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Change in departure time for a train trip to avoid crowding during the COVID-19 pandemic: A latent class study in the Netherlands

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ABSTRACT

After the outbreak of COVID-19 pandemic, crowding has been highlighted as a risk factor for contracting acute respiratory infections (ARIs) such as COVID-19, which has affected the demand for public transport. Although several countries, including the Netherlands, have implemented differential fare systems for peak and off-peak travel to reduce crowding during the rush hours, the problem of overcrowding on trains has remained prevalent and is expected to cause more disutility than even before the pandemic. A stated choice experiment in the Netherlands is conducted to understand the extent to which people can be motivated to change their departure time to avoid crowded trains during rush hours by offering them real-time information on on-board crowding levels and a discount on the train fare. To gain further insights into how travelers respond to crowding and capture unobserved heterogeneity in the data, latent class models have been estimated. Unlike the previous studies, the respondents were segregated into two groups before the start of the choice experiment based on their indicated preference to schedule a delay earlier or later than their desired departure. To study the change in travel behavior during the pandemic, the context of different vaccination stages was also provided in the choice experiment. Background information collected in the experiment was broadly categorized as socio-demographic, travel and work-related factors, and attitudes towards health and COVID-19. It was found that the coefficients obtained for the main attributes which were presented in the choice experiment (on-board crowd levels, scheduled delay and discount offered on full fare) were found statistically significant, and in line with previous research. It was concluded that when most of the people are vaccinated in the Netherlands, the travelers become less averse to on-board crowding. The research also indicates that certain groups of respondents, such as those who are highly crowd averse, and are not students, can be motivated to change their departure time if real-time crowding information was provided. Other groups of respondents who were found to value fare discounts can also be motivated to change their departure by similar incentives.

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1. Introduction

Crowding causes disutility in travel, especially during rush hours when public transport experiences overcrowding. Overcrowding is shown to lead to mental stress, increased risk to safety, security, and health (Cox et al., 2006; Evans & Wener, 2007). Several countries, including the Netherlands, implemented a differential fare system for peak and off-peak travel to reduce crowding during the rush hours, however, the problem of overcrowding on trains remains prevalent and is expected to cause more disutility than before the pandemic (Gkiotsalitis & Cats, 2020). Ever since the COVID-19 pandemic began, crowding has been also highlighted as a source of the spread of respiratory infections (Qingui et. al., 2020). To minimize the spread of the virus, social distancing was recommended and implemented in most public spaces, including public transit. If social distancing was enforced on-board at all times, only approximately 25 percent of peak-hour demand could be satisfied (Gkiotsalitis & Cats, 2020; Besinovic & Szymula, 2021).

The lack of physical space needed to accommodate for social distancing on board is a major constraint experienced by the supply side of the system, which are the transit agencies. This constraint is mainly present during the peak hours. The demand side, on the other hand, is more flexible as it is usually bounded by the times when passengers wish to travel. Therefore, from the demand side, if passengers can shift their departure times to avoid crowded trains, this could spread out the demand more evenly and contribute towards reducing on-board crowding level. Policies such as flexible work hours and staggered work hours, which allow people to shift their departure times, could help to reduce traffic congestion, improve productivity, and work-life balance (Eurofound, 2012). For more than a year after the COVID-19 pandemic began, it was instructed by the government to practice social distancing. Moreover, in the face of the uncertain trajectory of the pandemic, social distancing may be recommended in the future. To avoid crowding on trains, Dutch employers were instructed to allow for staggered work hours and people were encouraged to work from home as much as possible. Even studies prior to the COVID-19 pandemic have proven that such approaches are helpful in reducing peak hour rush by allowing passengers to change their departure time (Zong et al., 2013; Maunsell, 2007; Pel et al., 2014; O'Malley, 1975). Although past studies focused on the departure time change, it is still not known how people respond when they are provided with prior or real-time information on expected crowding level on the train or offered some incentives on the train fares, and to what extent it could motivate them to change their departure time to prevent crowded trains (Li et al., 2018). Based on this research gap and the literature review, the following research question is formulated:

During the pandemic and for different vaccination stages in the Netherlands, to what extent people can be motivated to change their departure time to avoid crowded trains? To answer the main research question, other relevant aspects such as trade-offs that people make between on-board crowding during train commutes and changing their departure time had to be examined. In detail, the study explored to what extent a discount offered on train fare motivates people to change departure time and how the trade-off varies across different sub-groups of people.

Using these research questions, the paper explores the willingness to change the departure time in multiple dimensions and provides a contribution in numerous areas. First, it provides a very comprehensive review and summary of past studies. Second, it looks at whether travelers prefer to leave early or late to avoid peak-hour crowding as well as their valuation of crowding. Third, it studies the travelers' responses in relation to the vaccination rate and lastly, it uses latent class models to gain more insights into travelers' demographics and preferences.

The remaining sections of the paper are organized as follows; in Section 2, a detailed literature review of previous experiments that included stated choice and revealed preference is shown. Section 3 presents the design of the stated choice survey, the procedure of data collection, and is followed by methods used in this study (Section 4). Sections 5 includes the estimation results and Section 6 provides the discussion, policy recommendations, and limitations of this research. Lastly, the direction for further research and conclusions are presented in Section 7.

2. Literature review

In this section, a thorough review of previous experiments and research related to mitigating overcrowding in transport, and departure time change experiments is presented. Here, the departure time change is highlighted as a key mitigation measure taken by people to avoid crowded public transport and car users to avoid traffic congestion. Because of the rapidly growing body of literature relating to COVID-19, the papers selected for the review and used as an inspiration for this work include literature published until the end of the first half of 2021. This review would lay a foundation for the design of the stated choice survey developed in this research by helping in selection of attributes and their measurement units. To achieve a comprehensive review, a backward snowballing technique was used in addition to the recommendations from experts (van Wee & Banister, 2016; Jalali & Wohlin, 2012).

2.1. Valuation of crowding in public transport

Ever since the COVID-19 pandemic began, crowding has been highlighted as a source of spreading of respiratory infections. Social distancing was termed as an antonym of crowding (LUMC-COVID-19 Research Group et al., 2020) and implemented worldwide to stop and slow down the spread of the virus. Even before the COVID-19 pandemic, several studies to measure the value of crowding in public transport have been conducted with the major objective of improving public transport assignment models and predicting passenger choices by adding the disutility experienced from crowding in the choice models (Yap et al., 2020). In Table 1, an overview of studies, including methodology implemented in several experiments related to the valuation of crowding, is presented. Inspired by these experiments, the methodology used for the design of the current experiment, attributes to be traded off and unit to measure on-board crowding and value of crowding are selected. The last row of Table 1 also shows the experiment that is conducted as a part of the current research.

It is worth noting that Whelan & Crockett conducted a stated choice experiment in 2009 to estimate people's willingness to pay to reduce rail overcrowding by asking their respondents to trade-off on-board crowding and travel time. The indicator of in-vehicle crowding included seat occupancy rate (percentage of seats occupied), number of passengers standing (per meter square) and their positions, as well as the layout of how people are seated by considering empty seats around a passenger. To compute the value of crowding, several researchers recommends using a time multiplier rather than monetary indicators, as it was argued that such form is easier to interpret, convert, and apply for understanding the influence of crowding on passenger's behavior and benefits that could be achieved if crowding is reduced (Li & Hensher, 2011).

Regarding comparing revealed preference methods to stated choice methods or a mix of revealed and stated preference methods, research on this topic found that stated choice experiments often overestimate the value of crowding in public transports (Kroes et al., 2013; Hörcher et al., 2017; Yap et al., 2020; Batarce et al., 2015). In the context of crowding in the Netherlands, Yap et al. (2020) concluded that crowding significantly impacts the route choices of passengers in public transport and that in-vehicle time multiplier of crowding increased from 1.16 to 1.31 for normal to more frequent users of public transport when all seats were occupied. In stated choice experiments, the passengers tended to choose higher waiting time levels, while in reality, they boarded a more crowded train with less waiting time. Changing departure times to avoid crowding in commuting was found to be a more strategic decision taken by the passengers to avoid crowding on trains or other public transport (Maunsell, 2007; Pel et al., 2014).

Table 1
Experiment of valuation of crowding in public transport.

Serial No.	Research title	Reference	Crowding location	Indicator of crowding	Method *	Trade-off for crowding	Value of crowding (measurement)
1	Estimating the passenger cost of station crowding, Sydney.	Karpouzis & Douglas, 2005	Train station and platform crowding	Time to enter the station and access the station platform during different levels of crowding	SP	Waiting time	Indicator of station crowding: waiting time (at platform) and walking time (to access platforms) multipliers
2	Estimating the passenger cost of train overcrowding, Sydney.	Douglas & Karpouzis, 2006	In-vehicle (trains)	Crushed or uncrushed standing time in-vehicle and getting a crowded/ uncrowded seat	SP	Waiting time and In-vehicle travel time	AUD per person per hour; different for total journey length and seated length
3	Amending the Incentive for strategic bias in stated preference studies: case study in users' valuation of rolling stock, UK.	Lu et al., 2008	In-vehicle (trains)	Probability of standing for the length of the journey	SP	Fare, in-vehicle travel time, headway	Pounds per person per hour of travel
4	An investigation of the willingness to pay to reduce rail overcrowding, UK.	Whelan & Crockett, 2009	In-vehicle (trains)	Percentage of seats occupied, passenger standing per m2	SP	Fare, in-vehicle travel time spent sitting and standing	Different time multipliers for standing and seated pax
5	Valuing crowding in public transport systems using mixed stated/ revealed preferences data: the case of Santiago.	Batarce et al., 2015	In-vehicle (metro and bus)	Percentage of seats occupied, passenger standing per m2	RP and SP mix	Waiting time, In-vehicle travel time, fare (in SP) transfers and walking time (in RP)	In-vehicle time multipliers
6	Crowding cost estimation with large scale smart card and vehicle location data, Hong Kong.	Hörcher et al., 2017	In-vehicle (metro)	Probability of standing, passenger standing per m2	RP	In vehicle travel time	In-vehicle time multipliers
7	Crowding valuation in urban tram and bus transportation based on smart card data, the Hague.	Yap et al., 2020	In-vehicle (bus and tram)	Percentage of seats occupied, passenger standing per m2	RP	In-vehicle time, waiting time, number of transfers, transfer time path size	In-vehicle time multipliers
8	Avoiding the crowd: how do passengers trade-off time and crowding in the age of COVID-19, the Netherlands.	Shelat et al., 2021	In-vehicle (train)	Number of seats occupied	SP	Waiting time and crowding levels in different contexts of infection risk	Waiting time multiplier
9	Change in departure time for a train trip to avoid crowding during the COVID-19 pandemic: a latent class study in the Netherlands	2021, current study	In-vehicle (train)	Number of seats occupied	SP	Departure time change with on-board crowding in different contexts of vaccination stage	Departure time change to reduce one person on board

* SP stands for stated preference survey and RP stands for revealed preference survey.

While most studies were done in the absence of global pandemic, the literature relating to crowding and pandemic has been growing. The results from a stated choice experiment conducted during COVID-19 pandemic in May 2020 in the Netherlands have confirmed that crowding will have a different value for different types of travelers (Shelat et al., 2021). The authors aimed to study people's willingness to wait for less crowded trains to minimize the risk of getting infected. The authors also asked about the respondents' trade-off between on-board crowd levels and waiting time relating to the infection risk and travel time. By estimating a latent class cluster model, it was found that people who belonged to a more COVID-19 conscious class had an approximately 75 percent higher value of crowding, which was estimated to be 8.75 min per person and this value rose if there was an option to sit alone. They also concluded that women respondents were found to be more conscious about contracting COVID-19 and thus had a different value of crowding.

In a stated choice experiment conducted in the United Kingdom in 2008 (Lu et al., 2008), crowding was indicated as a probability of standing for a length of the journey. In Australia, on the other hand, Douglas & Karpouzis (2006) represented crowding on trains to the respondents as standing time of 'x' minutes to get a seat which was crowded/uncrowded. Value of crowding as a time multiplier was found to be 1.17, which is in the range of estimated value from the research mentioned above (Whelan & Crockett, 2009). The monetary multiplier for the value of crowding was found to be 1.47 AUD (Australian Dollars) for a seated passenger per hour, and the total cost (travel time cost and crowding cost) was found to be 9.92 AUD per person per hour. It was observed that the relationship between load factor and the total cost was non-linear. The value rises sharply as the load factor on transit was approaching 100 percent.

Based on the experiments explained above, the value of crowding is computed as a time multiplier as it is simpler to use and interpret (Li & Hensher, 2011). The representation of crowding is discussed further in Section 3.

Table 2
Departure time change experiments with car and public transport users.

Serial No.	Research title	Reference	Method	Alternatives and attributes	Findings
1.	Transportation research board special report, Manhattan, New York.	O'Malley, 1975	Experiment with 220,000 people	Staggered commute with at least 30 min early or later departure in the morning	Reduced congestion at busiest subways by 26 percent
2.	Rewarding off-peak railway commuting: a choice experiment, the Netherlands.	Bakens et al., 2010	SP experiment with train commuters in hypothetical travel scenario from the Hague to Utrecht	Choice between a regular train travel pass and an off-peak hour pass	Most of the population either decided to travel early every time, or later. Traveling early has less dis-utility than traveling later
3.	Surveying Sydney rail commuters' willingness to change travel time, Sydney.	Henn et al., 2011	SP Experiment with train commuters	Departure time change, fare incentives and faster train options	Fare incentive is more effective in motivating people to travel early, than later, work, prior commitments and lack of sleep are few constraints
4.	Train commuters' scheduling preferences: Evidence from a large-scale peak avoidance experiment, the Netherlands.	Peer et al., 2016	RP experiment between 2012 and 2013 with train commuters	Time-table based alternatives. Reward for off-peak travel in morning and evening commute, scheduled delay early and late, unreliability, travel time, crowding on-board (as an indicator of comfort), transfers	22 percent decrease in peak hour travel amongst respondents. Time-based differential fare system is more cost-effective than increasing train capacity
6.	Modeling departure time choice of metro passengers with a smart corrected mixed logit model - A case study in Beijing.	Li et al., 2018	SP experiment on Beijing metros for morning peak hours	Metro departing early, late and at the usual time Other attributes: fare discount, in-vehicle crowding and travel time savings	More sensitivity to fare, effect of crowding was insignificant
5.	Heterogeneity in departure time preferences, flexibility and schedule constraints, Copenhagen.	Thorhauge et al., 2020	SP experiment on car users with 24 h trip diary as responses	Departing on-time, later or earlier using a hypothetical toll ring, the cost of the toll ring varied with departure time	People are constrained by household composition and flexibility at workplace for changing departure time
6.	Identifying Crowding Impact on Departure Time Choice of Commuters in Urban Rail Transit, Shanghai	Cheng et al.,2020	Mix of SP and RP experiment on metro users	Departing on time, later or earlier Other attribute: In-vehicle crowding	People changed their departure time to early or late significantly when the crowding level was high. People showed more disutility to arriving late than early
7.	Change in departure time for a train trip to avoid crowding during the COVID-19 pandemic: a latent class study in the Netherlands	2021, current study	Respondents divided into early and late group, SP experiment with unlabeled train alternatives	Two unlabeled train alternatives in same context of vaccination stages but vary in: scheduled delay, on-board crowd levels and discount on full fare	Hypothesis: fare discount and prior information on crowding level in trains can motivate some people to schedule delay, heterogeneity expected in respondents

2.2. Departure time change

Incentivizing or encouraging the departure time change has been found to benefit the public transport system and its passengers. One of the most popular tools used in Transportation Demand Management (TDM) are staggered work hours. This policy tool is known to reduce road traffic congestion as well as the occupancy on public transport services during peak hours, however, special attention is needed from the government in communicating with different industries to allow for staggered work hours, and with transport service providers to adjust their services (Zong et al., 2013). With staggered commute or flexible work hours, people may adapt their departure time to avoid the rush hour commute. In Table 2, an overview of the departure time change experiments reviewed in this research is presented. In the last column of the table, key findings from each study are reported.

One of the most significant experiments on staggering work hours was conducted in the 1970s in New York City (O'Malley, 1975). 220,000 participants were asked to stagger their work hours by at least 30 min before or after their previous work hours. Such shifts resulted in a reduction in congestion during peak time (9:00 AM) at the three busiest transit subway locations by 26 percent, which confirmed a correlation between work schedules and public transport operations and demand. In other work, the researchers used a stated choice approach that focused on metros in Beijing (Li et al., 2018). They presented the respondents with three alternatives, i.e., metro departing earlier or later than usual and metro departing at the usual time. The researchers offered the travelers a discount on metro fare and included it as an attribute in the choice experiment. Past research has found (Lurkin et al., 2017; Zhu & Long, 2016) that the price affects the demand, and not including the fare can lead to untrue results. Apart from these attributes, crowding inside the metro and travel time saved were some of the other attributes presented in the experiment. By estimating a mixed logit model, it was found that the metro passengers in Beijing were more sensitive to scheduled delays late rather than early. This was likely because the passengers were constrained by the activity at the end of their day (work/education). It was also concluded that the passengers were more sensitive to fare and travel time savings while crowding levels in the metros showed insignificant effects on scheduled delays (the change in the departure of passengers from their usual departure time), which was contrary to the previous research. This could be because crowding impacts travel demand significantly in a low-density environment or less crowded areas. However, this effect is not valid in the case of Beijing metro where people became accustomed to a crowded environment and have low expectations to arrive on time (Tirachini et al., 2013) (which was the case before the pandemic).

In research conducted in the context of Shanghai metro (Cheng et al., 2020), a mixed logit model was used to study the trade-off between crowding and scheduled delay (or change in the arrival time). The research used a mix of revealed preference and stated preference methods for collecting the data. Crowding was divided into five levels and was represented as occupancy rate (a ratio of occupancy and capacity). The developed model could also be integrated with the transit assignment models to predict the change in departure time. It was found that people changed their departure time to early or late significantly when the crowding level was high and between grade 3 to 5. People showed more disutility to arriving late than early (Cheng et al., 2020). In the European context, a study from Copenhagen in 2020 used a stated choice experiment and latent class clustering method to study departure time preferences of car commuters during morning hours by using a hypothetical toll ring. The respondents were asked to fill a 24-hour trip diary. Like in the Beijing Metro experiment, they were presented with three alternatives in the main choice experiment. It was found that flexibility in work hours and household composition (whether someone had a child) played an important role in a respondent being sensitive to the departure time change (Thorhauge et al., 2020). Therefore, it was suggested to explore the sensitivity to the departure time changes in different places and make policies to promote this behavior by focusing on specific socio-demographic groups.

In Sydney, on the other hand, the study on the willingness to change the departure time of rail commuters concluded that incentives, especially a fare discount, could be very effective in making people shift their departure time (Henn et al., 2011). Surprisingly, the same study was also able to identify certain groups of people who were unwilling to change their departure times regardless of the magnitude of the fare discounts. Getting proper sleep was a major reason given for not traveling early while lack of work flexibility was one of the other major constraints preventing the travelers from departing later. A significant number of people (37 percent) was willing to depart early by 30 min to avail the incentive of 30 percent fare discount. Comparatively, fewer people were willing to depart late (21 percent) for the same fare discount (Henn et al., 2011). The discrepancy in how fare discounts were valued depending on circumstances was also found in the Netherlands. A stated preference study on 1,400 Dutch train commuters offered them a choice between two passes for a train travel between the Hague and Utrecht (Bakens et al., 2010). One of the passes was their regular pass while the other was an 'off-peak hour pass' that was cheaper but was not valid during peak hours. Respondents were asked to indicate their pass preference and how they would change the timing of their journeys. It was found that departing early had less disutility than departing late, and most of the surveyed population, which opted for off-peak hour pass would either depart early or late. Very few selected the combination of early, late, and peak-hour travel. It should also be noted that in the 80 percent of the choice situations, the respondents chose to opt for their usual pass (Bakens et al., 2010; Liu and Charles, 2013). Most of the experiments offered a discount on the train fare as an incentive to change departure time. In another research, a model to compute an optimized Surcharge Reward Scheme was developed, which indicates a different incentive from proposing a discount on fare. In such schemes, people traveling during peak traffic/crowding hours accumulate surcharges which can be refunded to them if they travel during shoulder hours to peak hours within a certain time (Tang et al., 2020).

Scheduled delay early and scheduled delay late (Peer et al., 2016; Hendrickson & Kocur, 1981) refer to the time by which train passengers change their departure time to depart early or late respectively and are popular terms used in models and experiments related to the departure time change for peak crowding avoidance. The time-based differential fare system has been a successful measure in promoting travel during off-peak hours (Peer et al., 2016). In another Dutch experiment that was carried out for a prolonged period of time, the passengers were offered a monetary incentive to travel during off-peak hours via trains and their travel behavior was monitored using GPS. Although the sample was not representative of the Dutch train travelers, as the participation was voluntary, the results showed a 22 percent reduction in the peak hour travelers. The value of scheduled delay early was found to be 6.6 euros per hour of delay in the morning and 5 euros per hour in the evening, and the value of scheduled delay late was estimated to be 5.6 euros in the morning and 4 euros per hour in the evening. Although this result suggests that departing early has more disutility than departing late, other researchers have shown that people would rather travel early than late. Despite no relationship between the departure time changes and on-board crowding observed in this study, the results pointed out that a time-based differential fare system was more cost-efficient than increasing the supply during the peak hours (Peer et al., 2016).

3. Survey design and data collection

The scope of the current research is focused on reducing overcrowding during rush hours on the trains in the Netherlands, therefore in the stated choice survey only the train users in the Netherlands were asked to participate. Due to a limitation on the number of respondents, all train users were considered. Respondents were asked at the start of the experiment whether they travel by a train in the Netherlands or not, and the non-train travelers were excluded from the experiment. Before filling the rest of the questionnaire, the respondents were further asked to assume a context of a morning commute to work/education by a Sprinter train, which is a comparatively slower regional train than the intercity train in the Netherlands. They were asked to choose between departing early, late or at their usual time in a hypothetical scenario where: most of the population has been fully vaccinated within the Netherlands and the train they would plan to take is overcrowded. The respondents who chose to not change their departure time were still asked to make a hypothetical choice between departing early or late to reflect their preferences. Hence, they were segregated into two categories of Scheduled Delay Early and Scheduled Delay Late before the start of the choice survey. It should be noted that the Netherlands is a small country with great train connectivity across different cities. Commonly, people commute from one city to another using local or intercity trains. Regular commuters by train or public transport in the Netherlands have a personalized card, which can be used on all public transport in the country. The card is linked to their bank account, and it needs to be tapped on the card reader machines while checking in and checking out. Only the people with a card can subscribe to off-peak hour train discounts. The fare discount discussed in this study would be linked to such personalized cards.

3.1. Choice experiment

Based on the factors mentioned in the literature review (Section 2), three attributes and one context variable were selected for the design of this choice experiment. As the context variable multiplies the number of choice tasks with its number of levels, four levels for each attribute were selected to ensure the quality and prevent survey fatigue (Hensher et al., 2015). On-board crowding level was

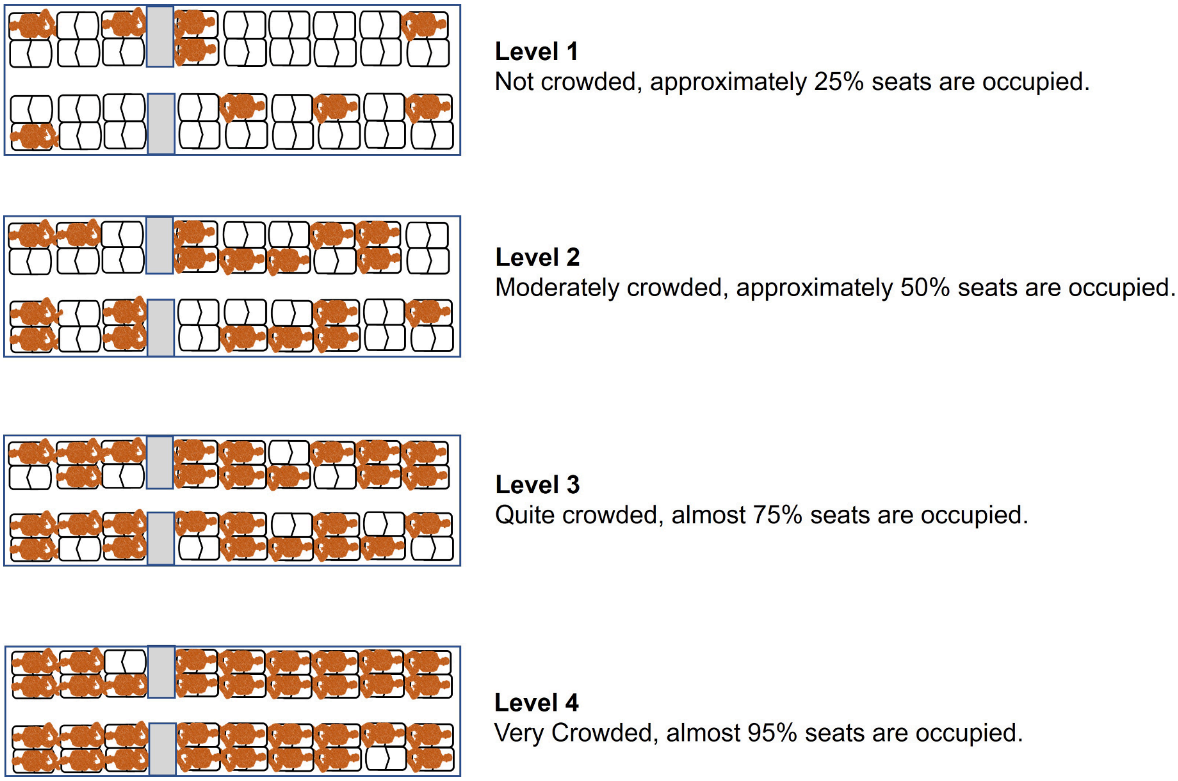


Fig. 1. Different levels of crowding on board.

indicated as the number of seats occupied in a train car (Fig. 1) using graphics and numerical information. The layout of the trains in the Netherlands is such that people do not usually stand in the seating area, and generally the mobile/web-based application to cater for departure time change shows the seat availability on the trains. These could be the reasons why the previous departure time change or crowd mitigation in public transport-related experiments conducted in the Netherlands also used the seat occupancy rate as an indicator for crowding (Peer et al., 2016; Shelat et al., 2021). Departure time change or scheduled delay was indicated as minutes of delay from one's usual time of departure, and fare discount was indicated as a percentage of discount offered on full fare, which could be availed by the train users using their personalized cards. The context of the vaccination stage had three levels, which indicated the share of the vaccinated population in the Netherlands. In each case, the respondents were provided with details of the ongoing infection risk. The levels of attributes in the choice experiment are presented in Table 3. The level of attributes shown in the second column of the table are the levels which were presented to the respondents in the choice survey. It is known from the previous research that on-board crowding has a non-linear effect on utility function (Whelan & Crockett, 2009; Shelat et al., 2021), which is why on-board crowding is effect coded. It is also expected that the effect of vaccination stage level 3 would be much higher on the utility of the alternatives in comparison with the effect of the remaining two levels, making the variable non-linear. To test this, the vaccination stage has also been effect coded.

Because the past literature found that people who shift their departure time (schedule delay) have strong preferences to either depart late or early (Li et al., 2018; Thorhauge et al., 2020; Bakens et al., 2010; Liu and Charles, 2013), the current experiment was designed to independently assess the two scheduled delays. Respondents who chose to adapt their departure time by boarding an earlier train were only presented with the options to depart early, and vice versa. In this research, an unlabeled experiment is designed because the two train alternatives are presented to the respondents, and their labels do not imply any meaning, which is also usually preferred over labeled experiment unless labels of the alternatives are necessary (de Bekker-Grob et al., 2010).

There was a possibility to add a base or an opt-out alternative. The opt-out option is considered good for capturing the demand for alternatives, however, a base/opt-out choice does not indicate any trade-off. Moreover, the respondents may select the base/opt-out alternative to avoid difficult trade-offs (Kontoleon & Yabe, 2003). To avoid these risks, no base or an opt-out alternative has been provided. Also, the main objective of this research is not to find out the expected share of the demand but to study the trade-offs that people make between scheduled delay, on-board crowding, and the fare discount.

As the experiment is unlabeled, both alternatives had the same attributes and same attribute levels and varied across the alternatives; hence the utility equation is the same for both train options. Individual characteristics introduced as interaction effects were also constant across both alternatives in all choice tasks. The vaccination stage was presented as contextual information and hence it remained the same across the two alternatives. Only the attributes, which varied across all the alternatives in a choice set, were introduced in the utility equation as main effects (Hensher et al., 2015). The techniques used to analyze the responses are described in detail in Section 4.

The choice tasks for the experiment were generated in Ngene and were orthogonal fractional factorial in design as this design was found to be practicable, manageable, and it made the estimated parameters reliable. Such design also minimizes the correlations between attributes to zero. Orthogonality in a choice experiment ensures that the variation in attributes is independent of each other. It makes the design statistically better, however, it is not a necessary condition for a good estimation of choice model (Hensher, 1994). In this design, sixteen rows are given as input in Ngene, which are the minimum number of rows to accommodate orthogonal design for three attributes of four levels each. The Ngene software generates two blocks of choice tasks with eight rows in each block. When these choice tasks were analyzed, three out of eight choice tasks in each block were found to be clearly dominant and were removed. After multiplying by three to account for different contexts of vaccination stages, in the end each block had fifteen choice tasks. For both scheduled delay early and late, there were two blocks each with fifteen choice tasks. An example of a choice set is shown in Fig. 2.

Table 3
Levels of attributes.

Attribute	Levels	Variable type
	Main effect	
On-board crowd level	9/36 seats occupied (25 %) 18/36 seats occupied (50 %) 27/36 seats occupied (75 %) 34/36 seats occupied (95 %)	Scale (Numeric) (Effect coded)
Fare discount	0 % 10 % 20 % 40 %	Scale (Numeric)
Scheduled delay (early/late)	15 min 30 min 45 min 60 min	Scale (Numeric)
	Contextual variable	
Vaccination stage (interaction with changing crowding levels)	30–50 % 60–80 % >90 %	Ordinal (Effect coded)

3.2. Background information

In the decision to schedule delay, it was found in the literature that apart from the socio-demographic characteristics such as income, gender, employment or age, other factors which are attitude, lifestyle, travel mode preferences and travel characteristics have an influence on choice making (Haustein et al., 2018; Thorhauge et al., 2020). Factors such as living with family and children were observed to constrain a person in changing the departure time as this decision is linked with activities or schedules of other family members, especially children. If an individual has no flexibility in work hours, then that person is expected to be more sensitive to schedule delay (Thorhauge et al., 2020). In other works, and slightly different context, attempts were being made to link mode choices to health-related individual factors (Boniface et al., 2015), and health indicators such as BMI (Body Mass Index) have been previously used to study such relationships (Barbour et al., 2019). As this research is linked with the COVID-19 pandemic, some background information was collected on the attitude of people towards COVID-19 and their physical health.

Based on these factors, the background information to be collected in the stated choice survey was divided into three broad categories: socio-demographics, travel and work-related factors, and attitudes towards health and COVID-19.

3.3. Data collection and analysis

The stated choice survey was developed and circulated using Qualtrics software where a web-generated anonymous link and QR code were distributed on social media platforms and used for data collection. An approval was taken by the ethics committee of Policy Department of TU Delft before circulating the survey. The social media platforms made the survey accessible to a significant number of people at no cost. A few limitations arise from using this method of circulation such as the survey is only accessible to people who use social media. Other limitations are discussed in Section 6. Only the responses, which included a completely filled choice experiment were considered. The data was collected between April 2021 to May 2021 when the Netherlands was in a partial lockdown and the vaccination program was in early stages. After the data processing and removing incomplete responses, a total of 182 responses were further analyzed. Based on their choices at the start of the choice survey, 120 respondents were processed in scheduled delay early group while 62 respondents were processed further in the scheduled delay late group. A total 1,800 choice observations were collected for scheduled delay early group, and 930 choice observations were collected for scheduled delay later group. Fig. 3 presents the collected sample composition.

Furthermore, from the data collected on the travel and health-related factors, it was observed that approximately 30 percent of the respondents indicated the willingness to work from home at least a few days a week even after the pandemic is over. Some respondents have also indicated a higher level of discomfort due to crowding during the pandemic compared to the pre-pandemic scenario. Amongst 182 respondents, only 8 percent have been diagnosed with COVID-19, but 41 percent of respondents' close ones had it. 23 percent of the respondents have indicated that they would like to continue wearing masks during traveling on public transit. 39 percent of respondents were willing to register their train journey in advance to help to mitigate crowding on transit whereas 46 percent said that they may register. Only 26 percent indicated having no flexibility at all in arrival time at their destination of work or education.

Regarding the respondents' sensitivity to crowding, when they were presented with a scenario in which they were informed

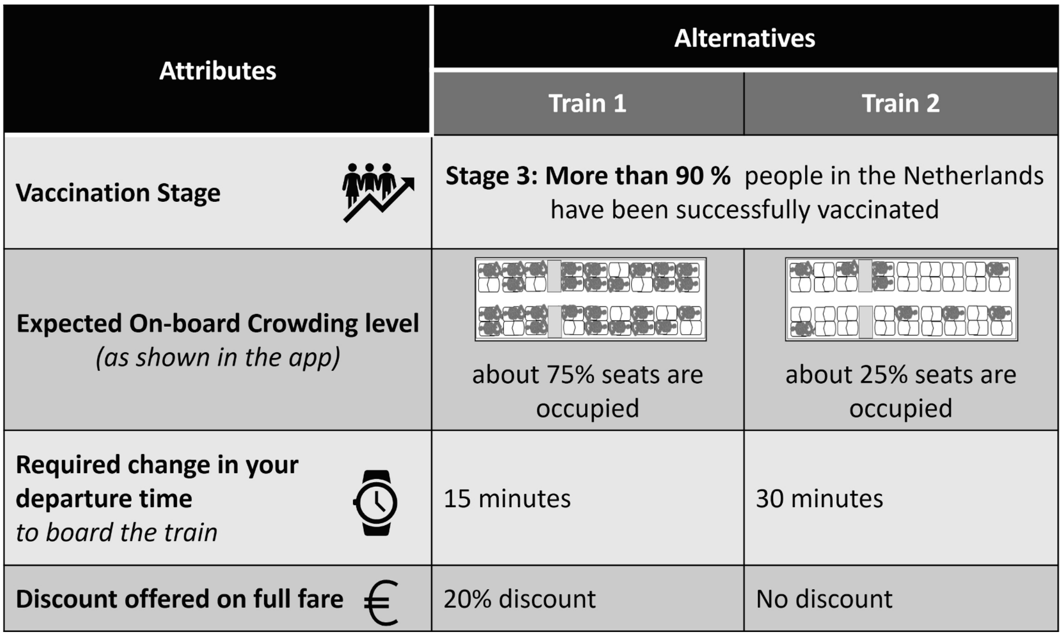
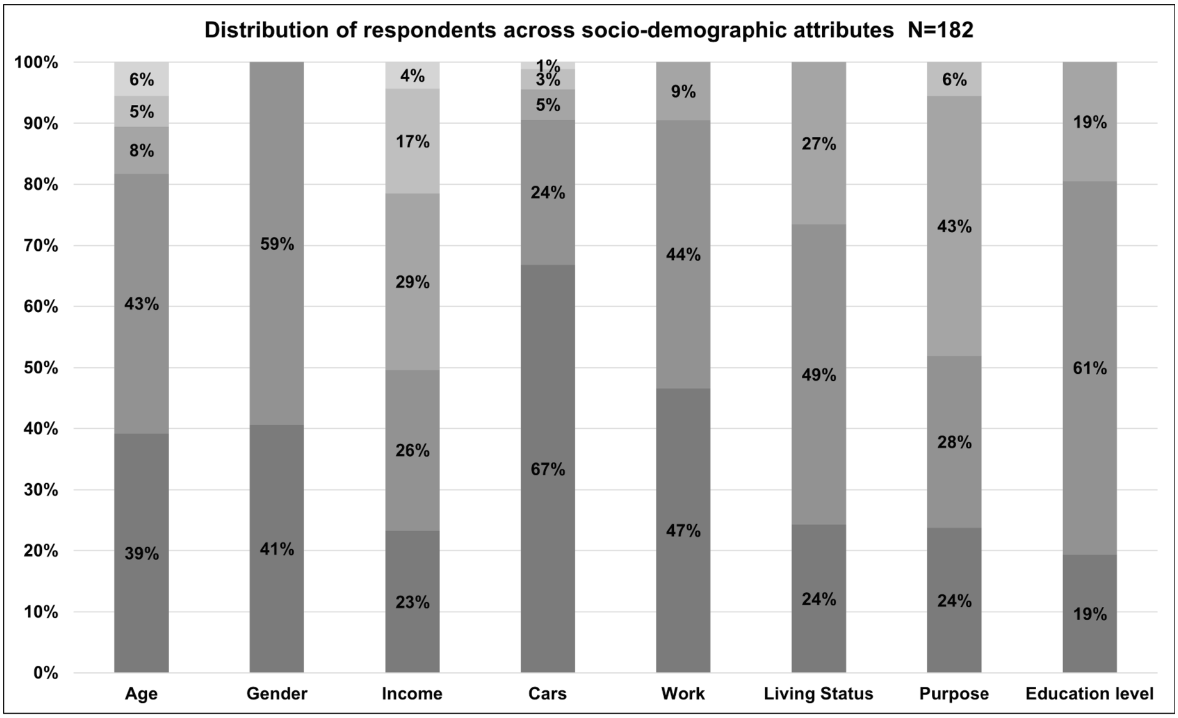


Fig. 2. An example of a choice set in the experiment.



Legend					
Age (years)	18-25	26-35	36 -45	46-55	55-65
Gender	Male	Female			
Income (€/month)	<500	500-1500	1500-3500	3500-7000	>7000
Cars (nos.)	0	1	2	3	>3
Work	Student	Employed full-time	Other		
Living status	Alone	With partner/ friends / housemates	Family		
Purpose	Education	Leisure	Work	Other	
Education level	Bachelor/ MBO/WO/ HBO	Master	PhD/ Doctorate		

Fig. 3. Full sample composition.

beforehand that 95 percent of the seats were occupied in their usual train, and they were asked whether they would depart early, late or at the same time, only 33 percent of the respondents chose to depart at the same time. Overall, 65 percent of the respondents would rather depart early than late.

4. Model estimation

4.1. Latent class cluster model

To analyze the choices made by respondents in the stated choice survey of this research, latent class cluster models (LCCM) were used. A multinomial logit model was initially estimated to see whether the collected data gave sensible results, and to set a comparison model for LCCM. These models are considered discrete choice models based on random utility maximization principle which simplifies the complexity of true behavior (McFadden, 1999). Multinomial logit models are one of the simplest and most extensively used random utility models (Ben-Akiva & Lerman, 1985; Bierlaire, 1998). The utility U of an alternative i for an individual r is given as a sum of its deterministic part V, stochastic part ε and an individual specific error term φ (refer to equation (1)). The systematic part of utility V is computed as a sum of product of attribute value $x(j)$ and its taste parameter β_j (refer to the equation (2)). The probability of an individual r to select an alternative i in a multinomial logit model is computed as shown in equation (3).

$$\mathrm{U}_{ir} = V_{ir} + \varepsilon_{ir} + \varphi_{\mathrm{r}} \tag{1}$$

$$\mathrm{V}_{ir} = \sum_{j}^{x} \beta_i {}^{*}\, \mathrm{x}_{ir}(j) \tag{2}$$

$$\mathrm{P}_{ri} = \mathrm{e}^{\mathrm{V}_{ri}} / \sum_{j} \mathrm{e}^{\mathrm{V}_{ri}(j)} \tag{3}$$

Because the standard multinomial logit model fails to capture unobserved heterogeneity across individual observations (Wen & Lai, 2010), a more advanced approach was used. To capture the unobserved heterogeneity in the data, particularly in an unlabeled experiment, latent class cluster models (LCCM) have been a standard approach that is often used in the departure time change experiments (Thorhauge et al., 2020). Another reason for estimating latent class cluster models is to analyze the data in this study is that it is comparatively simpler than other advanced techniques such as mixed logit in accounting for preference heterogeneity. Mixed logit is comparatively more flexible as it allows the parameters associated with observed variables for each individual to vary across a known population distribution (Shen, 2009). However, the nature of this distribution has to be assumed. In the case of the latent class cluster models, the preference heterogeneity is captured sufficiently by a discrete number of latent classes, but the parameters in a class remain fixed and no assumption regarding the distribution needs to be made. Latent class cluster model is not always better than the other modeling techniques, but it has proven to be statistically better in some cases, several market research and transport studies (Shen, 2009). The statistical superiority of the latent class cluster models over the multinomial logit model in the case of this study has been also confirmed (Fig. 4).

To arrive at the best model estimation, a statistically significant p-value (<0.1) for each exploratory variable was selected in this research (Yap et al., 2015). The class-specific utility function of the MNL and LCCM is the same, as MNL is an underlying model for LCCM. It is presented in the equation (4) below.

$$\begin{aligned}\mathrm{V_i} = {} & \beta_{\mathrm{crowd95\%}}{}^{*}\mathrm{Crowd}_{95\%} + \beta_{\mathrm{crowd75\%}}{}^{*}\mathrm{Crowd}_{75\%} + \beta_{\mathrm{crowd25\%}}{}^{*}\mathrm{Crowd}_{25\%} + \beta_{\mathrm{fare}}{}^{*}\mathrm{Fare} + \beta_{\mathrm{delay}}{}^{*}\mathrm{Delay} + \beta_{\mathrm{vaccstage(2)}}{}^{*}\mathrm{Crowd}{}^{*}\mathrm{VaccStage}_{(2)} \\ & + \beta_{\mathrm{vaccstage(3)}}{}^{*}\mathrm{Crowd}{}^{*}\mathrm{VaccStage}_{(3)}\end{aligned} \tag{4}$$

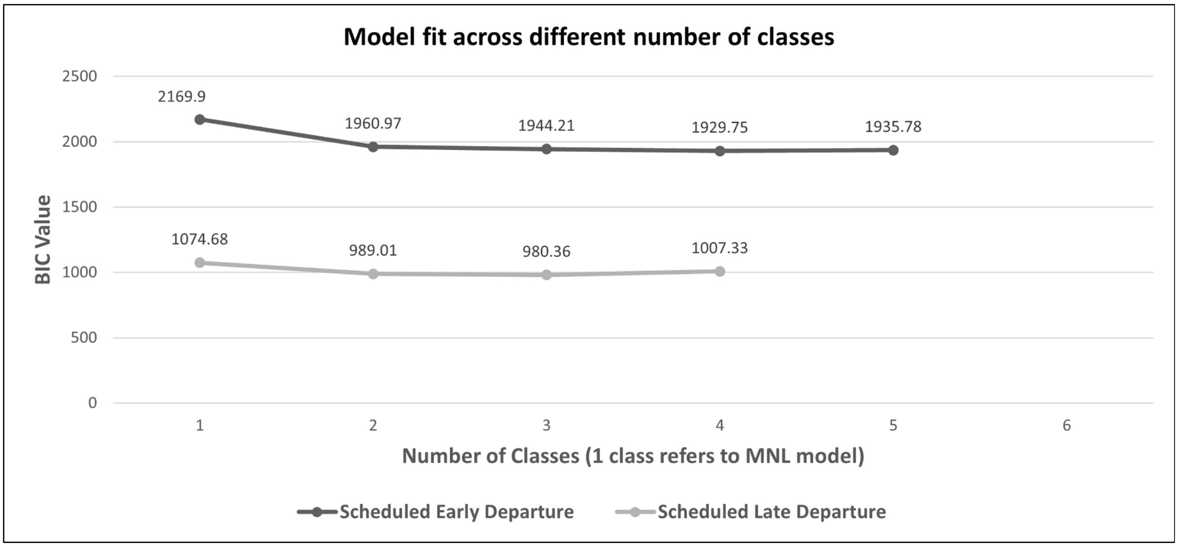


Fig. 4. BIC value for the MNL model and the LCCM.

Where $\beta_{crowd(g)}$ represents the taste parameter for different crowding levels, $Crowd_g$ represents attribute level g of crowding attribute. *Fare* and *delay* represent the attribute of discount offered on fare and scheduled delay (early and late in respective cases). $VaccStage_g$ represents attribute level g of vaccination stage attribute, and $\beta_{vaccstage(g)}$ represents taste parameter of the interaction effect between crowding and vaccination stage attribute. Crowding variable is introduced as a scaled variable instead of the ordinal variable, as the purpose of these terms is to study the impact of changing crowding levels with each additional stage of vaccination, and to discover the vaccination stage at which people become less crowd averse. Also, if both of the variables were introduced as effect coded variables in the interaction terms, it would have resulted in 12 taste parameters, which would create unnecessary complexity. The current model results in only 3 such parameters.

The latent class models divide the data set into a finite number of non-trivial classes by probabilistically assigning each individual to one class based on their choices and background information (Wen & Lai, 2010). To select the optimum number of classes first the models with a different number of classes were compared with each other in terms of the Bayesian Information Criteria (BIC) (Schwarz, 1978). The number of classes where the local minima of BIC lie is generally selected, however, in this study the number of classes was also selected by ensuring that the classes are non-trivial in size, i.e., > 5 % sample size (Nasserinejad et al., 2017), and they are interpretable with assigned meaningful labels. BIC was preferred over the AIC (Akaike Information Criterion) as it imposes a more stringent penalty on the number of parameters (Walker & Li, 2007; Wen & Lai, 2010).

In the estimated models, the panel effects are considered by basing the contribution of an individual r to the likelihood of assigned classes (s) on joint probability of the choices made by that individual (Hensher & Greene, 2003). The unit of observation for each model is not a single choice made by any individual, it is the entire sequence of choices made by the same individual. Along with this criterion, the probability of an individual r to select an alternative i, whose probability of belonging to a particular class s is π_{rs}, is given in equation **(5)**. β_s represents the taste parameter vector for a class s, p represents an iterator for S which is a set of all classes (Shelat et al., 2021; Hess, 2014):

$$P_{ri} = \sum_{p=1}^{S} \pi_{rp} * P_{ri}(\beta_s) \tag{5}$$

$$\pi_{rs} = e^{\delta s + \sum_k \gamma_{sk} * z_{rk}} / \sum_{p=1}^{S} e^{\delta p + \sum_k \gamma_{pk} * z_{rk}} \tag{6}$$

Here γ_{sk} and δ_s are defined as class membership coefficients while z_{rk} represents coefficient of background variable k for an individual r. In the latent class model estimation, several background variables were introduced in the class membership model. Only the variables which were significant, or improved the model fit significantly were kept in the final model. These background variables are discussed in Section 3.2. Some of those variables were: age, gender, income, education level, car ownership, frequency of train usage, profession, flexibility in work hours, history of COVID-19, living status among others.

4.2. Marginal rate of substitution

In addition to estimating the latent class models, two marginal rates of substitution were also estimated to gain more insights into travelers' preferences. The first one was the marginal rate of substitution between the fare discount and scheduled delay, and the second one was between the on-board crowding level and scheduled delay. As shown in equation **(7)**, the marginal rate of substitution is computed by taking ratios of partial derivatives of utility V with respect to each attribute in consideration $(x(1), x(2))$.

$$\mathrm{MR} = (\partial V/\partial x(1))/(\partial V/\partial x(2)) \tag{7}$$

The partial derivative of utility equation with respect to scheduled delay and discount on fare would result in their respective taste parameters (β). The marginal rate of substitution between the discount on fare and scheduled delay is computed as shown in the equation **(8)**.

$$\mathrm{MR}_{\mathrm{fare-delay}} = \frac{\beta_{\mathrm{delay}}}{\beta_{\mathrm{fare}}} \tag{8}$$

Because the past work on on-board crowding has found its non-linear effect on utility function (Whelan & Crockett, 2009; Shelat et al., 2021), it resulted in different taste parameters for each level of on-board crowding. The following equations were used to compute the marginal rate of substitution for on-board crowding and departure time change (Shelat et al., 2021):

$$\beta_{\mathrm{crowd:g\to g+1}} = (\beta_{\mathrm{crowd:g}} - \beta_{\mathrm{crowd:g+1}})/(\mathrm{x(crowd)}_{\mathrm{g}} - \mathrm{x(crowd)}_{\mathrm{g+1}}) \tag{9}$$

$$\mathrm{MR}'_{\mathrm{g\to g+1}} = \beta_{\mathrm{crowd:g+1}} * (\mathrm{x(crowd)}_{\mathrm{g}} - \mathrm{x(crowd)}_{\mathrm{g+1}}) / \beta_{\mathrm{delay}} \tag{10}$$

$$\mathrm{MR}' = \left(\sum_{\mathrm{g}} \mathrm{MR}'_{\mathrm{g\to g+1}} * (\mathrm{x(crowd)}_{\mathrm{g+1}} - \mathrm{x(crowd)}_{\mathrm{g}}))/\left(\sum_{\mathrm{g}} \mathrm{x(crowd)}_{\mathrm{g+1}} - \mathrm{x(crowd)}_{\mathrm{g}}\right)\right) \tag{11}$$

where crowd: $\mathrm{g} \to \mathrm{g}+1$ indicates the change in crowd level from g to $\mathrm{g}+1$. Furthermore $\mathrm{x(crowd)}_{\mathrm{g}}$ represents the attribute level g of the crowding attribute, and $\beta_{\mathrm{crowd:g}}$ represents the respective taste parameter of the crowding level g. MR is the marginal rate of substitution of crowding and scheduled delay for the effect coded part of the utility equation. The overall marginal rate of change of the crowding and scheduled delay is obtained as a sum of the marginal rate of effect coded part MR′ and the interaction part.

$$MR_{crowd-delay} = MR' + \sum_{g} \beta_{vaccstage(g)} / \beta_{delay} \tag{12}$$

5. Estimation results

When selecting the number of classes based on the BIC value for the latent class cluster models, it is suggested that if the difference between the BIC values of the two models is less than 2 to consider it negligible. Whereas if the difference greater than10 then the model with the lower BIC is highly recommended (Kass & Raftery, 1995; Dean & Raftery, 2010). From the Fig. 4, it can be observed that the BIC value of LCCM is much lower than in the MNL models of both Scheduled Delay Early and Schedule Delay Late. For the Scheduled Delay Early (model with scheduled early departure), the BIC value starts decreasing as the number of classes increases to 4 classes. For the models with 5 classes, the BIC starts increasing again. For the selection of the number of classes, the results with 3 and 4 classes are compared and it is found that the model with 3 classes explains the behavior of respondents more clearly. Later it is found that once the background variables (class membership function) are added to the models with 3 and 4 classes, the BIC of the model with 4 classes becomes more than the BIC of the model with 3 classes. Similarly, for the models with the Scheduled Delay Late (scheduled late departure), the local minima of the BIC value can be seen at 3 classes, however, since the difference between BIC value of 3 and 2 class models is less than 10, and the interpretation of the model with 2 classes is found to be capable of explaining the behavior of respondents within Scheduled Delay Late group, the model with 2 classes is selected for further analysis.

An overview of the results achieved by the latent class cluster model estimations is presented in Fig. 5. These values represent the marginal rate of substitution between scheduled delay and on-board crowding levels. It has been computed using the equations **(7) to (12)**. This is discussed further in Section 5.1 and 5.2.

5.1. *Latent class model: Scheduled delay late*

In Table 4, the results from a two-class latent class model for scheduled delay late with class membership function are presented. The naming of the two classes is based on their sensitivity towards changing on-board crowding levels. The description of the two identified classes is added below. Class 1 implies *crowd indifferent* travelers. From the results in Table 4, it can be observed that the share of the respondents who belong to this class is 54.8 percent. The coefficient of crowding was found to be insignificant ($p > 0.10$) for two of the crowding levels 50 percent and 75 percent, which indicates that this class is not affected by crowding unless the train becomes overcrowded, i.e., crowding level is 95 percent and around 34 of 36 seats are occupied. This group of respondents prefers a fare discount and can be classified as moderate to less averse to scheduled delay. Change in behavior of the respondents can be observed when vaccination stage 3 is attained, meaning more than 90 percent of the residents of the Netherlands are vaccinated. At this stage, the respondents become less averse to crowding.

In the class membership function, two additional variables were found to be significant and differentiate the behavior between the classes. Age has been also found to be a significant variable in this class and it can be concluded that the older the respondents are, the less likely they are to belong to this class (*crowd indifferent class)*. Regarding having the flexibility of travel, it can be concluded that having more flexibility in the arrival time at the destination increases the probability to belong to the *crowd indifferent class*.

The next class consists of the respondents who were found to be *crowd conscious*. The share of respondents who belonged to this class was estimated to be 45.2 percent. The behavior of the respondents in this class is more consistent with the previous research, which concluded that crowding levels inside a vehicle has a non-linear effect and the disutility due to crowding starts somewhere around 80 percent seat occupancy rate (Tirachini et al., 2013; Whelan & Crockett, 2009). In this class, the respondents derived high

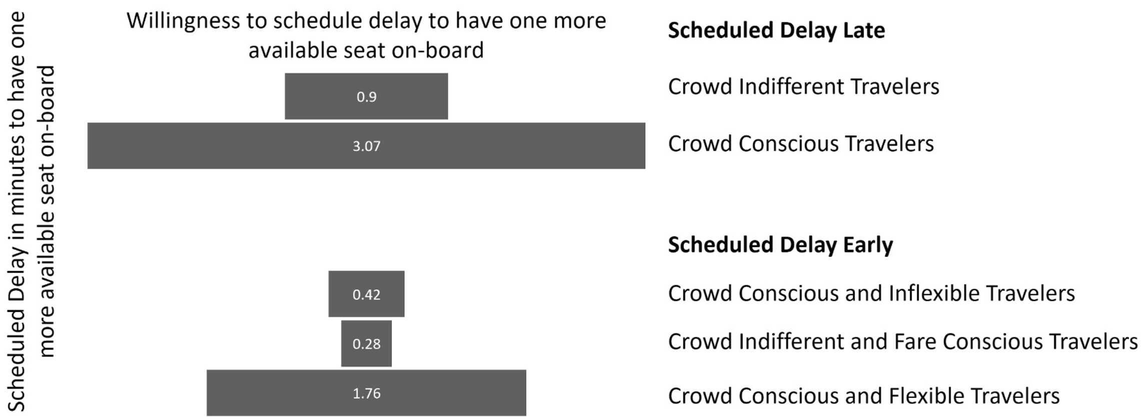


Fig. 5. Willingness to schedule delay for 1 less person on-board in a train compartment.

Table 4
Latent class model: scheduled delay late estimation results.

MODEL FIT		SCHEDULED DELAY LATE			
LL(start)		−644.63			
LL(final)		−438.65			
Adj Rho-Square		0.29			
BIC		993.49			
AIC		911.3			
Number of parameters		17			
Number of respondents		62			
Number of observations		1200			
ESTIMATED PARAMETERS		**Class 1: Crowd indifferent travelers**		**Class 2: Crowd conscious travelers**	
Class distribution		**54.80 %**		**45.20 %**	
Variable description		**Coeff**	***t*-ratio (p-value)**	**Coeff**	***t*-ratio (p-value)**
Attributes in choice tasks		**Class Specific Model**			
	Crowding level 25 % (9/36 seats occupied)	1.428	–	2.856	–
	Crowding level 50 % (18/36 seats occupied)	0.122	0.76 ($p > 0.10$)	2.255	6.04 ($p < 0.01$)
	Crowding level 75 % (27/36 seats occupied)	−0.169	−1.12 ($p > 0.10$)	−1.243	−3.94 ($p < 0.01$)
	Crowding level 95 % (34/36 seats occupied)	−1.381	−7.28 ($p < 0.01$)	−3.868	−7.33 ($p < 0.01$)
	Scheduled delay (early/late)	−0.065	−7.72 ($p < 0.01$)	−0.066	−3.81 ($p < 0.01$)
	Discount on full fare	0.059	5.61 ($p < 0.01$)	0.051	2.23 ($p < 0.05$)
	Interaction between vaccination stage 1, (30–50 %) and on-board crowding level	−0.06	–	−0.047	–
	Interaction between vaccination stage 2, (60–80 %) and on-board crowding level	0.013	1.14 ($p > 0.10$)	−0.038	−1.51 ($p > 0.10$)
	Interaction between vaccination stage 3, (>90 %) and on-board crowding level	0.047	3.96 ($p < 0.01$)	0.085	4.43 ($p < 0.01$)
Marginal rate of substitution	Marginal rate of substitution of fare discount offered and scheduled delay	−1.11	–	−1.29	–
	Marginal rate of substitution for scheduled delay and on-board crowding	0.9	–	3.07	–
Background variables		**Class Membership Model**			
	Class intercept	0.8	0.95 ($p > 0.1$)		
	Flexibility in arrival at destination of work or education (Likert scale: 1 No flexibility, 3 Very flexible)	0.553	1.69 ($p < 0.10$)		–
	Age (Ordinal range)	−0.786	−2.35 ($p < 0.02$)		–

utility from the train rides where they can comfortably sit alone with high chances of getting the adjacent seat vacant. This class of respondents derived positive utility from discounts offered on full fare. Similar to the first class discussed, it could be said that the class is moderate to less averse to scheduled delay. At the vaccination stage 3 (when more than 90 percent of the residents of the Netherlands are vaccinated), the members of this class also become less averse to crowding. A higher share of older people in this class could also explain a more crowd conscious behavior in this class.

Regarding comparison of the marginal rate of substitution of the fare discount and scheduled delay for both the classes, it can be observed that respondents who belong to Class 2 (Crowd conscious travelers) would require approximately 16 percent higher discount per minute of scheduled delay compared to Class 1 (crowd indifferent travelers) respondents. However, if the marginal rate of substitution of scheduled delay and on-board crowding is compared then the respondents of Class 2 are willing to depart approximately 3.1 min late to reduce one person on-board, which is 200 percent more than Class 1 who are willing to delay only by approximately 1 min.

5.2. Latent class model: Scheduled delay early

In the model where the respondents chose an option to depart early (scheduled delay early), three heterogeneous classes were identified. The estimation results of the model can be found in Table 5. The naming of these three classes was based on their sensitivity to changing on-board crowd levels, discount offered on full fare and scheduled delays.

Class 1, which in this model refers to *crowd conscious and inflexible* travelers, has a share of 36 percent, and the coefficients of the parameters for less crowded trains (crowding level not more than 50 percent) were found positive and statistically significant. At crowding level 75 percent, a higher, increasing disutility is observed. The coefficient of interaction between crowd levels and vaccination stage 3 was found positive and statistically significant, which indicates that the vaccination stage does play an important role in crowd avoidance behavior. Although the respondents within this class were likely to want to avoid crowded rides, they also had a very high disutility for scheduled delays for early departure (-0.102/minute). Interestingly, the effect of fare discount on such respondents and the marginal rate of substitution of fare discount for each minute of scheduled delay were found to be insignificant.

Table 5
Latent class model: scheduled delay early estimation results.

MODEL FIT		**SCHEDULED DELAY EARLY**					
LL(start)		−1247.67					
LL(final)		−873.66					
Adj Rho-Square		0.28					
BIC		1934.17					
AIC		1797.31					
Number of parameters		25					
Number of respondents		120					
Number of observations		1800					
ESTIMATED PARAMETERS		**Class 1: Crowd conscious and inflexible travelers**		**Class 2: Crowd indifferent and fare conscious travelers**		**Class 3: Crowd conscious and flexible travelers**	
Class distribution		**36 %**		**31.40 %**		**32.70 %**	
Variable description		**Coeff**	***t*-ratio (p-value)**	**Coeff**	***t*-ratio (p-value)**	**Coeff**	***t*-ratio (p-value)**
Attributes in choice tasks		**Class specific model**					
	Crowding level 25 % (9/36 seats occupied)	1.792	–	0.634	–	1.738	–
	Crowding level 50 % (18/36 seats occupied)	1.044	3.87 ($p < 0.01$)	−0.273	−1.32 ($p > 0.10$)	0.829	4.57 ($p < 0.01$)
	Crowding level 75 % (27/36 seats occupied)	−0.423	−1.80 ($p < 0.10$)	0.206	1.06 ($p > 0.10$)	−0.51	−3.20 ($p < 0.01$)
	Crowding level 95 % (34/36 seats occupied)	−2.413	−8.61 ($p < 0.01$)	−0.567	−3.14 ($p < 0.01$)	−2.057	−5.93 ($p < 0.01$)
	Scheduled delay (early/late)	−0.102	−7.64 ($p < 0.01$)	−0.105	−4.83 ($p < 0.01$)	−0.029	−3.02 ($p < 0.01$)
	Discount on full fare	0.033	1.36 ($p > 0.10$)	0.069	3.93 ($p < 0.01$)	0.044	2.50 ($p < 0.02$)
	Interaction between vaccination stage 1, (30–50 %) and on-board crowding level	−0.151	–	−0.011	–	−0.029	–
	Interaction between vaccination stage 2, (60–80 %) and on-board crowding level	0.052	3.98 ($p < 0.01$)	−0.001	−0.07 ($p > 0.10$)	−0.046	−2.15 ($p < 0.05$)
	Interaction between vaccination stage 3, (>90 %) and on-board crowding level	0.099	5.69 ($p < 0.01$)	0.012	0.79 ($p > 0.10$)	0.075	3.97 ($p < 0.01$)
Marginal rate of substitution	Marginal rate of substitution of fare discount offered and scheduled delay	−3.135	–	−1.526	−7.67 ($p < 0.01$)	−0.651	–
	Marginal rate of substitution for scheduled delay and on-board crowding	0.42	–	0.28	–	1.76	–
Background variables		**Class Membership Model**					
	Class intercept	0.234	0.737 ($p > 0.1$)			0.033	0.085 ($p > 0.1$)
	Student (1 if a respondent is a student, 0 otherwise)	–	–		–	−0.964	−3.53 ($p < 0.01$)

Therefore, this class could be referred to as being the inflexible class of respondents.

Class 2, on the other hand, includes *crowd indifferent and fare conscious* travelers. As shown in Table 4, 31.4 percent of the respondents belong to this class. Only when the train becomes too crowded, i.e., at 95 percent crowding level, the coefficient of crowding becomes significant. At this level, the class derived disutility due to crowding but this disutility is the lowest amongst the three classes identified in the model. It can be observed that the respondents in this class were indifferent to crowding unless it became difficult for them to find an empty seat. Willingness to depart early to have one more available seat on the train is also the lowest in this class (0.4 min). One thing that this class has in common with Class 1 (*crowd conscious and inflexible)* is the high disutility that it obtained from scheduled delay, but as opposed to Class 1, this class valued discount offered on the train fare significantly ($p < 0.01$). The respondents were found willing to depart early by 1 min for approximately a 1.5 percent discount on train fare. With changing vaccination stages, the impact of crowding does not change significantly within this class. Therefore, it can be speculated that the behavior of this class will remain the same during and after the pandemic.

Class 3 includes *crowd conscious and flexible* travelers. Like in the case of Class 1, the travelers in this class were found likely to prefer comfortable and empty train rides and derived disutility from train rides with crowding levels above 75 percent. This class shows the lowest disutility from scheduled delay, and hence this class can be categorized as flexible in departing early. Compared to Class 2 (*crowd indifferent and fare conscious)*, this class would derive positive utility from train alternatives that offered a discount on the train fare, but the marginal rate of substitution of fare discount and scheduled delay was found to be insignificant in this class. The respondents were willing to depart early by 1.8 min for 1 extra free seat on the train. As the vaccination stage advances, the respondents who belong to this class become less crowd averse.

Only one independent variable was found to have a significant effect on at least one class and this variable was a student indicator. It showed that students exhibit different behavior in the context of crowding and the pandemic. The significant effect of the student variable ($p < 0.01$) was found in Class 3 (*crowd conscious and flexible)*, which could be interpreted as the respondents who were students having a lower probability to be *crowd conscious and flexible* travelers.

To ensure that the marginal rates of substitution are of a consistent magnitude compared to the prior studies, the revealed data on the departure time change experiment that was conducted in the Netherlands between 2012 and 2013 was reviewed. In the study, the train commuters were rewarded for scheduling delay outside peak hours and for morning delay late was estimated to be -0.02/minute and marginal rates of substitution for morning delay early was -0.024/minute (Peer et al., 2016) (refer to Section 2 for more details). Although the sensitivity to the departure time change found in the current experiment was higher than before, it could be speculated that in almost a decade the people might have changed their valuation, behavior, or priorities.

6. Discussion

Managing overcrowding in public transport would not only make public transport more comfortable and attractive but it could also decrease the risk of getting infected with illnesses such as COVID-19 while traveling. This research shows that promoting change in the departure time could be a successful measure to reduce overcrowding. To promote such behavior, new policies that involve different stakeholders are required. The policy discussion is provided in Section 6.1. In Section 6.2 the limitations of the study as well as and the recommendations for the future research are discussed in detail.

6.1. Policy implications

The study provides a few new insights and policy recommendations. The estimation results have shown that the respondents are willing to adapt their departure time if they are provided information on expected crowding levels or offered incentives such as a discount on fare. However, without flextime and staggered commute policies, the workers will not have an option for scheduling delay. Such policies are important for maximum benefits from policies related to fare discounts for demand management in public transports. A cost-benefit analysis can be conducted by train operators to study if providing fare discounts is more economically beneficial for them in managing overcrowding compared to increasing the supply of trains during rush hours. A policy proposal for a real-time crowd management inspired by the policy proposed in the departure time change experiment conducted in Beijing in 2018, is to offer discounts on the train fare in real-time based on expected overcrowding (Li et al., 2018). Such policy requires a system to predict the demand during rush hours and to predict the timing of the peak rush on a day-to-day basis as well as offer this information to the train passengers. To motivate the travelers to shift their departure times to reduce crowding, fare discounts can be proposed in real-time for different time windows. Another study proposes a Surcharge Reward Scheme, where people traveling during peak crowding hours accumulate surcharges which can be then refunded to them if they travel during off peak hours (Tang et al., 2020). Further experiments and pilot studies are required to evaluate the exact details of such policies. Providing a real-time information on crowding levels on the trains without any other incentive could itself motivate certain groups of people to shift their departure time. In the current study, this group of respondents is represented as a latent class group of people who are willing to depart early (Class 3: crowd conscious and flexible travelers).

Policies to mitigate crowding are also expected to involve multiple stakeholders. Railway operators in the Netherlands such as NS, Arriva, Connnexxion etc. would be directly impacted as it would affect their demand and supply. As the demand is more evenly spread, the supply model would change, and with an increase in attractiveness of the trains, the demand may increase. Other Dutch local public transport operators such as NS, GVB, HTM, RET and other private operators such as Qbuzz, Syntuss, Arriva, Connexxion and Transdev may also be affected as their demand would change with the increase of the attractiveness of the train trips, and indirectly as the demand of these transport modes used for access/egress to/from the train stations may also change. Government authorities and policymakers would consequently have to be involved in the development and implementation of such policies. A social cost benefit analysis could be conducted to analyze whether to increase the supply of trains or spread the demand by offering information and incentives. Companies that offer railway information through software applications such as 9292, Google Maps etc. could provide information on expected crowding levels on the trains in their applications. Other organizations may be involved in developing highly predictive models. ProRail, that are the infrastructure managers of train platforms, may also benefit from such policies as there will be changes in the passenger demand during rush hour. Environmentalists are expected to be in support as such policies as they would increase the attractiveness of public transport. Medical facilities and authorities are also likely to be in favor of such models and policies as they have the opportunity diminish the spread of the COVID-19 infections, or any other raspatory infections in the future. Lastly, cooperation and support from the public transport users and the companies to offer and support flex hour/staggered commute are also required for a successful implementation.

6.2. Limitations and recommendations

One of the main limitations of this work is the sample size. The sample was limited in terms of the number of observations; however, this was compensated by including a very detailed literature review. The number of respondents who chose to schedule delay late was almost half of the number of respondents who chose to schedule delay early. Classes in the latent class cluster model for Scheduled Delay Late showed major variation in behavior in terms of the crowding parameter only. Whereas, in the latent class cluster model for Scheduled Delay Early group, the heterogeneity in the preferences is observed in other parameters as well, including delay and fare discount. Nevertheless, to compare the results of the Scheduled Delay Early and Scheduled Delay Late groups, it was important to have results for both groups using the same modelling technique. A higher number of classes could have been estimated for the Scheduled Delay Late group of the respondents to capture more unobserved heterogeneity, however, as the sample size was limited, more classes made the size of some of the classes very small and therefore harder to interpret.

Furthermore, the data collected from the survey is non-representative of the Dutch population who travels by train. Nevertheless, the results show statistical significance indicating that a conclusion can be drawn based on the experiment. It is recommended to conduct pilot experiments before making policy changes in the entire country.

The models were a simplified version of reality, and to develop such simplified yet informative experiment, multiple assumptions had to be made. In this research, it was assumed that when people change the departure time, they would either like to depart earlier or later than usual. The research did not take in consideration the psychological aspects of COVID-19 either.

With respect to the future research direction, it would be also important to understand the emotional impacts of the COVID-19 pandemic on travel behavior as well as study the value and role of health in making travel related choices or mitigating exposure to respiratory viruses while traveling.

7. Conclusion

To mitigate crowding, the departure time change has proven to be a strategic and effective measure (O'Malley, 1975). In this research, an exploratory study based on a stated choice experiment was conducted in the Netherlands in order to understand the extent of which people can be motivated to change the departure time to avoid crowded trains with an incentive of a discount on the train fare. This study is performed in a hypothetical context of increasing vaccination stages amidst a pandemic emergency.

65 percent of the respondents indicated that they would like to depart earlier rather than later in a post-pandemic scenario for a home to work trip. Like in the previous experiments, the disutility obtained from the scheduled delay early is less than from scheduled delay late (Bakens et al., 2010), but the group of respondents who chose to schedule delay late were willing to delay more than the respondents from scheduled delay early group to have one less person on-board. It could be speculated that these respondents have a difficulty in being too early due to their morning schedule (Henn et al., 2011). On-board crowding level is found to have a non-linear effect (Douglas & Karpouzis, 2006; Shelat et al., 2021) and disutility starts at 75 percent seat occupancy rate which is at 5 percent lower level than stated in the past research (Tirachini et al., 2013). According to the study, it is likely that the COVID-19 pandemic made the travelers in the Netherlands more crowd sensitive compared to the pre-pandemic periods.

Nearly all the classes in the latent class model of scheduled delay early and late groups had the same share of respondents. In the latent class model of scheduled delay late group of respondents, two heterogeneous classes were found. Crowd conscious class (Class 2) showed a predisposition to prefer empty trains and had a high and increasing disutility from crowding as the trains become more crowded. Respondents belonging to the crowd indifferent class (Class 1), on the other hand, were only affected by crowding when the train became significantly overcrowded (more than 95 percent seats were occupied). In comparison with the Class 2, this class included a higher share of younger people and people with relatively flexible work hours. Class 1 (crowd conscious and inflexible class) of scheduled delay early group was found to be the most rigid class and most challenging to motivate changing the departure times. Class 2 (crowd indifferent and fare conscious travelers) obtained the highest utility from fare discount. Respondents belonging to Class 3 (crowd conscious and flexible travelers) in scheduled delay early groups were the most suitable to motivate to change their departure time. They were highly sensitive to on-board crowding; they had low sensitivity (disutility) towards scheduled delay, and they were moderately sensitive (positive utility) to fare discount.

The coefficient of vaccination stage and on-board crowding level was found to have an impact on the choices in most of the classes. It showed that as more people were vaccinated, the respondents became less averse to on-board crowding on trains.

Lastly, the data collected indicated that 67 percent of the respondents would either like to depart early or later to avoid overcrowded trains even in a scenario where more than 90 percent of the people in the Netherlands are vaccinated. Only 15 percent of the respondents were unwilling to register train journeys in advance to help to reduce crowding on trains and 48 percent of respondents indicated that they would not prefer to wear masks in public transport after the pandemic.

While the post-pandemic world remains to be seen, there is an opportunity to use some of the lessons learned during the pandemic to leverage the heterogeneity in people's behavior and preferences to design more efficient systems that ensure and support travelers' comfort.

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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