioural estimates we note limitations arising from the information provided to respondents and the nature of such experiments. Firstly, the prevalent infection rates given as an contextual attribute can only be estimated, and trusted estimations may not be available everywhere. Even if they were available, one might question whether travellers actually consider this information directly or respond to more abstract cues, such as the intensity of regulations or media coverage. However, since it is difficult to recreate the entire context for the experiment, we used this single indicator (which is correlated to such cues). Furthermore, travellers were helped in anchoring the prevalent infection rates to abstract cues by providing the prevalent infection rates at two different dates. Nevertheless, care must be taken when transferring estimations to other situations. Future studies could focus on analysing the impacts of specific societal, political, and media cues on pandemic-related travel behaviour.

Secondly, crowding information is not commonly available although a growing number of public transport networks and trip planning applications now try to provide predictions in some format (see review in (Drabicki et al., 2020)). In their smartphone application, the Dutch railways show a (qualitative) three-level crowding indicator for most trains and a more precise 'seat-finder' on some trains showing seat availability in different coaches (Nederlandse Spoorwegen). By prominently displaying crowding information, we may have drawn respondents' attention to this aspect more than usual. On a related note, depending on factors such as trust in the information provided by the operator, travellers may consider waiting time and crowding attributes of the second train to be uncertain and therefore attach a higher disutility

to it. Here, however, we presented these attributes as if they were objectively true. We believe reliable crowding information could be key in regaining travellers trust. Studies assessing travellers' responses to different presentation formats and reliability levels would be critical for such developments.

Thirdly, we note that choices observed here are hypothetical and the situations do not directly reflect the various constraints arising from societal positions of individuals. These constraints have been previously found to play a significant role in travellers actual capacity to change behaviour (Kim et al., 2017). Thus, although we find an intent to avoid trains amongst COVID Conscious travellers their ability to do so may be limited because of employer constraints. In contrast, some Infection Indifferent travellers may indicate intent to use the trains but do not actually do so as they can work/study from home. We attempted to control for such factors by marking the opt-out option as 'I will not make this trip by train' and asking respondents if they had alternative modes for the stated trip purpose. We also asked respondents' family income range and (for working/studying individuals) how effectively they could work/study at home. None of these variables were found to contribute towards explaining choice behaviour. Nevertheless, the precise distribution of travellers between the different classes and their propensity to opt-out must be used with care in applications, accounting for other individual constraints that might affect behaviour. We can, however, confidently interpret crowding valuations and the existence of significant risk-averse and indifferent traveller segments.

Finally, we stress that we have observed a snapshot of behaviour (and intent) for present and future circumstances. Since the global outbreak of the COVID-19 pandemic in March 2020, the situation has developed quickly and unpredictability. Given the widespread and extended impact of this pandemic, people have been rapidly adopting and changing behaviours for the evolving new realities encountered during the course of this crisis. Yet, these acquired behaviours also fluctuate as the level of precaution changes depending on a number of factors, such as local infection rates, personal impact assessment, and 'pandemic fatigue'. Thus, the trade-offs estimated here may change with new and significant developments; for instance, if a significant proportion of the population is vaccinated.

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## DECLARATION OF INTEREST

The authors declare that there is no conflict of interest.

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