DEPARTURE TIME CHANGE TO AVOID CROWD IN TRAINS

-A STATED CHOICE EXPERIMENT STUDY IN THE NETHERLANDS IN A PANDEMIC CONTEXT

MASTER THESIS
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Departure time change to avoid crowd in trains

-A stated choice experiment study in the Netherlands in a pandemic context

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Preface

This thesis has been written as an essential part of completing the course of Master of Science in Transport Infrastructure and Logistics from Delft University of Technology. The idea for the topic of this thesis originated from the motivation to work on COVID-19 pandemic related problems linked with public transports. The duration of this project was around six months. With the help of my committee this journey was as smooth as it could have been, although the learning curve was sharp which only made this experience more interesting. The chairperson of the committee was Prof. Bert van Wee. My daily supervisor was Dr.Natalia Barbour and my external supervisor was Dr. Gonçalo Correia.

I would like to express my gratitude towards my thesis committee for giving me the opportunity to work under their guidance. First, I would like to deeply thank Professor Bert van Wee for his support, counsel and timely responses. His clear and concise feedback helped me to shape the objective of this research and make a quality report. Secondly, Dr. Natalia's regular supervision not only helped me with technical aspects of the thesis, but she has been a source of motivation which made my graduation experience richer. I am profoundly grateful for her supervision, efforts and time. Thirdly, I am extremely thankful to Dr. Gonçalo for his expertise and detailed feedback which made me explore further, and that immensely helped with the quality of the thesis.

Besides my committee, I would like to truly thank Dr. Jan Annema from TU Delft for helping me to figure out the thesis topic, and bring together the committee. I would also like to thank Sanmay Shelat from TU Delft for his availability to help me streamline the topic.

Constant emotional support of friends from back home, and those I became friends with here in Delft kept propelling me for this long and intense experience, and made it memorable. I really appreciate their support. Last but not the least, I would like to extend my gratitude towards my family who made all this possible. Without their support I could not have even dreamed about studying at TU Delft.

With gratitude,
Jyotsna Singh

Summary

Crowding in trains during rush hour is a well-known problem. After the outbreak of COVID-19 pandemic, crowding has also been highlighted as a risk factor of catching Acute Respiratory Infections (ARIs) such as COVID-19 which has affected the demand of public transport. Several countries, including the Netherlands, have differential fare systems for peak and off-peak travel, however, the problem of overcrowding in trains is still prevalent and is expected to cause more disutility than before the pandemic. To reduce peak hour rush, change in departure time has proven to be an effective measure. In this research, a stated choice experiment is conducted to test such a method which could increase the attractiveness of public transport by managing crowds during rush hours. The main research question which is answered in this research is: ***During a pandemic, for different vaccination stages in the Netherlands, to what extent people can be motivated to change departure time to avoid crowded trains?*** To answer the main research question, following sub-research questions are framed:

- **SQ1)** What is state-of-the art in Acute Respiratory Infection (ARI) transmission in public transport?
- **SQ2)** What could be the suitable indicator and measure of crowding as perceived infection risk in commuting by trains in the Netherlands?
- **SQ3)** What are the mitigation measures that people take to avoid crowds in train commutes?
- **SQ4)** What is the trade-off that people make between on-board crowding in train commutes and changing departure time?
- **SQ5** To what extent a discount offered on train fare could motivate people to change departure time?
- **SQ6)** How does the trade-off vary across different sub-groups of people?
- **SQ7)** What is the impact of vaccination stages on the trade-offs that people make?

SQ1 to 3 are answered using literature review. To answer the main research question and remaining sub-research questions a Stated Choice survey is conducted in the Netherlands whose results are analysed using Multinomial Logit (MNL) model and Latent Class Cluster Model (LCCM). From literature review, a significant association between public transports and risk of having an ARI is found. This risk exists majorly because of the confined and crowded environment in public transports. Crowding in public transport especially during rush hours has been a cause of discomfort even before the risk of ARI such as COVID-19 became well-known. To measure the disutility caused by crowding in trains, in this research crowding is indicated as the number of seats occupied in a (Sprinter) train. As a mitigation measure from the demand side of trains (passengers), scheduling delay or changing departure time is selected. Scheduled Delay Early and Scheduled Delay Late are popular terms used in previous models and experiments related to peak avoidance to refer to the time by which train passengers change their departure time to depart early or late respectively. To understand if behavior of people changes as there is an improvement in pandemic scenario, a context of advancing vaccination stages is provided in the choice experiment. To motivate people to change departure time, an attribute of discount offered on train fare is also provided. The experiment is only focused on train users in the Netherlands, and is based on a context of morning commute using trains within the Netherlands. Respondents are segregated into two independent groups of early departure (Scheduled Delay Early) and late departure (Scheduled Delay Late) at the start of the choice experiment based on their indicated preferences. Separate analysis is performed on the two groups.

The choice sets are developed in Ngene using orthogonal design with two unlabeled train alternatives. The context of vaccination stages has three levels, and other attributes have four levels. The dominant

choice sets are removed to reduce the load on respondents. The final design has fifteen choice sets per respondent. The background information which is collected from the survey, and is anticipated to affect the choice making, is broadly divided into three categories: socio-demographics, travel and work related factors, and attitude towards own health and COVID-19. The survey was circulated between April 2021 and May 2021. The processed and cleaned data had a total 120 respondents who chose to depart early and 62 respondents who chose to depart late. The sample of data collected is non-representative of Dutch population but gives highly significant results. From the MNL models it is observed that only when the crowding level is <50% , it has positive utility and the effect is non-linear. It was noted that the group of people who chose to depart late showed a steeper change in utility, and also have higher utility (and disutility) with changing crowd levels. The group of people who chose to schedule delay late are willing to delay more than the Scheduled Delay Early group to have one less person on-board. Fare discount has positive sign, which means that utility of train alternatives increases with increase in fare discount. A positive relationship is found between on-board crowding level and vaccination stages which indicates that at higher vaccination stages people will become less averse to on-board crowding. Some background variables also have a significant effect on the model. Although interaction between gender and scheduled delay had no significant effect, for both early and late models female respondents who live with their family are found to be less willing to schedule delay ($p<0.05$). Some counter-intuitive results were also found.

In LCCM for Scheduled Delay Early, 3 class model is selected to best represent the heterogeneity in respondents, and in LCCM for Scheduled Delay Late, 2 class model is selected. In LCCM of Scheduled Delay Late group of respondents, the Crowd Conscious Class of respondents (Class 2) enjoys empty trains and has high and increasing disutility from crowding as trains become crowded. Both the classes obtain similar disutility from departure time change and utility from discount on fare. In the Scheduled Delay Early group, Class 1 (Crowd Conscious and Inflexible Class) is one of the most rigid groups of people in terms of unwillingness to change departure time. Class 2 (Crowd Indifferent and Fare Conscious Class) is also highly sensitive to departure time change, but this group of people have high sensitivity to fare discounts as well which can motivate them to schedule delays. Class 3 (Crowd Conscious and Flexible Class) is the most ideal group to motivate for departure time change as they are highly sensitive to on-board crowding with low sensitivity (disutility) towards scheduled delay. In the Scheduled Delay Early model of LCCM, it is found that less students are represented in Class 3 which is the most flexible class. This indicates that students are more sensitive to depart earlier than usual. In Scheduled Delay Late model of LCCM it was found that Class 1 which is crowd indifferent has a higher share of younger people in comparison with Class 2 which is crowd conscious, which makes sense as crowding is associated with perceived risk of catching an infection such as COVID-19, and older people are expected to be more crowd averse. Class 1 also has a higher share of people with more flexible work hours. With respect to the context of advancing vaccination stages, it is found that people become less averse to on-board crowding in trains at the last stage of vaccination which is when more than 90% residents of the Netherlands are vaccinated.

The results obtained from this research are mostly consistent with previous research in terms of the values and signs of taste parameters of main attributes. It is observed that students are less likely to depart early. This is supported by results from both MNL model and LCCM. Respondents who indicated flexibility in work hours are more likely to depart late, which is intuitive. When more than 90% people are vaccinated in the Netherlands, respondents are expected to become less crowd averse. The research suggests that certain groups of people can be motivated to schedule delays by simply offering them prior information on crowding levels in trains or by offering them incentives. This research could be used as a basis for further research into implementing new policy to manage public transport demand but it should be noted that policies related to flexible work hours, staggered commute and occasional work from home are required to make it possible for people to schedule delays.

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Terms and Acronyms

Load Factor	Ratio of number of passengers on-board and total number of seats in a public transport vehicle. It is expressed in percentage (Pel, Bel, & Pieters, 2014).
Standing Passenger Density	Number of passengers standing in a public transport vehicle divided by the amount of space allocated for standing in that vehicle (Pel et al., 2014).
SC	State Choice Experiment
RP	Revealed Preference Method
PT	Public Transport
ARI	Acute Respiratory Infection
ILI	Influenza Like Illness
MERS/MERS-CoV	Middle East Respiratory Syndrome Coronavirus (Guarner, 2020)
SARS/SARS-CoV	Severe Acute Respiratory Syndrome Coronavirus (Guarner, 2020)
COVID-19/SARS-CoV-2	Severe Acute Respiratory Syndrome Coronavirus-2 (Guarner, 2020)
MNL	Multinomial Logit
LCCM	Latent Class Cluster Model
BIC	Bayesian Information Criteria (Schwarz, 1978)
AIC	Akaike Information Criteria (Akaike, 1974)
Scheduled delay (SDE and SDL)	**Scheduled Delay Early and Scheduled Delay Late** (Peer, Knockaert, & Verhoef, 2016) (Hendrickson & Kocur, 1981) refers to the time by which people change their departure time and depart early or late respectively.

Chapter 1

Introduction

Public transport has assisted in overcoming spatial and temporal limits (Borrell, 2015), moreover, when transport modes are weighed on the ground of health related attributes, public transport and active modes such as bicycles are the most efficient, cheap and healthy modes of transport (Boniface, Scantlebury, Watkins, & Mindell, 2015). But one aspect of public transport usage which was in hindsight before the outbreak of COVID-19 is its potential to spread Acute Respiratory Infections (ARI) (Troko et al., 2011) (Goscé & Johansson, 2018). Ever since the COVID-19 pandemic outbreak in December 2019 public transport ridership has tremendously fallen (Jenelius & Cebecauer, 2020). This could be attributed to government policies to work from home and stay home (Gkiotsalitis & Cats, 2020) but it is undeniable that the confined and crowded environment in public transports increases the transmission risk of Acute Respiratory Infections (ARI) such as COVID-19 (Goscé & Johansson, 2018). Even before the pandemic started, crowding in public transport has been a popular cause of discomfort and disutility obtained from this mode of transport . After the pandemic this disutility has increased (Z. Li & Hensher, 2011), and in the aftermath of COVID-19 it is anticipated that the public transport ridership would remain less than pre-COVID times (Gkiotsalitis & Cats, 2020). Measures are required to make public transport attractive again (Gkiotsalitis & Cats, 2020) (Jenelius & Cebecauer, 2020).

1.1 Research objective

It has been more than a year since the pandemic started, and people have accustomed themselves to a new normal way of living. Governments across the world have started the process of vaccination. In the Netherlands, most of the people are expected to be vaccinated by the year 2022 (NL Times, 2021). Soon the government will ease down the restrictions and people will start travelling again. With work from home policies and less travel during the pandemic time, there is a good opportunity to reshape travel and tackle crowding in public transports (Hensher, 2020) (Kogi, 1979). Crowding in trains during rush hour is a well-known problem (Kogi, 1979) (Cox, Houdmont, & Griffiths, 2006). In a research conducted by NS along with TU Delft in mid-2020, it was found that many travelers would prefer not to commute during peak hours anymore (Jacob, 2020). Several countries, including the Netherlands have differential fare systems for peak and off-peak travel (NS, n.d.), however the problem of overcrowding in trains is still prevalent and is expected to cause more disutility than before the pandemic. Change in departure time has proven to be an effective measure to reduce peak hour rush (Zong, Juan, & Jia, 2013) (Maunsell, 2007) (Pel et al., 2014) (O'Malley, 1975). The main research objective is to fill the gap in research which is discussed subsection 3.5.1 in detail: It is not known if people are provided with prior or real-time information on expected crowding levels in trains in the Netherlands, and if they are offered some incentive on train fare, it could motivate them to change their departure time to avoid crowded trains. This in turn can reduce peak hour demand. Change in sensitivity to crowding in train travel as more people get vaccinated in the Netherlands is not researched upon. Research is required to see people's willingness to avoid crowds while traveling in trains. Such research could be helpful in managing crowd in trains during and after the pandemic, and it could also add to the attractiveness of trains in the Netherlands.

1.1.1 Research question

The main research question is formulated based on the research objective and research gap presented above and in the subsection 3.5.1. As discussed in subsection 3.2.1, crowding represents perceived risk of infection amongst train travelers (Z. Li & Hensher, 2011) (Hu et al., 2020) (Troko et al., 2011) (Goscé & Johansson, 2018) (LUMC-COVID-19 Research Group, Qingui, Toorop, & et. al., 2020). To study the sensitivity of train commuters towards crowding in train in present and coming times, and to take measures to manage crowding the main research question is:
During a pandemic, for different vaccination stages in the Netherlands, to what extent people can be motivated to change departure time to avoid crowded trains?

Sub-Research questions

To answer the main research question, following sub-research questions are framed:

- **SQ1)** What is state-of-the art in Acute Respiratory Infection (ARI) transmission in public transport?
- **SQ2)** What could be the suitable indicator and measure of crowding as perceived infection risk in commuting by trains in the Netherlands?
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- **SQ6)** How does the trade-off vary across different sub-groups of people?
- **SQ7)** What is the impact of vaccination stages on the trade-offs that people make?

1.1.2 Relevance

Once the government lifts restrictions and people start traveling again, with social distancing on-board approximately only 25% of peak-hour demand could be satisfied (Gkiotsalitis & Cats, 2020) (Besinovic & Szymula, 2021). Even though social distancing is recommended by the government, train operators have allowed usage of all seats in the trains (Dutch Railways, 2020). There is a constraint from the supply side to mitigate crowding in trains. From the demand side, passengers have the option of waiting at stations for less crowded trains but waiting for another train also causes high disutility (Peftitsi, Jenelius, & Cats, 2020) (K. Kim, Hong, Ko, & Kim, 2015). Another measure that passengers can take to avoid crowded trains is to shift their departure time (O'Malley, 1975) (Y. Liu & Charles, 2013) (Peer et al., 2016).

In a report by Eurofound (Eurofound, 2012) flextime is defined as work hour flexibility, i.e., flexibility offered to employees to start and finish the work. Such a policy is said to reduce traffic congestion, improve productivity and work life balance. Soon workplaces will re-open in the Netherlands, but it is instructed by the government to do so by following the norm of 1.5 meters social distance, to keep people safe. Employers are instructed to allow for staggered work hours and people are encouraged to work from home as much as possible (DLA Piper, 2021) (Intyre et al., 2020). Only with staggered work hours or flextime policy in offices, people will be able to make a shift in departure time (Y. Liu & Charles, 2013).

Based on this research, people's sensitivity to departure time changes and crowd level in current times, and how this sensitivity varies across different vaccination stages could be inferred. Departure time change experiments in the past have proven to be an effective method to reduce crowding in public transports (Zong et al., 2013) (Maunsell, 2007) (Pel et al., 2014) (O'Malley, 1975). If the research indicates positive results for the Netherlands in present time, then the government may motivate workplaces to allow for flextime and communicate this to train operators so that they can adapt their services as per anticipated demand. Currently, there is a 40% discount package which train passengers can avail for off-peak hour travel in the Netherlands (NS, n.d.). Sensitivity to lower discount on fare incentive within peak hours in case passengers adapt departure time could be helpful in determining other feasible offers for public transport usage. This is only possible when people register their journey and can check expected crowding levels in advance. In the Netherlands, both these processes are possible hence they should be actively promoted (Pel et al., 2014) (Jacob, 2020). This research will also study the heterogeneity in a group of people, and different passenger characteristics which allow for less or more sensitivity to departure time change. This could allow authorities to motivate specific groups of passengers to change departure time.

1.1.3 Research scope

Public transport services are readily available in many countries; however, the scope of this research is limited to the residents of the Netherlands. This is so because transport policies, travel preferences and transport services vary from country to country. Transport usage and travel preferences are expected to change due to the COVID-19 pandemic. A similar research with changes in some information provided in the stated choice survey could be conducted in other countries as well. This research is valid for people who use trains, even if rarely, to travel within the Netherlands. However, the experiment could be easily adapted to other public transport modes such as trams or metros. The reason for selecting trains in this research is that trains are one of the most popular public transport in the Netherlands (Bakker & et.al., 2018). The rail network is of high quality and is one of the busiest in the world. Major part of the country is easily accessible by trains (Expatica NL, 2021).

1.1.4 Stakeholders

Policies which promote flex hours/staggered commutes and offer discounts within peak hours are required to allow people to shift their departure time of train travel (Kogi, 1979) (Y. Liu & Charles, 2013) (Eurofound, 2012). The research urges to make models to predict crowding in trains and provide such real-time information to train passengers. Development and implementation of such policies and models will involve several primary and secondary stakeholders (PIARC, n.d.).

Primary stakeholders: Companies which offer railway information through software applications such as 9292, Google Maps etc. could provide information on expected crowding level in trains on their applications. Such companies are expected to have low power yet high interest in resultant policies. Other organizations which could be involved in making predictive models will also benefit from such policies in terms of employment and new project opportunities. This research is related to train travel within the Netherlands. For making policies to offer more fare discount or motivate people to shift their departure time, Nederlandse Spoorwegen (NS), which is the major passenger train operator within the Netherlands (Expatica NL, 2021), will be directly involved and affected. Other train operators such as Arriva, Connexxion, Keolis Nederlands, NMBS, DB Regio etc. (Wikipedia, 2021a) which operate in certain regions of the Netherlands will also be involved as such policy is expected to be implemented in the entire country. International train operators such as NS international, Thalys, Eurostar and InterCity Express (ICE) who also operate high speed trains in the Netherlands (Wikipedia, 2021a), may also be impacted by such a policy.

If more fare discount offers are considered for all public transport networks within the Netherlands, then the research will involve other public transport operators directly. Some of the other public transport operators who operate trams, buses and metros in the Netherlands are: GVB, HTM, Qbuzz, Syntuss, NS, Arriva, Connexxion, Transdev and RET (Wikipedia, 2021b) (Utrecht, 2014). Overall, public transport operators are expected to have high interest and high power in development and implementation of policy related to more fare discounts and offering information on expected crowding in trains. They may oppose the policy if more fare discounts result in monetary losses, however, they may support the policy if offering more discounts reduces the burden on supply of public transport to meet the rush hour demand which reduces the expenses. Policies such as flextime and staggered work hours in workplaces are significant to allow people to make departure time shifts. This would involve government authorities and policy makers to make new policies, and motivate workplaces to implement such regulations. Government authorities will have high power and interest in such policies, and policy makers will have low power but high interest. Management of workplaces will have to make some adjustments based on such new policies. They are expected to oppose such policies. Another important group of primary stakeholders are the public transport users and employees of companies which may be offered flex hour/staggered commute. The policies would require cooperation of these people, and they are expected to show positive interest.

Secondary stakeholders: Such policy will affect the demand of other public transports and shared modes directly/indirectly which are used as main transport modes or access/egress modes to/from train stations. Increase in attractiveness of trains can reduce the demand for buses/trams as main transport modes. But it may also result in an increased demand for trams/buses/bicycles for access and egress to and from train stations. There can also be a change in peak time and peak demand for such modes. ProRail which is the infrastructure managers of train platforms may also benefit from such a policy as there will be changes in passenger demand during rush hour. Environmentalists are expected to support such policies as it would increase the attractiveness of public transports. Medical facilities and authorities are expected to support such models and policies as it may reduce the spread of COVID-19 infection by reducing overcrowding in train stations and inside trains.

1.2 Research methodology

The research methodology followed during the course of this research is presented in the figure 1.1. These steps are discussed in detail below. Further, in chapter 2 all these steps and their specifications used in this study are elaborated.

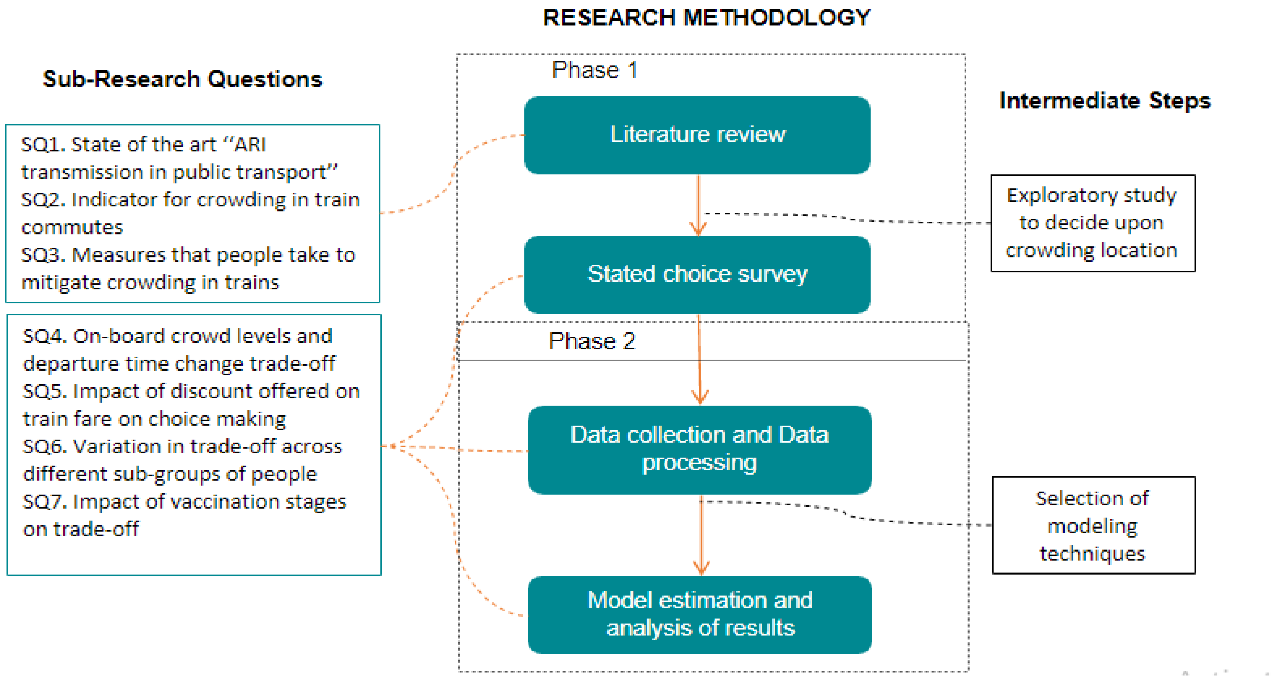


Figure 1.1: Research methodology followed in this study

1.2.1 Literature review

To answer the first three sub-research questions (SQ1, SQ2, SQ3) discussed in subsection 1.1.1, a thorough literature review is undertaken. A popular indicator of perceived Acute Respiratory Infection (ARI) risk amongst people could be crowding 3.2.1 (Z. Li & Hensher, 2011). This indicator can be quantified in several ways which are briefly explored further using literature from previous experiments related to valuation of crowding3.2. The literature also highlights the impact of COVID-19 pandemic on public transport (refer subsection 3.1.2). To explore various measures which people can take to avoid crowding in trains, the literature elaborates upon the impact of crowding on travel behavior (refer section 3.3). As crowding can be experienced in various locations on trains and also at stations (access or exit of stations, boarding and alighting, inside trains) (Karpouzis & Douglas, 2005), a small exploratory research is conducted to understand which crowding location must be considered in the design of stated choice survey (section 2.1). After selecting the attributes for the choice experiment and the type of background variables that could be required to understand travel behavior of different groups of people, a conceptual model is developed and several hypotheses are laid out which can be found in subsection 3.4. The conceptual model and the hypotheses are tested using the results from the survey and choice models in section 5.4.
Note: Scheduled Delay Early and Scheduled Delay Late which refers to the time by which train passengers change their departure time to depart early or late respectively (Hendrickson & Kocur, 1981) (Peer et al., 2016) are popular terms used in models and experiments related to departure time change for peak avoidance.

1.2.2 Stated choice survey

To answer the main research question and SQ4 to SQ7 mentioned in subsection 1.1.1, a web-based stated choice survey would be conducted. It is the state of the art in identifying responses of people for situations and attribute levels that could not be captured using revealed preference methods. Compared with other state preference methods, a stated choice survey gives respondents choices between different alternatives (Hensher, 1994). This is more practical and reasonable in this research's case as the objective here is to see the trade-off in hypothetical contexts of vaccination stages, crowding levels and other attributes by presenting a choice between train alternatives. Their underlying preferences would be analysed based on the choices they make. The structure of the survey would be determined along with literature review. The first step in setting up the survey is to select attributes, their levels and alternatives, and the second step is to make choice sets with different attribute levels for respondents. The choice sets are designed using Ngene (Molin, 2019b), and complete survey development and circulation is done using Qualtrics. The first phase of the thesis will be completed as the survey is ready for circulation.

1.2.3 Data collection and data processing

This process marks the beginning of Phase 2 of the thesis as represented in figure 1.1. It is in overlap with the first phase because once the stated choice survey is ready, a pilot survey would be circulated amongst a small number of people in the Netherlands (15-20 people). After the results are received, the survey might be modified to incorporate a few required changes. After this, the final survey would be circulated amongst approximately 200 people by means of personal contacts and social media platforms. When the survey responses are received, the data would be cleaned to remove incomplete or foul responses, and then data will be processed to generate the data in a format which can be used in model estimation. The main tools which are used for the data cleaning process are SPSS, MS-Excel and Python language.

1.2.4 Model estimation

The cleaned data obtained from data processing phase is analysed further using Mutinomial Logit (MNL) model and Latent Class Cluster Model (LCCM) to explore underlying preferences of people for different attribute levels. Significance of attributes is to be studied along with impact of different personal factors in making the choices. This would be done using discrete choice models. The estimation of discrete choice models is done using the Apollo package in R language (Hess & Palma, n.d.). The analysis of the results obtained using a discrete choice model is used to answer the sub-research questions 4, 5, 6 and 7, and the main research question mentioned in subsection 1.1.1.

1.3 Report outline

The thesis report is broadly divided into six chapters which are described in figure 1.2. *Chapter 1 Introduction* is divided into 3 sections. Section 1.1 presents research objectives, research questions, relevance of the research along with scope of this research and possible stakeholders. In section 1.2, the research methods used to answer all research questions are presented. In section 1.3, which is the current section, a layout of the entire thesis report is discussed. *Chapter 2 Methodology* presents the background of main research methods used in this research to find the research gap and answer all research questions. Section 2.1 discusses the method of selection of background literature, and describes a small exploratory study conducted to select the most discomforting location of crowding in public transports. In section 2.2, a background on the stated choice survey is provided along with the details on the steps followed in designing such surveys. This section also discusses the statistical method used in designing the stated choice survey. The last section 2.3 describes discrete choice models, MNL, LCCM, marginal rate of substitution and methods used to measure the fit of models.

Chapter 3 Literature review is divided into 5 sections. In section 3.1, literature linking health and ARI to public transport is discussed. In section 3.2, the problem of crowding in public transport including the impact of COVID-19 pandemic on public transport is elaborated. In this section several research related valuation of crowding in public transports are also discussed. In section 3.3, literature on measures taken by people to avoid crowded public transports are discussed. In this section several departure time change experiments conducted are also presented. in section 3.4 a conceptual model is presented and several hypotheses are laid which are tested in chapter 5 Results and Analysis. In the last section 3.5, answers to first three sub-research questions and the research gap found using literature review are summarised. *Chapter 4 Survey design* discusses the design of the final survey which is circulated, processed and analysed. It is divided into 3 sections. In section 4.1, the main attributes and context selected for stated choice (SC) survey are presented in detail along with a discussion on unlabeled train alternatives. In section 4.2, all the background information collected in the survey is elaborated in detail. In the last section 4.3, the design of choice sets using Ngene is discussed along with the changes made from the pilot survey.

Chapter 5 Results and Analysis is divided into 4 sections. Section 5.1 discusses the characteristics of data collected and processed. This section provides descriptive statistics of the responses collected. Section 5.2 and section 5.3 discuss the results from MNL model and LCCM respectively. Utility specifications are also discussed in 5.2. In the last section 5.4, a comparison of models and results with previous research is done along with hypothesis tests. The last *Chapter 6 Conclusion and Discussion* presents the conclusion drawn from this research. A discussion on policy implications and limitations of this research is also performed, and recommendations are made.

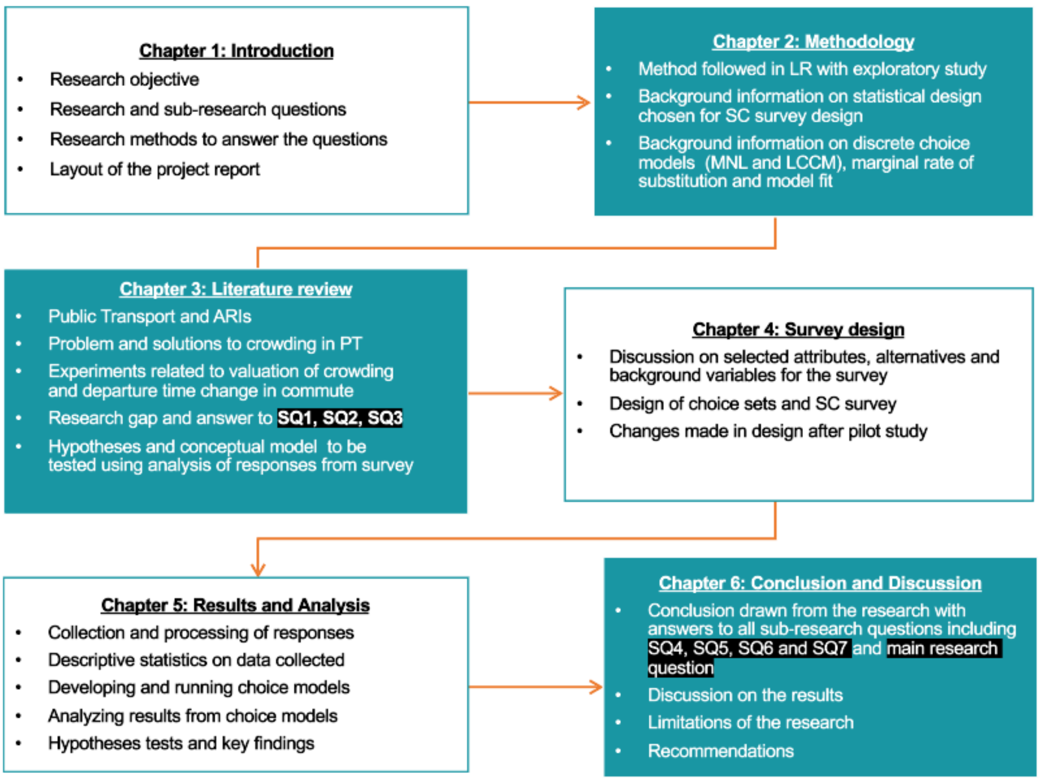


Figure 1.2: Layout of the thesis report

Chapter 2

Methodology

In this chapter, the background of research methodologies which are used in this research are presented in detail. In section 2.1, the technique used to select papers for literature review is described followed by an explanation of the exploratory study conducted to select one location of crowding from crowding on trains and at stations. In section 2.2, an introduction to the stated choice survey and its statistical characteristics has been elaborated in reference with this research. Section 2.3 presents the choice modeling techniques used to analyse the responses collected from the survey designed and circulated in this study. The detailed design of the stated choice survey conducted as a part of this research can be found in chapter 4, and the estimation of choice models based on the responses gathered from the survey is performed in chapter 5.

2.1 Literature selection and exploratory study

2.1.1 Literature selection

Different literature review methods are used in this research as literature in transport research is different from other fields such as medicine or physics. One of the reasons for this difference is that transport science is closer to social science, and one attribute is often affected by multiple attributes. This results in a complex relation between variables under study (Wee & Banister, 2016). The topic of this research is focused on infection risk in public transport. Literature review undertaken in this study revolves around this theme, and the literature reviewed includes a mix of primary and secondary studies (Jalali & Wohlin, 2012) (Wee & Banister, 2016). The literature review, which is presented in chapter 3 of this thesis report, assisted with finding out gaps in literature, and to provide an overview of the research done in the domain of infection risk in public transport and crowding in public transport. Here, literature review also helped in finding the attributes for the stated choice experiment and defining their quantification method for choice experiment design (Wee & Banister, 2016). A conceptual model is also developed using the literature, and hypotheses are laid, which are tested using the results from the stated choice survey.

Before defining the research questions, the literature review began by using a subjective criterion of brainstorming. Few experts also recommended papers at some point which helped in drawing a boundary to scope the topic (Wee & Banister, 2016). The search for literature is performed using Google Scholar platform. Keywords used in finding the literature include- ***infection risk and public transport, COVID-19 and public transport, health, and transport mode choice.*** Backward snowballing (Jalali & Wohlin, 2012) is also used in scoping the thesis, and finding more specific literature. Crowding references were found in several papers related to infection risk in public transport. More research papers on crowding were found by searching the keywords- ***crowding in public transport and valuation of crowding in public transport***. Again, with backward snowballing, reference of measures to avoid crowding in public transport was found. Followed by keyword searches of- ***staggered commute, departure time change experiment, travel behavior change, and crowding in public transport,*** other parts of the literature was concluded.

2.1.2 Exploratory study

Literature says (subsection 3.2.2) that discomfort due to crowding can be experienced in several places within train stations or trains such as inside the vehicle, at platform, entrance of vehicle, entrance of stations, yet most of the researches are focused on crowding experience inside the vehicle (Z. Li & Hensher, 2011). Using a small exploratory study, the location of crowding in this research's stated choice experiment is selected. In the study, a small questionnaire was circulated amongst 10 people within the Netherlands. 8 out of 10 respondents found in-vehicle crowding to be most inconvenient. 2 of them found crowding while boarding and alighting as most uncomfortable. Other options included entry/exit to stations and waiting area (platform) at the stations. In this study, people were also asked to choose a maximum of three of the mitigation measures presented that they would take to avoid crowding in trains during COVID-19 pandemic. Amongst the following options of- taking a longer train, travel in first class, pay a little extra, wait for less crowded train, change departure time from home, board the crowded train and change mode of travel; 7 out of 10 people chose changing departure time as one of the three options. This question was simply asked to see if people would be interested in the option of changing departure time. In the subsection 3.3.2 of literature review change in departure time experiments conducted in the past are discussed in detail. Based on the results from exploratory study and literature review, the stated choice experiment is focused on changing departure time to avoid in-vehicle crowding in trains.

2.2 Stated choice survey

The methodology used in answering the main research question and sub-research questions formulated based on the research objective and literature review is a stated choice experiment which involves conducting a stated choice survey and analysis of the responses gathered in this study. Similar to the real world, in a stated choice survey people are presented with alternatives (such as train alternatives in this research's case) which may vary in attributes and their levels. An advantage of stated choice experiment is that the respondents can be presented with hypothetical contexts (such as different vaccination stages in this study), alternatives and attributes (such as crowding level in trains, discount on train fare and departure time change in this research) (Hensher, 1994). As per the choices that people make, their behavior towards presented alternatives can be analysed using choice models based on utility maximisation theory (Bierlaire, 1998) (refer section 2.3 in this chapter for more detail on choice models).

Stated choice experiments are also state-of-the-art in predicting real world choices in transportation (Hensher, 1994). To be able to analyse such choices, the design of choice experiments is done systematically. There are seven major steps involved in the design of a choice experiment. The first step is to select the attributes and context of the experiment. The second step is two select the unit of measurement of each attribute. The third step is to select the number of levels of all attributes along with their values. The fourth step is the statistical design of the experiment and assignment of choice sets to alternatives (Hensher, 1994). Fifth step is to prepare the survey for circulation and collect responses. Sixth step involves estimation of the choice model and the last step is the analysis of results from the choice model. In this section fourth step, i.e., the statistical design of the experiment is explained briefly (Hensher, 1994). Step 1, which is the selection of attributes and context has been performed in the subsection 3.5 of literature review. It will be brought up again in Chapter 4 along with the other steps related to design of the experiment and the survey (step 2 to 3 and step 5). Step 6 and 7 are elaborated in Chapter 5 Results and Analysis.

To estimate a good choice model and make a useful choice experiment it should be ensured that the attribute combinations simulate real world scenarios. The attributes are selected such that they serve the purpose of research and are also important for respondents. The range of attribute levels should be wide, and the correlations between the attributes should be minimised. (Molin, 2019b). To select combinations of attributes and alternatives, different types of designs are available. In this research an orthogonal design with unlabelled alternatives is selected for the experiment. A full-factorial design has all possible combinations of attributes and their levels. Such a design is simple and does not have correlations between attributes. It also accounts for all possible interactions between attributes, but it results in a very large number of choice situations which is impractical to circulate amongst respondents, and it is also impractical to estimate the model. In a fractional-factorial design some combinations of attribute levels are selected from a full-factorial design mathematically or by using a software called Ngene (Molin, 2019a). In such designs some statistical efficiency is lost but these are more practical and manageable (Hensher, 1994) (Molin, 2019b). There are several fractional-factorial designs but in an orthogonal fractional-factorial design there are no correlations between the attributes as each level appears an equal number of times in the experiment. This makes the parameters more reliable (Molin, 2019b). 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 orthogonal or other fractional factorial designs, the assignment of choice sets to alternatives is based on whether the experiment has labelled or unlabelled alternatives. In this research an unlabelled experiment is designed which is usually preferred over labeled experiment unless labels of alternatives are necessary in a research. Although labelled experiments provide meaning to alternatives and are more realistic, unlabelled experiments result in a smaller number of choice sets, and in such experiments trade-offs can be easily studied as all the alternatives share the same attributes and attribute levels. In an unlabelled experiment, a universal set of all alternatives is not required. Attribute levels are considered sufficient to replicate real world scenarios (de Bekker-Grob et al., 2010). More detailed explanation on selection of unlabelled alternatives is providen in subsection 4.1.2. The assignment of choice situations to alternatives is done sequentially where each alternative is randomly assigned a choice situation such that no combination of choice situations in alternatives is repeated (Molin, 2019b).

2.3 Discrete choice models

Decisions related to transport choices are usually discrete. For e.g., choosing between car, metro or tram as a mode of transport for work commute, selecting a vacation destination. In this research also a stated choice survey is conducted which provides respondents with a set of discrete choices. To analyze such choices, discrete choice models based on random utility maximization principle is used here which simplifies the complexity of true behavior to the form of a model. These models help in predicting choices by assuming that people make choices such that they maximize the utility obtained from alternatives. The utility (U_i) of an alternative 'i' and choice set 'a' is defined as a sum of its deterministic and stochastic components. It is impossible to always correctly predict the choices based on the deterministic utility, therefore there is an error term in the utility specification which captures the uncertain (stochastic) component in choice making (Bierlaire, 1998).

$$U_{ia} = V_{ia} + e_i \tag{2.1}$$

Here 'V' is the deterministic part of utility and 'e' is the error term (uncertain/stochastic part). The deterministic utility is a linear additive function of attributes that people trade-off in choice experiments. It is computed by taking product of each attribute that the respondents trade-off with the taste parameter for that attribute and then taking a sum of these products (Bierlaire, 1998)(Ben-Akiva & Lerman, 2018). This deterministic utility equation of an alternative 'i' for a respondent 'r' is given as (Bierlaire, 1998):

$$V_{ir} = \sum_{k=1}^{n} \beta_k * X_{ir}(k) \tag{2.2}$$

Here 'n' represents a set of all attributes in the choice experiment. In this study a MNL (Multinomial Logit) model and LCCM (Latent Class Cluster Model) are estimated to analyse the responses collected from the survey. A standard MNL model fails to capture heterogeneity across individuals, and if heterogeneity exists in the data, then MNL models can give biased results (Wen & Lai, 2010). To capture the heterogeneity in the data set collected, latent class cluster models (LCCM) are developed in this study. The results from these models help in answering the main research question and sub-research question four to seven (refer subsection 1.1.1 for research questions).

2.3.1 Multinomial Logit Model

Multinomial Logit models are one of the simplest and most extensively used random utility models. It is based on two property assumptions which reduces the complexity of the model. First one states that the error term of each alternative is identical and independently distributed (IID). Second one is the independence from irrelevant alternatives (IIA) which states that ''the ratio of probability of choosing any two alternatives is independent of the systematic utility of any other alternative" (Ben-Akiva & Lerman, 2018) (Bierlaire, 1998) (Cascetta, 2009). In MNL models the probability of a respondent 'r' to choose an alternative 'i' is computed as-

$$P_{ir} = e^{V_i} / \sum_{i=1}^{I} V_{ir} \tag{2.3}$$

Here 'I' represents a set of all alternatives in the choice experiment. As the experiment conducted in this research is unlabeled, there is no meaning of alternative labels. Both the alternatives share the same attributes and levels, hence there is no difference in the utility specification of the alternatives (Hensher, Rose, & Greene, 2015). An alternative specific constant could be added to all alternatives but one to capture the bias in choice selection based on the position of alternatives in the choice set displayed. Equation 2.2 shows the systematic utility obtained from the choice experiment attributes. To improve the model and to study the impact of background variables such as socio-demographic, travel related characteristics of individual and attitude towards health and COVID-19 in choice making , these variables are introduced as interaction effect in utility equations of all alternatives (refer subsection 4.2 for more details on background variables used in this research). This is done because to capture the effect of each variable it must show some variation across alternatives otherwise the taste parameters cannot be computed in discrete choice models (Hensher et al., 2015). These interaction terms consist of at least one variable which is not constant across alternatives. Similarly, to study the effect of contextual variables (vaccination stages) in the experiment they are also added as interaction terms.

Any model may have taste parameters within different significance ranges. For this research a 10% significance level (t-ratio >1.65) is chosen to decide whether a parameter has a significant effect on the model or not. A high threshold of p-value is selected in this research so that at least the sign of background variables which may be lost because of a very high threshold is captured (Yap, Correia, & van Arem, 2015). The significant taste parameters are simply kept in the model, however, the decision to keep or remove an insignificant parameter in utility specification is taken by Log-likelihood ratio test in which log-likelihood of models with and without the insignificant taste parameter is compared using a chi-square significant test. Note that this test is only possible when models can be nested (Chorus, 2019). The selection of models and how to determine the fit of a model is discussed below in detail.

Model fit tests

In this research, log-likelihood ratio tests are used to determine the better fitting MNL model. As a model has different attributes, there can be several combinations of taste parameters (β_s). The resultant model is hence computed by model runs for multiple iterations till the point when the final model is most likely to represent the behavior from observed choices. Instead of likelihood, log-likelihood is computed for better presentation as the values are larger and easily comparable. The equation to calculate log-likelihood (LL) can be found below (Hauser, 1978) (Chorus, 2019):

$$LL(\beta) = \sum_{n} \sum_{i} y(i) * ln(P_n(i|\beta)) \tag{2.4}$$

Here 'y(i)' is a binary variable which takes value 1 if alternative 'i' is chosen, otherwise it takes the value 0. 'n' represents an observation from choice sets. '$P_n(i|\beta)$' is the probability of choosing an alternative 'i' for the given value of taste parameters in observation 'n'. The value of ρ^2 indicates the model fits in a relative sense. It ranges between 0 to 1 where 0 means that the model does not represent any behavior and is coincidental, and 1 indicates that the model depicts true behavior. It is computed as:

$$\rho^2 = 1 - LL(\beta)/LL(0) \tag{2.5}$$

If any two models are nested, which means they have the same number of observations and one of them can be obtained by restricting parameters of the other, then Likelihood ratio test is performed in this research to compare the fit of those two models. The null-hypothesis in such tests is: *A model is a better fitted model due to coincidence.* In this research this null-hypothesis is rejected at less than 10% significance level.

Assume that model 'A' has higher LL than model 'B'. To compute the t-ratio, first Likelihood Ratio Statistic (LRS) is calculated as shown in equation 2.6. The degree of freedom (df) of the two models is computed by taking a difference of the number of parameters of the two models. From the χ^2 table and degree of freedom, threshold value of χ^2 is found such that LRS becomes less than the threshold. The significance level at the threshold indicates the significance at which model 'A' is coincidentally better than model 'B'.

$$LRS = -2 * (LL(B) - LL(A)) \tag{2.6}$$

For models on which Log-likelihood ratio test cannot be used, Bayesian Information Criteria (BIC (Schwarz, 1978)) and Akaike's Information Criteria (AIC (Akaike, 1974)) values can be used for comparison (Chorus, 2019) (Hauser, 1978). Its application is described in detail in the subsection 2.3.2 below.

2.3.2 Latent Class Choice Model

To capture the heterogeneity in the data set collected, latent class cluster models (LCCM) are a popular choice, and have been successfully used before in departure time change experiments (Thorhauge, Vij, & Cherchi, 2020). The LCCM divides 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). Each class has their own taste parameters and likelihood. In development of LCCM, generally an underlying MNL model specification is used (Equation 2.2). The first step is to select the number of classes and then the final model with the selected number of classes is developed. A class membership function is also added to the selected model to allow for the effect of background variables in the model (Hess, 2014).

To select the optimum number of classes first the model is run with increasing number of classes starting from 2 to 4 and so on. The models are then compared with each other in terms of Akaike's Information Criteria (AIC (Akaike, 1974)) or Bayesian Information Criteria (BIC (Schwarz, 1978)). Number of classes where the local minima of BIC or AIC lies is generally selected. A log-likelihood estimator with chi-square test is not preferred here because as the number of classes increases the number of parameters increases, and so LL of the models increases. AIC and BIC are computed by taking into account LL values and a penalty on the number of parameters (Wen & Lai, 2010).

$$AIC = -2LL + 2K \tag{2.7}$$

$$BIC = -2LL + (ln(N))K \tag{2.8}$$

'LL' is the log-likelihood of the model at convergence, 'K' is the number of parameters in the model and 'N' is the number of observations in the sample. A low value of AIC and BIC is preferred as it indicates a balanced trade-off between model fit and parsimony (Lanza, Collins, Lemmon, & Schafer, 2007). In this study, BIC is preferred over AIC as it imposes a more stringent penalty on the number of parameters (Walker & Li, 2007) (Wen & Lai, 2010). Along with AIC and BIC values it is important that the classes are non-trivial in size, and they are interpretable with assigned meaningful labels.

The probability of an individual 'r' to select an alternative 'i', whose probability of belonging to class 's' is π_{rs}), is given in equation 2.9. β_s represents the taste parameter vector for a class 's' and 'S' represents a set of all classes (Shelat, Cats, & Cranenburgh, 2021) (Hess, 2014):

$$P_{ri} = \sum_{s=1}^{S} \pi_{rs} * P_{ri}(\beta_s) \tag{2.9}$$

$$\pi_{rs} = e^{\delta_s + \sum_k \gamma_{sk} * z_{rk}} / \sum_{p=1}^{S} e^{\delta_p + \sum_k \gamma_{pk} * z_{rk}} \tag{2.10}$$

Here γ_{sk} and z_k are class membership coefficients.

2.3.3 Marginal rate of substitution

Marginal rate of substitution indicates the trade-off between any two attributes in the choice experiment. When there is a small change in the value of one attribute, how much the other attribute in consideration changes is given by the marginal rate of substitution. This value is computed by taking ratios of partial derivatives of utility with respect to each attribute in consideration (refer equation 2.11) (Chorus, 2019).

$$MR = (\delta V/\delta X_1)/(\delta V/\delta X_2) \tag{2.11}$$

In this research, two marginal rates of substitution are computed. First one is to observe the amount of discount on train fare that respondents expect to schedule delay by one minute, and the second is to observe the minutes by which respondents may delay their commute to have one more free seat in trains. This is computed in chapter 5 Results and Analysis. It is known that on-board crowding has non-linear effect on utility function (Whelan & Crockett, 2009) (Shelat et al., 2021), that is why on-boarding crowding is effect coded (this is discussed more in section 4.1) which results in different taste parameters for each level of on-board crowding. As mentioned in the last row of table 3.1, a summary of valuation of crowding experiments, this research gives crowding in terms of departure time change. To calculate the marginal rate of change of crowd and scheduled delay two major steps are required. First marginal rate for effect coded crowd taste parameters is computed (refer equation 2.14) (Shelat et al., 2021) and then it is added to the marginal rate obtained from the interaction effects of crowd with background variables (refer equation 2.15). Crowding coefficient for each range of crowding (seat occupancy change from 9 to 18, 18 to 27 and 27 to 34) is calculated as shown in equation 2.12. Then the marginal rate for each range of crowd is computed by using equation 2.13. A weighted average of marginal rates for each segment is taken (as shown in equation 2.14) to get the marginal rate of substitution for the main effect of on-board crowding attribute (Shelat et al., 2021).

$$\beta_{crowd:g \rightarrow g+1} = (\beta_{crowd:g} - \beta_{crowd:g+1})/(x_g - x_{g+1}) \tag{2.12}$$

$$MR'_{g \rightarrow g+1} = \beta_{crowd:g+1} * (x_g - x_{g+1})/\beta_{delay} \tag{2.13}$$

$$MR' = (\sum_g MR'_{g \rightarrow g+1} * (x_{g+1} - x_g))/(\sum_g (x_{g+1} - x_g)) \tag{2.14}$$

$$MR = MR' + MR^{inter} \tag{2.15}$$

MR' is the marginal rate of substitution of crowd and scheduled delay for the effect coded part of the utility equation. The overall marginal rate of change of crowd and scheduled delay is obtained as a sum of marginal rate of effect coded part (MR') and interaction part (MR^{inter}) as shown in equation 2.15.

Chapter 3

Literature review

In the past 20 years, the world has witnessed an outbreak of three contagious coronaviruses which lead to severe Acute Respiratory Infections (ARIs). These viruses in the chronological order of their occurrence are: SARS-CoV (Severe Acute Respiratory Syndrome Coronavirus) , MERS-CoV (Middle East Respiratory Syndrome Coronavirus) and SARS-CoV-2 popularly known as COVID-19 (Guarner, 2020). Studies conducted in UK (Hayward, Beale, Johnson, Fragaszy, & Group, 2020) and South Africa (Zhen et al., 2020) after the outbreak of COVID-19 pandemic show that the way Acute Respiratory Infections spreads is similar to how seasonal respiratory viruses and coronaviruses spreads, i.e., through droplets and direct or indirect exposure to infectious secretions and aerosol-based transmissions. Exposure to public places including public transport increases the risk of being infected by such diseases. These studies also show that measures like social distancing, hand hygiene, respiratory etiquette and active communication reduced the transmission rate of such infections in public transports (Hayward et al., 2020) (Zhen et al., 2020).

In section 3.1, an introduction to health in transport is added followed by a review of how public transport could be responsible for the spread of ARIs. This subsection answers **sub-research question 1**. In the next section, 3.2, a literature review on crowding in public transport and its quantification and mitigation strategies are discussed. This section answers **sub-research question 2**. In section 3.3, adaptation of travel behavior to avoid crowding in trains is discussed which answers **sub-research question 3**. Section 3.4 presents the hypotheses laid out and conceptual model developed which is tested later in section 5.4. The last section 3.5 presents a summary of the entire literature review. Based on the literature review, attributes which are to be used in stated choice experiments are determined. Subsection 3.4 presents the designed conceptual model and hypotheses made based on research objectives. This would help in the design of a stated choice survey, and testing of conceptual model and hypotheses would be performed using analysis of responses gathered from the survey.

3.1 Public transport and ARIs

3.1.1 Risk of ARIs in public transport

Since a few years attempts have been made to link transport (commute) and health. Most of the literature linking health and transport includes aspects of physical and mental health, and social interaction (where physical health is about physical activities, contribution to air pollution and vulnerability to injuries). If health is weighed in terms of societal benefits and environmental impacts, then one of the healthiest modes of transport would be a public transport network. It is cheap, safe, efficient and comprehensive (Boniface et al., 2015). Public transport has assisted in overcoming spatial and temporal limits. To reduce emissions, congestion, inequity and to improve physical and mental health, policies are being developed (especially across EU) to promote a switch from cars to more active modes of travel and public transport (Borrell, 2015) (Boniface et al., 2015).

One major aspect that is missing in these literature linking health and transport is the risk of being exposed to an infection while travelling in public transport. Crowded and confined environments such as that of transport hubs have the potential to become a source of spread of diseases (Goscé & Johansson, 2018). There are a few studies which show correlation between spread of Acute Respiratory Infections (ARI) and use of public transport. One such study was conducted on the London Underground Transport Network (Goscé & Johansson, 2018). This study used an analytical microscopic model to study the spread of Influenza Like Illness (ILI), i.e., common airborne infections in the underground metro of London during rush hours. Another study in the UK during the influenza period (2008-2009) conducted on bus and tram networks shows a statistically significant association between ARI development and use of bus/tram a few days before symptoms' onset. This could be attributed to lack of ventilation and air circulation in trams and buses; however, despite good ventilation, it cannot be denied that a confined, and crowded environment increases the risk of exposure of an individual to such diseases (Troko et al., 2011).

Old models which depict how a disease/infection such as influenza, measles or SARS spreads, ignored the possibility of people getting infected while travelling. In 2006, a model was developed which included this possibility as well. During that period, the spread of such diseases was curbed by introducing travel restrictions and placing screening systems at the entry and exits of public transport systems (X. Liu & Takeuchi, 2006). In 2020, an epidemiological study was conducted on COVID-19 cases that travelled on high speed train across mainland China between December 2019 and March 2020, 14 days before the onset of symptoms (Hu et al., 2020). The study found that risk of infection can vary between 0 to 10.3 % depending on seating arrangement relative to an infected passenger and travel time with an infected passenger on-board. The research suggests that apart from personal hygiene, seating distance inside the trains, co-travel time with infected passengers on-board and passenger density can influence the infection risk significantly (Hu et al., 2020).

3.1.2 Impact of COVID-19 on public transport

Since the outbreak of COVID-19 in December 2019, public transport ridership of several countries has experienced a severe fall. In China, it was studied that cities which banned intra-city public transport, public gatherings and entertainment events experienced fewer cases than the rest. This action was a response to curb the spread of the virus (Tian, Liu, & et. al., 2020). During the spring of 2020, an analysis of the impact of COVID-19 on public transport ridership in three major cities of Sweden was conducted. It was observed that the public transport ridership decreased by 40%-60%, and it was the period when service frequency was not changed (Jenelius & Cebecauer, 2020). People were advised to make use of public transport only when necessary. This period also witnessed a sudden change in mobility pattern. Usage of bikes and cars increased, and people who don't have a choice of other modes remain to use public transport (Jenelius & Cebecauer, 2020).

In the aftermath of COVID-19 pandemic, it is anticipated that public transport ridership may remain less than before, even in the Netherlands. People who have access to other modes of transport would be reluctant to switch back to public transport after the pandemic is over (Gkiotsalitis & Cats, 2020). Literature shows that there is need for solutions to increase attractiveness of public transport and make it resilient to spread of such infections, while keeping at most the same ticket prices (Gkiotsalitis & Cats, 2020) (Jenelius & Cebecauer, 2020). Crowding is associated with discomfort and safety issues in travel, hence it causes a disutility to travel in public transport or shared rides. If infection transmission while travelling is also taken into consideration then crowding has much more disutility in travel by public transports (Z. Li & Hensher, 2011) than any other mode. This aspect of crowding, i.e., risk of exposure to infectious diseases, which causes more disutility is also a health concern associated with public transport. To curb this risk, the government is working on new policies and operation plans for public transport (Gkiotsalitis & Cats, 2020). During COVID-19, governments in different countries have decreased the service capacity of public transport as the demand has reduced drastically. There has been active research on trade-offs between crowding and travel times in public transport, and more research is required to make new strategies for safer and resilient public transport (Gkiotsalitis & Cats, 2020).

In a research conducted by NS along with TU Delft in mid-2020 (Jacob, 2020), it was found that many travelers would prefer not to commute during peak hours anymore. Seat reservation system is approved by a large population yet there is also some criticism and skepticism regarding its accessibility to the entire population, and extension of this facility to other public transport modes in the Netherlands (Jacob, 2020). After the COVID-19 outbreak, the passenger demand for public transport has reduced by 90-95% during peak hours. And even when the pandemic is over, and restrictions are lifted, social distancing of approximately 1.5 meters might be prevalent (Besinovic & Szymula, 2021). In a research conducted to estimate what the train capacity would be as an impact of COVID-19 (Besinovic & Szymula, 2021) it was pointed out that with social distancing in practice, trains would fall short to meet passenger demand during rush hours. This research estimates the new transport capacity of trains in the Netherlands during the pandemic. It states that, in the Netherlands, once the demand goes back to 100%, i.e, normal demand during peak hours, with social distancing of 1.5m in practice, 50% of the demand would remain unsatisfied during peak hours, and the difference would be 30% unsatisfied for 50% of normal demand. Demand more than 25% of pre-Covid times would be a constraint, and a huge portion of the demand might remain unserved (Gkiotsalitis & Cats, 2020) (Besinovic & Szymula, 2021). For an intercity train in the Netherlands, the original capacity is 400-1100 passengers, and during COVID-19 time the capacity is reduced to 100-250. For a local train it is reduced from 320-540 to 80-140, i.e. new capacity is 25% of the original capacity (Besinovic & Szymula, 2021). Although most of the governments across the world are recognising social distancing measures varying from 1 to 2 meter, and it is known that transmission of infection does not vary linearly with social distancing, less than 1 m distance can lead to drastic increase in transmission rate of infection (Gkiotsalitis & Cats, 2020) (Jarvis, Zandvoort, Gimma, Prem, & et.al., 2020), all the seats are available for use in the trains. This is also the case in the Netherlands (Dutch Railways, 2020). As the government lifts the restrictions on travel, crowd management in public transport will become very essential.

3.2 Crowding in public transport

3.2.1 Introduction

Ergonomics in public transport refers to satisfaction of the needs of passengers (Kogi, 1979). Out of all the physical, environmental and mental factors that cause discomfort in travelling via public transports, crowding is the most significant one (Kogi, 1979). Crowding causes disutility in travel, and it is specific to public transport as a mode of travel. It can be defined as a state in public transport, especially trains, which can lead to mental stress, and increase the risk to safety, security and health (Cox et al., 2006).

As demand for train travel is increasing in different countries, the service capacity is reaching its peak. Overcrowding is becoming a common phenomenon, especially during peak or rush hours of travel (Whelan & Crockett, 2009). Crowding levels affect the quality of public transport service (Z. Li & Hensher, 2011). When the demand exceeds 40-70% of seating capacity, crowding starts to cause disutility in travel (Whelan & Crockett, 2009). Experience of overcrowding may vary with seasons, weeks or days, but the most problematic one to deal with is the rush hour or peak hour crowding (Kogi, 1979). Study shows that people across the world experience dissatisfaction in travel during rush-hours in trains. It has been observed in a research done in New York city on train commuters in 2007 that sometimes people choose to stand rather than sit on a middle seat in a train (Evans & Wener, 2007).

Before the outbreak of COVID-19 pandemic in December 2019, the major reasons why crowding caused such disutility in travel was that people wanted to avoid unnecessary physical and social interaction. They feel uncomfortable and unsafe (Evans & Wener, 2007). Ever since the pandemic began, crowding has been highlighted as a source of spread of respiratory infections. In a research done for BMC Public Health journal (LUMC-COVID-19 Research Group et al., 2020) in the Netherlands, association of transmission of respiratory infectious diseases (viral infections) such as influenza, rhinovirus and COVID-19 with crowded environments was established. The research compared the transmission patterns of COVID-19 and Influenza (2017-2018) pre and post crowded gathering for a carnival. The results from this research confirmed that mass gatherings can increase the transmission of viral respiratory infections. Hence, social distancing has been a successful measure in controlling the spread of such infections and ***social distancing can be termed as an antonym of crowding*** (LUMC-COVID-19 Research Group et al., 2020).

3.2.2 Crowding valuation in trains

Before the COVID-19 pandemic began, 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, Cats, & van Arem, 2020). Crowding in public transports is not limited to crowding inside the vehicle. It can be experienced at various other locations inside public transport stations such as inside the vehicle, platform, entrance of vehicle, entrance of stations. Most of the research is focused on crowding experience inside the vehicle (Z. Li & Hensher, 2011). Several studies using Stated Choice Experiments and Revealed Preference data have been performed to measure the value of crowdedness. Most of these studies focus on crowdedness in-vehicle. In the following subsections, various researches on estimating value of crowdedness in terms of monetary multipliers and time multipliers are discussed-

Valuation of in-vehicle crowding as time multipliers, SC Experiments:

In 2008-2009, MVA Consultancy in UK conducted a Stated Choice research to estimate people's "willingness to pay to reduce rail overcrowding" (Whelan & Crockett, 2009). 2318 responses were collected. Respondents were given choices between crowding and travel time, and instead of a choice to pick an alternative, they were asked to indicate how strongly they prefer each alternative. In this experiment strong emphasis was laid on quantifying crowding attributes with the help of a focus group so that respondents do not get confused, and changes in their responses as crowding level varies could be very well captured. The indicator of in-vehicle crowding included ***seat occupancy rate (percentage of seats occupied), number of passengers standing and their positions, and the layout of how people are seated by considering empty seats around a passenger***. Sixteen levels of crowding were selected, and standing capacity played a role when seating capacity exceeded 100%. With the help of graphics and texts the crowding levels were presented to respondents and they were asked to trade-off between crowding and travel time. The research recommends the value of crowding as a time multiplier than monetary indicators as the former is easy to interpret, convert and apply to understand the influence of crowding on passenger's behaviour and benefits that could be achieved if crowding is reduced (Z. Li & Hensher, 2011). It also states to indicate standing passengers, once all the seats are occupied, in terms of passenger standing per meter square. It was found that time multiplier's value increased from 1 to 1.63 for seated passengers, and from 1.53 to 2.04 for passengers standing as number of passengers standing increased from 0 to 6 per meter square (Whelan & Crockett, 2009) (Z. Li & Hensher, 2011). The time multiplier of crowdedness was found to have significant variations with journey purpose and region of travel (Whelan & Crockett, 2009) (Z. Li & Hensher, 2011).

In the research paper "Avoiding the Crowd: Traveller Behaviour in the Age of COVID-19 (Shelat et al., 2021)", researchers used a stated choice experiment with contextual information on COVID-19 infection risk in the Netherlands to find out people's willingness to wait for a less crowded trains to avoid risk of getting infected while traveling. The data was gathered in May 2020 when lockdown was relaxed. Crowding in trains was represented graphically as the number of seats occupied at five levels. Total of 513 good responses were gathered from the Netherlands. Using latent class choice models, people were divided into two classes and it was found that people who are more COVID conscious have a higher value of crowding- 8.75 min per person and this value rose if there was a chance to sit alone. This research also points out that government and public transport authorities need to make efforts to increase attractiveness of public transports in order to restore the demand of public transport once the pandemic is over.

Valuation in-vehicle crowding in monetary terms, SC Experiments:

Another unit of measure of disutility caused by crowding inside a vehicle is monetary value per person for per unit time of travel. In a State Choice Experiment conducted in the UK in 2008 (Lu, Fowkes, & Wardman, 2008), five attributes were included in the experiment: fare, travel time in-vehicle, punctuality, crowding in-vehicle and frequency. Crowding was indicated as a probability of standing for a length of journey. Using a Multinomial Logit estimation of choice model, value of crowding was found to be 7.23 pounds per person for one hour of travel which was more than two times of value of time (in-vehicle) (Z. Li & Hensher, 2011) (Lu et al., 2008).

In another SC Experiment conducted in Sydney Australia in 2005 (Douglas & Karpouzis, 2006), value of crowding as a time multiplier was found to be 1.17 which is in range of estimated value from research mentioned in 3.2.2 (Whelan & Crockett, 2009). The attributes of two train alternatives varied in terms of on-board crowding, waiting time for the trains and in-vehicle travel time. In terms of crowdedness levels, the alternatives varied as a combination of standing time (crushed/uncrushed) of 'x' minutes and getting a crowded seat or choosing a train with an uncrowded environment and getting an uncrowded seat. The monetary multiplier for the value of crowding was found to be 1.47 AUD (Australian Dollars) for a seated passenger per hour and total cost (travel time cost and crowding cost) of 9.92 AUD per person per hour. The monetary value was computed by translating time into a monetary indicator using the value of time. It was observed that the relationship between load factor and total cost is non-linear. The value rises sharply as the load factor increases to 100%. Similar to the experiment mentioned above (Douglas & Karpouzis, 2006), many researches on crowding in public transports used a Stated Preference Experiment, and crowding was indicated by using a mix of number of passengers standing (0-120 for a train) and percentage of passengers seated (25-100%) (Hensher, Rose, & Collins, 2011) (Z. Li & Hensher, 2011).

Valuation of in-vehicle crowding, RP Experiments:

In a revealed preference study conducted in the Netherlands in 2020 to estimate value of crowdedness for bus and trams (Yap et al., 2020) the indicator of crowding for in-vehicle crowding is similar to previous studies, i.e. seat occupancy and density of standing passengers in per meter square. It was found in this study that crowding significantly impacts the route choices of passengers in public transports, however, stated choice experiments often overestimate the value of crowding in public transports. In-vehicle time multiplier of crowding increases from 1.16 to 1.31 for normal to more frequent users of public transport when all seats are occupied. The value of coefficients obtained from this study is in orientation with previous SC Experiment studies, and similar to other studies value of crowding found here for frequent users of public transport is higher than that of less frequent passengers, but the value of time multiplier is less than the values obtained from other SC Experiment studies such as that of MVA Consultancy (Whelan & Crockett, 2009).

Another revealed preference study (Hörcher, Graham, & Anderson, 2017) performed in 2017 in Hong Kong mass transit railway to estimate value of crowding in public transport as in-vehicle time multiplier agrees with the research results mentioned above (Yap et al., 2020). Both the studies were performed using Automated Fare Collection (AFC) and Automated Vehicle Location (AVL) data provided by operators of public transport. These results are also in line with a mixed study (revealed and stated preference experiment) conducted in Santiago in 2015 (Batarce, Muñoz, Ortúzar, S. Raveau, & Ríos, 2015). The indicator of crowding in this research was also standing passenger per meter square for crowded bus and trains.

Valuation of crowding for other locations:

Although passengers experience disutility from crowding on platforms and access ways of train stations (stairs, elevators, check-in/check-out), very limited research is available on this. Crowding at these locations can affect waiting time valuation of passengers. A stated choice experiment research done in Sydney in 2004 (Karpouzis & Douglas, 2005) estimates crowding valuation in terms of waiting time multipliers on the platforms and walking time multipliers for access and entrance to the stations. Crowding in this experiment is presented using images for three levels on the station entrance and access to the platform: uncrowded, average crowding and crowded. Under highly crowded situations, 1 minute of estimated waiting time on platform ranged from 1.7 to 2.5 minute of average crowding waiting time, and 1 minute of walking for access to platforms or entrance under the same circumstance ranged from 1.5 to 1.8 minute of walking under average crowding situation (Karpouzis & Douglas, 2005) (Z. Li & Hensher, 2011).

A number of researches done for metros show that in-vehicle crowding in different carriages of rail cause an impact on carriage choices and route choices of passengers. The distribution of crowd on-board depends upon layout of the platform, service frequency, length of trains and access layout to the platform (Peftitsi et al., 2020) (H. Kim, Kwon, Wu, & Sohn, 2014). Staircases and elevators in stations is also a potential location for crowding. Research conducted in China to develop an emergency evacuation process for a subway station shows that staircases during rush hours can become very crowded especially when two trains going in opposite directions arrive at the same time during rush hours (Jiang, Deng, Hu, Ding, & Chow, 2009). To avoid on-board crowding, passengers sometimes board a slower train or wait for a less crowded train or adapt their departure times or choose cars at further end (Pownall, M.Prior, & Segal, 2008). In another study conducted in Seoul for metros, it was found people often choose a different route to avoid the delays due to crowding and also to escape the crowding (K. Kim et al., 2015). Dwell time for another train causes more disutility than transfer time. Apart from the delay, people want to avoid crowding stress and other discomforts (K. Kim et al., 2015).

3.2.3 Mitigation of crowding in public transport

In a congested public transport, people are less willing to pay the same fare as the service quality experienced is lower than it should be (Batarce et al., 2015). All the studies which estimate value of crowdedness have the major objective of improving public transport assignment models and predicting passenger choices by adding the disutility experienced from crowding in the choice models.The assumption in such studies that people choose a route based on previous experiences limits the investigation into the impact of real-time crowding information on route choices. Frequent travellers are familiar with expected crowding levels on the routes of public transports, however, ***providing prior information on expected crowding to less frequent travellers can affect their route choices and in turn improve the load factors of public transports*** (Yap et al., 2020). Mitigation measures to avoid overcrowding on-board include some real-time measures which come under the operational stage of decision making. Few popular measures taken during COVID-19 times include: to skip stops when the train is overcrowded, deny passenger boarding once the capacity is met and to regulate flow of passengers inside station to maintain social distancing which is similar to ramp metering (Gkiotsalitis & Cats, 2020). Denying passengers to board trains is a measure which has been in discussion since a decade (Gkiotsalitis & Cats, 2020).

These measures are from the supply side of public transport operations. From demand side, people can be expected to change their departure times to avoid crowd, because it is feared that even if the demand grows back to 25% of normal rush hour times, trains would fall short of satisfying the demand if social distancing is practiced (Gkiotsalitis & Cats, 2020). However, like many other countries, in the trains in the Netherlands all seats are available for use, and there are general instructions to maintain distance while boarding and alighting (Dutch Railways, 2020). This means that trains can get overcrowded again once the restrictions imposed by the government are lifted. The load factor at which people perceive that the vehicle is crowded is usually when more than 80% seats are occupied (Tirachini, Hensher, & Rose, 2013), but it is expected to change during pandemic times, and it can remain so for a long time. With a transition to work from home, and online activities, the pandemic times could be a good base to attempt to reduce congestion on road and crowding in public transports, especially trains, by flattening the peak demands. When firms reopen, there is a high probability that they will have to allow staggered work hours to maintain social distancing (Hensher, 2020). Staggered work hours will help in promoting staggered commute which is an essential part of planning of city transport to avoid overcrowding (Kogi, 1979).

3.3 Impact of crowding on travel behavior

As crowding in public transports affects the passengers the most, it results in changes in travel behaviour of people. Several travel attributes which passengers may trade-off with in-vehicle crowding include: trading speed of train (more crowded faster Vs. less crowded but slower alternatives), changing departure times to take a more comfortable train, waiting at stations to avoid crowd in trains, switching to first class alternative or in extreme cases, changing travel mode (such as switch to cars) (Whelan & Crockett, 2009) (Pownall et al., 2008) (Peftitsi et al., 2020).

3.3.1 Real-Time behavior adaptation

Some studies have observed the behaviour of passengers in further detail. Crowding in metros during rush hours results in uneven distribution of passengers across train cars (H. Kim et al., 2014). This variation in train car density is a result of passenger preference for a particular carriage, still the influence of individual factors on such choices is hardly researched upon, even when it is known that individual factors affect choices significantly. In a research conducted on Seoul metro networks to study these individual factors, it was found that the factors affecting this distribution includes platform layout, entry/exit of the platform, length of the train and service frequency. In this research, these factors are categorized as individual (socio-demographics), trip related (frequency of services), attitudinal (personal preferences), and physical environment (accessibility to and from train cars) related factors. It was found that the major reasons why people choose a particular carriage is minimizing walking distance and increasing comfort (especially for young women) (H. Kim et al., 2014).

Similarly, a research conducted on Sweden metro network used several automated data sources to evaluate the impact of crowding based on different factors such as station layout, arriving flow of travelers and layout of platform. It was inferred that more frequent travelers are more averse to crowding. This paper also highlights the trade-off between walking and crowding in selecting a carriage in metros. The factors which affect passengers' boarding choices of cars depend on train loading (in-vehicle crowding), layout of the station (dimensions of platform, station), OD demand and inflow at access points of stations (Peftitsi et al., 2020). There are studies on public transports which consider walking speed at platforms or passenger occupancy at platforms as station indicators of crowding. It has been observed that as the in-vehicle crowding level reaches 90%, passengers start to change train cars (Storstockholms Lokaltrafik, 2017) (Peftitsi et al., 2020). Hence, to avoid on-board crowding, passengers sometimes also choose cars at further ends (Pownall et al., 2008) (Peftitsi et al., 2020). It is also found in another research that people often choose a different route to avoid the delays due to crowding (waiting for a later train) and also to escape the crowding (K. Kim et al., 2015) (Peftitsi et al., 2020).

3.3.2 Departure time change

Previous Experiments

A very popular policy for Transportation Demand Management (TDM) is staggered work hours. This policy is known to reduce road traffic congestion as well as load 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).

In 1970, an experiment began in the Manhattan area of New York, in which more than 220,000 people working in 400 different organizations participated to stagger their work hours by at least 30 minutes before or after (O'Malley, 1975). The survey conducted in 1972 and 1973 to understand the influence of the staggered work hours showed a reduction in congestion at a peak time (9:00 AM) at three busiest transit subway locations by 26%. This resulted in staggered commute hours. The research points out that there is a correlation between work schedules and public transport operations. In the experiment it was observed that demand of the transit system in the area changed as people changed their work schedules, and some transit operators adapted their services accordingly (O'Malley, 1975).

In a research conducted on metros in Beijing in 2018, to build departure time choice model, a stated choice experiment was used to collect data (H. Li, Li, Xu, Liu, & Ran, 2018). In the departure time models for activity based bottlenecks, usually three groups of commuters are considered- commuters who arrive early at office, commuters who arrive late at office and commuters who arrive on time (Zhu & Long, 2016). Similarly, in the research on Beijing metros (H. Li et al., 2018), three alternatives were presented in the survey, i.e., metro departing earlier or later than usual and metro departing at usual time. Price affects the demand, and not including fare can lead to biased results (Lurkin, Garrow, Higgins, Newman, & Schyns, 2017), hence discount offered on fare was included as an attribute in the choice experiment. Apart from these attributes, crowding inside the metro and travel time saved are the other attributes presented in the experiment. Mixed logit model was used to model choices from the survey. According to the findings of this experiment, metro passengers of Beijing were more sensitive to scheduled delays late than early. This is probably because passengers are constrained at activity end (work/education). It was also found that passengers are more sensitive to fare and travel time savings (H. Li et al., 2018). Surprisingly, crowding levels in the metros showed insignificant effects on scheduled delays (the change in departure of passengers from usual departure time), which is contrary to previous research. ***More frequent commuters were found to be less sensitive to crowding*** (Zhu & Long, 2016) (H. Li et al., 2018). But these results can be expected to vary during and after the COVID-19 pandemic time.

Another interesting study in Copenhagen in 2020, used state choice experiment and latent class clustering method to study departure time preferences of car commuters during morning hours using a hypothetical toll ring. The respondents were asked to fill a 24 hours trip diary. In the main choice experiment, similar to the Beijing Metro experiment, they were also presented with three alternatives- early, on-time and later departure. The toll cost varied with the time of departure. It was found that flexibility in work hours and household composition (whether or not someone has a child) played an important role in making a respondent sensitive to departure time change (Thorhauge et al., 2020). Therefore, these researches suggest to explore sensitivity to departure time changes in different places, and make policies to promote this behavior by focusing on specific socio-demographic groups and problems.

In 2011, willingness to change time of travel, i.e. departure time, of rail commuters in Sydney was researched (Henn, Douglas, & Sloan, 2011). A questionnaire was given to passengers in which they were offered fare discounts along with faster train options against changing their departure time. It was found that these incentives, especially fare discount, could be effective to make people shift their timings, however, a certain group of people were unwilling to change their departure times majorly due to inflexibility in timings at their work, prior commitments. In case of early departure, getting proper sleep was a major factor for not traveling early. In case of late departure, one of the major constraints was shifting departure time from work to home end of the trip. A significant number of people (37%) were willing to depart early by 30 minutes to avail the incentive of 30% fare discount. Comparatively, less people were willing to depart late (21%) for the same fare discount (Henn et al., 2011).

In 2009, in the Netherlands, a stated preference study was conducted where approximately 1400 Dutch train commuters were offered a choice between two passes for train travel between the Hague and Utrecht (Bakens, Knockaert, & Verhoef, 2010). One was their regular pass, the other was an 'off-peak hour pass' which was cheaper but was not valid between peak hours. Respondents were asked to indicate their pass preference and how they would adapt their journeys. It was found that departing early had less disutility than departing late, and a majority of the population which opted for off-peak hour pass would either depart early or late. Very few selected a combination of early, late and peak-hour travel. However, in 80% of choice situations, respondents chose to opt for their usual pass (Bakens et al., 2010) (Y. Liu & Charles, 2013).

The time based differential fare system has been a successful measure in promoting travel during off-peak hours (Peer et al., 2016). Between 2012 to 2013, another experiment was conducted in the

Netherlands which was carried out for months. Approximately 544 responses were selected to be analysed. In this experiment, passengers were offered a monetary incentive to travel during off-peak hours via trains. Participants were asked to select an OD pair for this experiment and were asked to fill in logbooks. Their travel behavior was monitored using GPS data. Although the sample was not representative of Dutch train travelers, as the participation was voluntary, the results showed a 22% drop in peak hour travelers amongst the participants. The value of Scheduled Delay Early (SDE) was found to 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 (SDL) was found to be 5.6 Euros in the morning and 4 Euros per hour in the evening. This result shows that departing early has more disutility than departing late, however other research shows that people would rather travel early than late. Contrary to other research, this study found no relation between departure time change and on-board crowding, but this is possibly because passengers in the RP experiment were uninformed about the crowding levels in train options. The study points out that a time based differential fare system is more cost efficient than increasing the supply during peak hours. It has to be kept in mind that the study offered incentives for off-peak travel. The results may vary when there is a surcharge instead during peak hour travel (Peer et al., 2016).

From all such research, it is inferred that people are more likely to depart early than late, and peak hour crowding can be avoided by a differential fare system. To make all this possible, there should be flexibility available to commuters to change their departure times. Government should promote policies which allow for staggered work hours (Y. Liu & Charles, 2013), however, it is recommended to do a pilot study before implementing such policy on a wide scale (Thorhauge et al., 2020).

3.4 Conceptual model and hypotheses

In this research, a stated choice experiment is performed to study the trade-off between on-board crowding level in trains, departure time change and discount offered on train fare in different contexts of vaccination levels (refer section 1.1). Along with the choice experiment, in this research the stated choice survey will collect some background information to capture the variation in preferences of people. Attributes and background information will also form a basis for several hypothesis tests and layout of a conceptual model.

Socio-demographics are known to influence the choices made by an individual in the field of transportation. But even when individuals belong to the same background, there still can be differences in the choices made by them (Thorhauge et al., 2020). This is also the case for departure time change models which were developed to find out the psychological factors that affect departure time change decisions (Haustein, Thorhauge, & Cherchi, 2018). In the decision to schedule delay, apart from socio-demographics characteristics such as income, gender, employment, age etc., attitude, lifestyle, travel mode preferences and travel characteristics are also highlighted as influencing factors. Factors such as living with family and children constrain a person in changing departure time as this decision is linked with activities or schedules of other family members, especially of 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).

Some research links mode choices to health related factors of an individual (Boniface et al., 2015). A bike sharing choice experiment in the USA (Tempa, Florida) in 2018 asked people to mention their Body Mass Index (BMI) along with other information on travel behavior, travel history and socio-demographics. In this research BMI is used as an indicator of health of an individual, and from this research a relationship between BMI and selection of bike as a mode of transport was found (Barbour, Zhang, & Mannering, 2019). As this research is taking place during COVID-19 pandemic time, and one of the objective here is to see if sensitivity to attributes such as crowding changes as more people get vaccinated in the Netherlands, some background information is collected on 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 is divided into three broad categories: *Socio-demographics, Travel and work related factors, Attitude towards health and COVID-19*. Based on the selected attributes for choice experiment and background information which is to be collected by the stated choice survey, a few hypotheses are laid out, and a conceptual model is drawn.

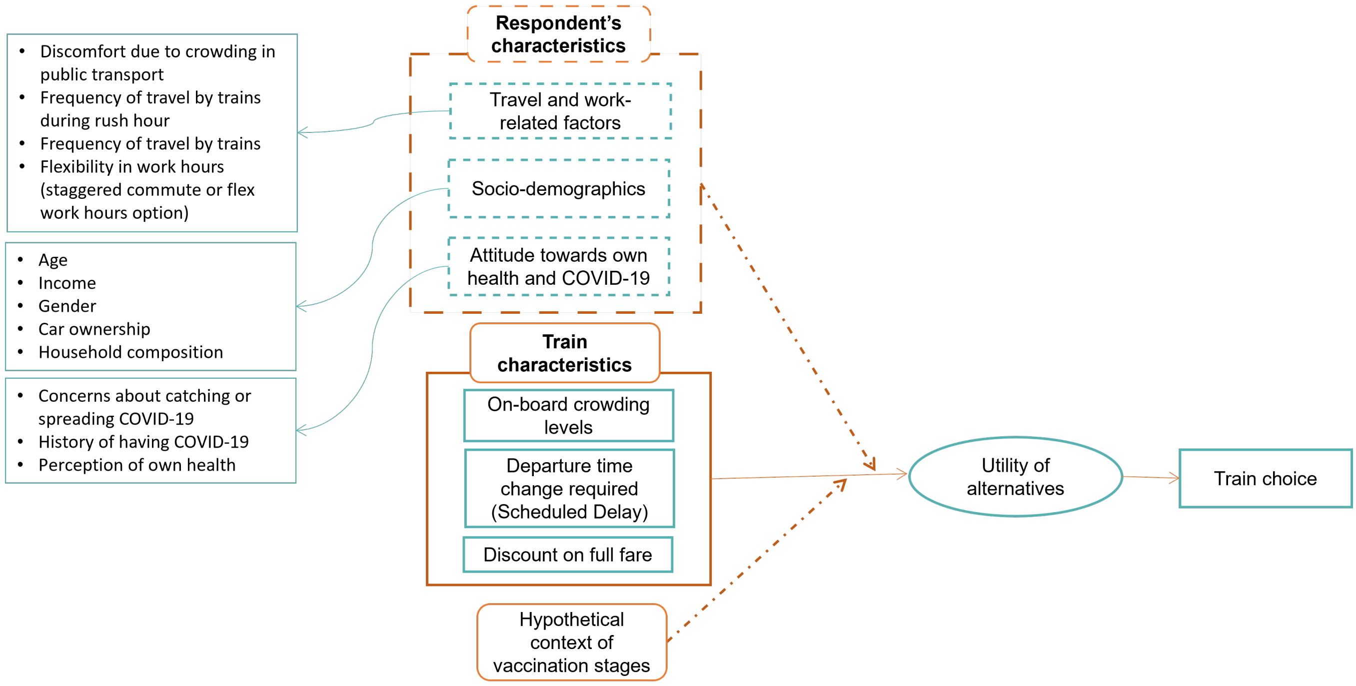


Figure 3.1: Conceptual model

The conceptual model is presented in figure 3.1. It is a conceptualisation of selection of alternatives made by respondents. It can be seen that the characteristics of train alternatives affect the choice of train directly. This is based on the principle of utility maximization (Bierlaire, 1998). The contextual information which is provided to all respondents will also affect the utility of alternatives as sensitivity of a respondent to an attribute may vary with contexts. Individual characteristics will influence sensitivity of respondents to different attributes as there can be variations in individual preferences. For example: some people may be more inclined towards gaining a discount on fare whereas some people may be very averse to high crowd levels inside trains. To test the conceptual model, few hypotheses are laid out:

- *Hypothesis 1: The people who choose to schedule delay early have less disutility in changing departure time than the people who choose to schedule delay late.* Previous departure time change experiments have found different results for Scheduled Delay Early and Late alternatives. E.g., Scheduled Delay Late has more disutility than Scheduled Delay Early alternative (Bakens et al., 2010) (Y. Liu & Charles, 2013). This hypothesis will help in understanding the differences in behavior of the two groups which could help in finding ways to motivate the two groups to change departure time.
- *Hypothesis 2: During the pandemic as more people get vaccinated, people become less crowd averse.* From a previous research it is know that people value ongoing infection risk in choosing

train alternatives (Shelat et al., 2021). The test of this hypothesis will help in exploring if people value vaccination levels, and if behavior of people may change with vaccination levels. It will also give an idea about the vaccination stage at which preference changes significantly.

- *Hypothesis 3: On-board crowding has non-linear effect on utility function. After a certain level of crowding, disutility will start and increase sharply* (Tirachini et al., 2013) (Hess, 2014). Understanding the changed sensitivity towards crowding in trains could help in increasing the attractiveness of trains.

- *Hypothesis 4: Scheduled delay in both early and late departure has a negative impact on utility function* (Thorhauge et al., 2020) (H. Li et al., 2018). The extent to which people are averse by scheduled delay could help in understanding which groups could be motivated to change departure time and how.

- *Hypothesis 5: Discount offered on train fare has a positive impact on utility function for both early and late departing group of people* (Lurkin et al., 2017). Effect of fare discount on utility function will help in understanding if people can be motivated to change departure time using discounts on fare.

- *Hypothesis 6: Females who live with their family are more sensitive to departure time change.* In LCCM of a departure time change study conducted in Copenhagen on car commuters in 2020, gender, living status and flexibility in work schedule were found to affect distribution of respondents (Thorhauge et al., 2020). Based on these factors hypothesis 6 is formulated to test the effect of gender together with living status.

- *Hypothesis 7: Females are more sensitive to on-board crowd levels in trains than males.* In a stated choice research conducted in the Netherlands during COVID-19 pandemic to estimate value of crowding in trains in terms of waiting time for less crowded trains, it was found that females are more conscious about the crowd levels in trains (Shelat et al., 2021). Using this hypothesis, it can be explored whether gender has an effect on sensitivity to crowd levels during the pandemic in a departure time change experiment.

- *Hypothesis 8a: Respondents with history of COVID-19 are more sensitive to on-board crowding levels. Hypothesis 8b: Respondents who are more concerned about catching COVID-19 are more sensitive to on-board crowding levels. Hypothesis 8c: Respondents who are more concerned about spreading COVID-19 are more sensitive to on-board crowding levels. Hypothesis 8d: Respondents who indicate that they are in good physical health are less sensitive to on-board crowding levels.* All these hypotheses are intuitive and relevant as this study is based on context related to pandemic.

- *Hypothesis 9: More frequency of travel using trains (before COVID-19) results in less sensitivity to on-board crowd levels.* In a departure time change experiment conducted on Beijing metro in 2018, it was found that people who travel less by public transport are more sensitive to on-board crowd levels (Lurkin et al., 2017). In another revealed preference study conducted on trams/buses in the Netherlands in 2020 to estimate value of crowding, it was found that value of crowding in terms of in-vehicle time multiplier is higher for more frequent travelers (Yap et al., 2020), which is contrary to the Beijing experiment.

- *Hypothesis 10: People who have flexibility in work hours are less sensitive to scheduled delay.* This hypothesis is based on results from previous departure time change experiments which found that flexibility in work hours is an important factor which affects the sensitivity of people to schedule delay (Thorhauge et al., 2020) (Henn et al., 2011).

- *Hypothesis 11: There are heterogeneous groups of respondents with different preferences towards crowd level in trains, scheduled delay, fare discount and vaccination stages* (Thorhauge et al., 2020) (H. Li et al., 2018).

Hypothesis 1 and Hypothesis 11 are not directly represented in the conceptual model, however, these are derived from the model indirectly. This conceptual model is a foundation for designing the stated choice survey (refer Chapter 4) and defining the utility specification which are used in choice modelling (refer section 5.2). The hypotheses and conceptual model would be tested using the results from the stated choice survey and are discussed in section 5.4. The significance level selected for acceptance/rejection of any hypothesis is kept same as the significance level set for determining model fit as described in subsection 2.3.1 ($p<0.1$).

3.5 Summary of Literature Review

The literature review presented in this chapter serves two purposes. It leads to a research gap which is further translated into a research question presented in subsection 1.1.1. The second purpose it serves is that it answers three sub-research questions. These sub-research questions are used in building a stated choice experiment whose results are used to answer the main research question. In the subsections below the research gap is presented followed by the answer to three sub-research questions. Finally, a summary of previous choice experiments which are discussed in section 3.2 are presented in tabular form (see table 3.1 and 3.2). Last rows of these tables have information on this research with respect to the previous experiments.

3.5.1 Research gap

In the Netherlands, the last experiment related to departure time change by offering off-peak fare discount was conducted in 2010 (Bakens et al., 2010), and another study based on revealed preference method was conducted in 2012-2013 to research how people adapt their behavior if they are offered reward to not to travel during peak hours (Peer et al., 2016). It is not known what the train passengers' sensitivity to change in departure times is now if they are provided with the information of on-board crowding beforehand. Dutch rail government launched an application in 2014 which informs people of the expected level of crowding in trains. Such application gives real-time information on crowding that can assist passengers to adapt their behavior and resolve crowding problems on a wider scale (Pel et al., 2014). A research in the direction of finding out sensitivity to departure time change and on-board crowding is required as COVID-19 pandemic has made public transport passengers more sensitive to crowding, and research is required to increase attractiveness of public transports (Gkiotsalitis & Cats, 2020) (Shelat et al., 2021) (Hensher, 2020).

In the Netherlands, peak hours are between 6:30 to 9:00 AM and 16:00 to 18:30 (excluding holidays) (NS, n.d.). Even though there is 40% off-peak discount package on train travel in the Netherlands (NS, n.d.), crowding during rush hours is still a problem and is anticipated to be more troublesome during COVID-19 once all facilities start to open up again (Gkiotsalitis & Cats, 2020). As more people become vaccinated in the Netherlands their sensitivity to crowding in trains shall reduce which can be tested in a stated choice experiment. The ongoing pandemic of COVID-19 gives a strong ground to conduct a choice experiment to study the trade-offs between on-board crowding level, scheduled delay and fare incentives in a hypothetical context of vaccination stages in the Netherlands.

3.5.2 Answer to research questions

Literature review done in this chapter is used to answer three out of seven sub-research questions. The answers are described briefly below:

Sub-research question 1: What is state-of-the art in ARI transmission in public transport? As described in section 3.1, most of the literature linking health and transport includes aspects of physical and mental health, and social interaction (where physical health is about physical activities, contribution to air pollution and vulnerability to injuries). If health is weighed in terms of societal benefits and environmental impacts, then one of the healthiest modes of transport would be a public transport network. It is cheap, safe, efficient and comprehensive (Boniface et al., 2015). But crowded and confined environments such as that of transport hubs have the potential to become a source of spread of diseases (Goscé & Johansson, 2018). A study conducted on London Underground Transport Network (Goscé & Johansson, 2018) used an analytical microscopic model to study the spread of Influenza Like Illness (ILI), i.e., common airborne infections in the underground metro of London during rush hours. Another study in the UK during the influenza period (2008-2009) (Troko et al., 2011) conducted on bus and tram networks shows a statistically significant association between ARI development and use of bus/tram a few days before symptoms' onset (Troko et al., 2011). In 2020, an epidemiological study was conducted on COVID-19 cases that travelled on high speed train across mainland China between December 2019 and March 2020, 14 days before the onset of symptoms (Hu et al., 2020). The study found that risk of infection can vary between 0 to 10.3% depending on seating arrangement relative to an infected passenger and travel time with an infected passenger on-board. The research suggests that apart from personal hygiene, seating distance inside the trains, co-travel time with infected passengers on-board and passenger density can influence the infection risk significantly (Hu et al., 2020).

Sub-research question 2 What could be the suitable indicator and measure of crowding as perceived infection risk in commuting by trains in the Netherlands? Crowding can be termed as an antonym of social distancing (LUMC-COVID-19 Research Group et al., 2020). Literature from experiments presented in table 3.1 and discussed in subsection 3.2.2 suggests that the most suitable indicator for crowding is percentage of seat occupied (load factor) and passenger density (number of passengers standing per meter square). From subsection 3.2.2 it is known that crowding penalty is best indicated as time multipliers for its comparison. The penalty can vary with transit systems. In metros standing capacity is more, and in trains it is more obvious to sit. When seating configuration or availability of seats is considered for seeing the impacts of crowding, then in-vehicle crowding is more relevant and is the key focus area (Pel et al., 2014). In the Netherlands, the two most popular trains to travel within the Netherlands are a Sprinter and Intercity (Expatica NL, 2021). For this research, the layout of a Sprinter train is considered which has 36 seats in one car. Crowding is represented as the number of seats occupied on an average in a car of a Sprinter train. This representation of crowding is inspired from a stated choice experiment conducted in 2020 in the Netherlands to study the trade off between on-board crowding in trains and waiting time at platforms (Shelat et al., 2021). Standing capacity (Whelan & Crockett, 2009) is ignored in this research to reduce the complexity of the survey which could increase by adding more levels of an attribute (Bech, Kjaer, & Lauridsen, 2011). More information on on-board crowding attribute can be found in subsection 4.1.1.

Sub-research question 3 What are the mitigation measures that people take to avoid crowds on the train commute? Major travel attributes which passengers may trade-off with in-vehicle crowding include: trading speed of train (more crowded faster Vs. less crowded but slower alternatives), changing departure times to take a more comfortable train, waiting at stations to avoid crowd in trains, switching to first class alternative or in extreme cases, changing travel mode (such as switch to cars) etc.(Whelan & Crockett, 2009) (Pownall et al., 2008) (Peftitsi et al., 2020). Amongst the mitigation measures taken by passengers, more research is needed to see whether passengers change their departure time to avoid crowded environments in trains (Pel et al., 2014). Measures to avoid crowding such as waiting for another train are more at the operational level, and impact of crowding on such attributes can be measured more accurately by using real-time data in revealed preference study. Passengers choose higher waiting time levels in the stated choice experiments, whereas in reality they board a more crowded train with lesser waiting time (Kroes, Kouwenhoven, Debrincat, & Pauget, 2013) (Yap et al., 2020). Research also indicates that changing departure times to avoid crowd is a more strategic and strong decision taken by passengers to avoid crowding in trains or public transports (O'Malley, 1975) (Zong et al., 2013) (Peer et al., 2016). A survey conducted in UK in 2006 shows that significant number of passengers adapt their departure time to travel in less crowded trains (Maunsell, 2007) (Pel et al., 2014). Some of the experiments related to changing departure times are summarised in table 3.2. These studies show that passengers can be given an incentive of reduced fare to motivate them to change departure time as passengers are more sensitive to incentives on fare than travel time savings and crowding on-board (H. Li et al., 2018). These experiments are from before COVID-19 pandemic outbreak, and the sensitivity of people to crowding levels is expected to change during COVID-19 pandemic time.

Even before the start of this pandemic, the government in the Netherlands urged educational institutes to shift their morning classes by a few minutes so that crowding in trains during rush hours could be reduced (Delta TU Delft, 2019). Although few institutes showed reluctance in changing timings, there were a few institutes, such as Radbound University and University of Applied Sciences in Arnhem and Nijmegen, who shifted classes by 15 minutes. This resulted in reduction of crowd by 10-20% during a particular time (around 8:15 AM) in morning peak hours. It is impractical to pressure only educational institutes to adjust their timings, and it would not be possible to make all students travel during off-peak hours. However, this pandemic has enforced working from home and online education on a huge population. Flexibility in work timings and option to work from home can be more easily availed in the future when the restrictions are lifted. This could reduce pressure due to overcrowding in public transport services and pressure due to congestion on roads as well (Delta TU Delft, 2019).

Table 3.1: Valuation of crowding experiments (Karpouzis & Douglas, 2005)(Douglas & Karpouzis, 2006)(Lu et al., 2008)(Whelan & Crockett, 2009)(Batarce et al., 2015) (Hörcher et al., 2017)(Yap et al., 2020)(Shelat et al., 2021)

S. No.	Research title	Crowding location	Indicator of crowding	Method	Trade-off for crowding	Value of crowding (measurement)
1	*Estimating the Passenger Cost of Station Crowding (2005), Sydney*	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 (2006), Sydney*	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 (2008), UK*	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 (2009), UK*	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 (2015), Santiago*	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 (2017), Hong Kong*	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 (2018), the Hague*	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 [Working paper]. (2020), the Netherlands*	In-Vehicle (Train)	Number of seats occupied	SP	Waiting time and crowding levels in different contexts of infection risk	Waiting time multiplier
9	*Departure time change to avoid crowd in trains -A stated choice experiment study in the Netherlands in a pandemic context(2021, Master thesis)*	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

Table 3.2: Departure Time Change Experiments (O'Malley, 1975)(Bakens et al., 2010)(Henn et al., 2011)(H. Li et al., 2018)(Peer et al., 2016)(Thorhauge et al., 2020)

S. No.	Research title	Method	Alternatives and attributes	Findings
1.	*Transportation Research Board Special Report (1975), Manhattan, New York*	Experiment with 220,000 people	Staggered commute with at least 30 minutes early or later departure in the morning	Reduced congestion at busiest subways by 26%
2.	*Rewarding Off-Peak Railway Commuting: A Choice Experiment (2010), the Netherlands*	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 (2011), Sydney*	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 (2016), the Netherlands*	RP Experiment between 2012 to 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% 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 (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. Affect of crowding was insignificant.
5.	*Heterogeneity in departure time preferences, flexibility and schedule constraints (2020), Copenhagen*	SP Experiment on Car users with 24 hours trip diary as responses	Departing on-time, later or earlier using a hypothetical toll ring. Cost of the toll ring varied with departure time.	People are constrained by household composition and flexibility at workplace in changing departure time.
6.	*Departure time change to avoid crowd in trains -A stated choice experiment study in the Netherlands in a pandemic context (2021, Master thesis)*	Respondents divided into early and late group. SP Experiment with unlabeled train alternatives	Two unlabeled train alternatives in same context of vaccination stage and which vary in: scheduled delay, on-board crowd levels and discount on full fare	Expectations: Some fare discount can motivate some people to schedule delay. Heterogeneity expected in respondents.

Chapter 4

Survey design

In this chapter the design of the stated choice survey is discussed in detail. As described in section 2.2, there are seven major steps to design a stated choice experiment (Hensher, 1994). In this chapter step one to three, and step five have been discussed in reference to this research. The first step is to select the attributes and context variable. Second step involves selection of units of measurement of the attributes. Third step is to select the attribute levels, and the fifth step is to build the survey and collect responses. The selected alternatives, attributes and context variables along with the attribute levels are described in section 4.1. In section 4.2, other information collected from the survey related to individual characteristics and background variables are discussed in detail. In section 4.3 the design of the final survey using Ngene and Qualtrics is elaborated. In the subsection 4.3.1 details of the pilot study conducted and changes made after the pilot are discussed. *Note that the design of the survey discussed in other sections of this chapter is the design of the main survey, not the pilot survey.* The final survey can be found in Appendix D.

4.1 Attributes and alternatives

In a stated choice experiment there are few important design dimensions which can affect the complexity of a survey for respondents. In a complicated survey some respondents find a strategy to answer quickly or to simplify the experiment. To avoid this, the number of attributes and alternatives should is kept in check (Caussade, de Dios Ortúzar, Rizzi, & Hensher, 2005). Selection of attributes and context variable along with second and third step of design which are to select the unit and levels of attributes are discussed in subsection 4.1.1. In subsection 4.1.2, the selected alternatives and model estimation method with respect to chosen alternatives and attributes are discussed.

4.1.1 Selected attributes and context variable

A good choice experiment is the one which resembles real world situations, and has enough variations in contexts, alternatives and attribute levels to capture the behavior of people closest to what they would choose (Hensher, 1994), however, it should be kept in mind that if a respondent is presented with too many choice sets and multiple alternatives then there can be large variances in responses as respondents may find the experiment tedious or confusing(Bech et al., 2011). It is recommended to have at least four levels of an attribute. More than two levels are needed to test whether the effect of that attribute is linear or not over the utility of alternatives, and even at three levels it becomes

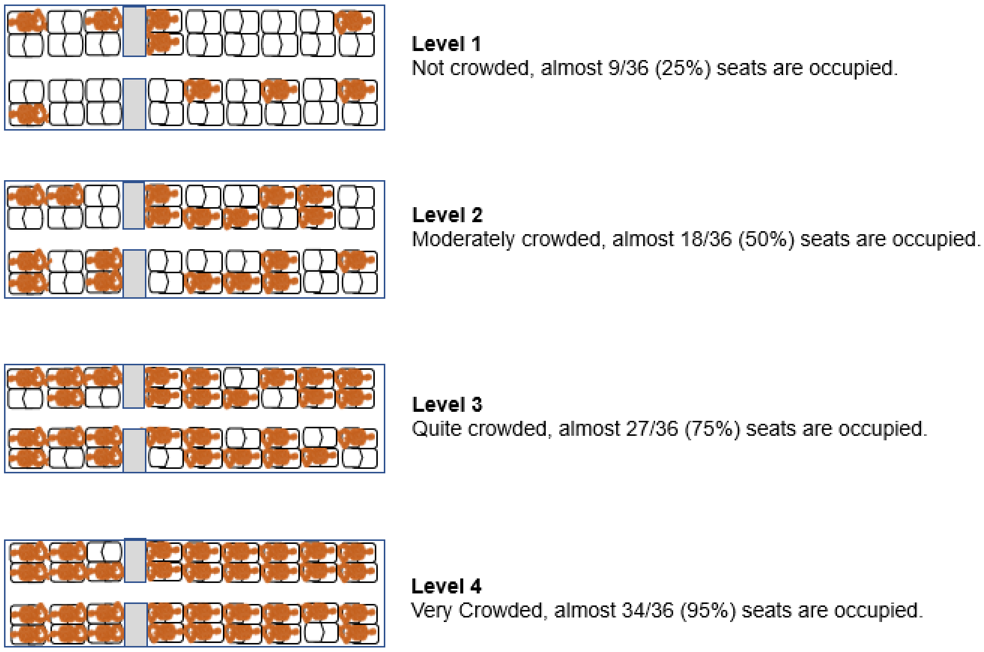


Figure 4.1: On-board crowding attribute and its levels

hard to approximate the true behavior of people using the taste parameters (Hensher et al., 2015). It is a good practice to have either odd or even number of levels in all attributes. This is so because in design of the entire experiment using Ngene minimum number of choice sets are provided which is based on Basic Plans. Switching from even to odd or vice versa increases the number of choice sets required in an orthogonal experiment by a large number. Also, a context variable multiplies the size of choice experiment by the number of levels it has (Molin, 2019c). To avoid too many choice sets it has been tried to keep the number of levels in all attributes as four without compromising on the study of trade-off. While selecting the levels of attributes it has been tried to keep the levels equidistant which helps in maintaining orthogonality between attributes (Molin, 2019a).

On-board crowding

On-board crowding is used here as an indicator for perceived risk of infection amongst train passengers. It is an antonym of social distancing (LUMC-COVID-19 Research Group et al., 2020). Several stated choice experiments conducted with resolving the issue of on-board crowding, or measuring the trade-offs that passengers make to avoid on-board crowding use load factor (percentage or ratio of seats occupied in trains) and standing passenger density as an indicator of crowding levels. For this research, seat occupancy rate, i.e., number of seats occupied in a (Sprinter) train is used to represent on-board crowding (refer section 3.5). This is similar to a SC experiment conducted in the Netherlands in 2020 to study waiting time vs. crowding trade-off with contexts of ongoing infection risk and travel time (Shelat et al., 2021). Moreover, the effect of standing passenger density could be observed when the train is overcrowded (Whelan & Crockett, 2009). To add standing density or crowding level more than 100% (Whelan & Crockett, 2009) it would require adding more levels to the attribute of on-board crowding which could increase the size of the choice experiment. Therefore, these factors are ignored in this research. Four levels of on-board crowding are used in different choice sets. These are presented by means of graphics and numeric information to respondents.

Departure time change:

Change in departure time to avoid crowded trains is a strategic and more firm decision. Over the years, policies have been implemented to promote shift of travel from peak to off-peak hours. Staggered commute and flex work timings are one of the key drivers of this change. In the Netherlands, train passengers can avail 40% discount on full fare for traveling during off-peak hours using special plans(NS, n.d.). All the experiments related to departure time change found that generally people either opt for early departure or late (Bakens et al., 2010) (Y. Liu & Charles, 2013). The duration of departure time shift in these experiments usually ranges from 15 minutes to 2 hours.
For this research, the respondents are first asked to select whether they would like to depart early or late to avoid crowding inside trains. They are also presented with an option to board their usual train, but then to capture the trade-offs, those passengers still have to choose between early or late departure. In short, the respondents are segregated into two groups and the analysis of both the groups will be done independently. Four levels of departure time change are used in different choice sets and alternatives. Those are 15 minutes, 30 minutes, 45 minutes and 60 minutes, same for both early and late departures. This would allow to compute Scheduled Delay Early (SDE) and Scheduled Delay Late (SDL) parameters (Peer et al., 2016) for all respondents which would give the value of departure time change.

Discount on full fare

As mentioned above, a time based differential fare system is a cost-effective way to manage crowding. Not including fare could lead to biased results (Lurkin et al., 2017) (subsection 3.3.2, as it affects demand. Also, giving some discount on fare could be treated as an incentive for respondents to change departure time. Already, for travel during off-peak hours using trains in the Netherlands, there is a 40% discount offer (NS, n.d.). Keeping this in mind, four levels of fare discount are varied across alternatives and choice sets. These are- No discount, 10% discount, 20% discount and 40% discount.

Vaccination stages

As vaccination stages are advancing in the Netherlands, travel behavior is expected to change. To capture such changes in the model, each choice set provides a contextual (hypothetical) information about the ongoing vaccination stage. There are three levels of vaccination which are used in the experiment.

- **Vaccination Stage 1:** Almost 30-50% residents of the Netherlands are vaccinated with all doses. The ongoing rate of spread of infection is Level 3 (Serious) out of 4 (NL Times, 2020),i.e., roughly 8000 cases of COVID-19 arrive per day which is similar to present time (April 2021).
- **Vaccination Stage 2:** Almost 50 -80% residents of the Netherlands are successfully vaccinated. The ongoing rate of spread of infection is Level 2 (Worrisome),i.e, roughly 2000 cases of COVID-19 arrive per day (similar to the summer of 2020).
- **Vaccination Stage 3:** More than 90% residents are vaccinated in the Netherlands. The ongoing rate of spread of infection is almost negligible, and all the restrictions are removed.

All the information mentioned above is provided to respondents in the choice experiment. For Stage 1 and 2, people were asked to assume that the government has relaxed restrictions. People were also asked to assume that they can go to office/university or work from home, and there are some restrictions related to social distancing, sanitising and wearing masks indoors in public transports. To avoid variation in assumptions respondents were asked to assume that any information which is not provided for the alternatives is the same as that of the usual train option. The research aims to find solutions to manage peak hour crowding in trains. Hence the respondents are provided with the context that they are commuting for work or education related travel purposes via train during morning peak hour and there is some flexibility in work/education hours. It is assumed that people who have some train travel experience in the Netherlands can successfully imagine the hypothetical contexts in the survey. People who never travel by train were excluded from the survey at the beginning.

4.1.2 Unlabeled alternatives

In subsection 3.3.2 it is discussed that generally people who shift their departure time (schedule delay) prefer to depart either late or early (Bakens et al., 2010) (Y. Liu & Charles, 2013). Therefore, the experiment is designed to independently assess the two scheduled delays. In previous choice experiments related to departure time change, usually there were three labeled alternatives: one base alternative with no scheduled delay, one alternative with early scheduled departure and last with late scheduled departure (Thorhauge et al., 2020) (H. Li et al., 2018). In this experiment only two train alternatives are presented to the respondents as people are already segregated in early and later departing categories. These alternatives are unlabelled as no meaning is required to be associated with them. Both the alternatives have same attributes and same attribute levels, hence the utility equation will be the same for both the train options. And as individual characteristics are also constant across both the alternatives in all choice sets, these will be introduced as interaction effects. Vaccination stage is also a variable in the choice experiment, but it is a contextual information and hence it remains the same across the two alternatives in a choice set. Only the attributes which vary across all alternatives in a choice set will be introduced in the utility equation as the main effect (Hensher et al., 2015). The basic utility specification (utility equation 5.1) is discussed in section 5.2.An example of a choice set which is presented to respondents in the survey is shown in figure 4.2.

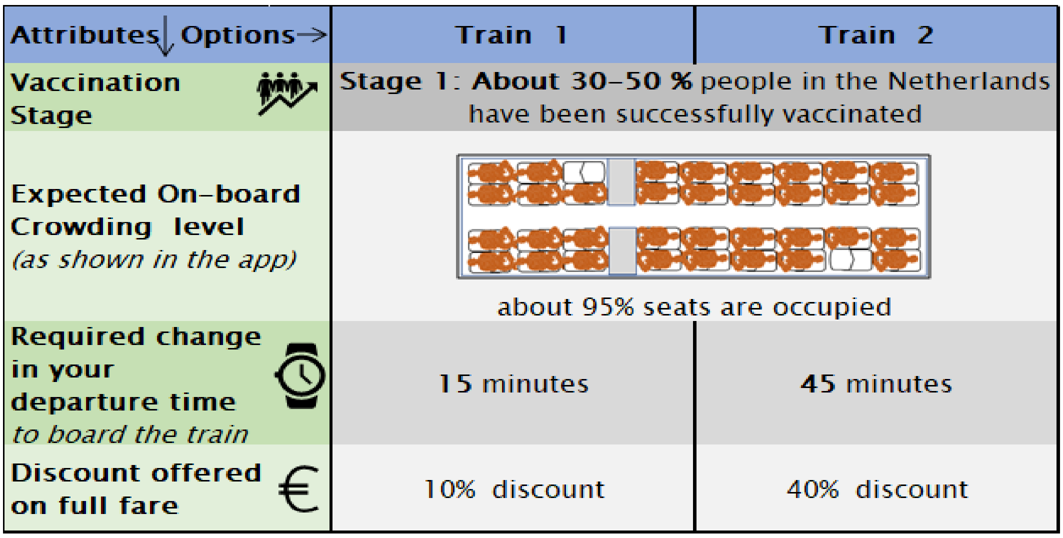


Figure 4.2: An example of choice set from stated choice survey

The respondents are required to select the alternatives based on the attribute levels associated with them. More than two alternatives is not required in this experiment and it would have added to the complexity of the experiment. There was a possibility to add a base or an opt-out alternative. The opt-out option is considered good for capturing the demand of alternatives, however a base/opt-out choice does not indicate any trade-off, and if a number of people select this alternative then there would not be enough responses to estimate reliable taste parameters (Molin, 2019b). Moreover, 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 is provided. Also, the main objective of this research is not to find out the demand but to study the trade-offs that people make between scheduled delay, on-board crowding and discount on fare. The respondents are asked before the start of choice experiment whether they would like to depart early,late or at the same time in case the on-board crowding level is expected to be 90 % and vaccination is at stage 3. This gives an idea of the proportion of respondents who would not change their departure time in the long-term.

4.2 Background information collected

As explained in section 3.4, the background information to be collected using stated choice survey is broadly categorised as: Socio-demographics, travel and work related factors and attitude towards health and COVID-19. Individual characteristics related to each of these categories which are collected in the survey are discussed in detail below. A table of all the background information collected from the survey can be found in Appendix C.

Socio-demographics

- **Age:** Respondents are asked to indicate their age by selecting the age group they belong to. In previous departure time change experiments in Denmark and China it was found that age has no significant effect on choices made by people (Thorhauge et al., 2020) (H. Li et al., 2018). In another research aimed to find out heterogeneity in departure time change behavior it was found that the older (>60 years) male population is more likely to be on time (Haustein et al., 2018). Influence of age on choice making will be checked in this research also. Moreover, due to COVID-19 some change in behavior is expected. It is possible that older people are more sensitive to crowd levels as crowd is an indicator of perceived risk of catching COVID-19 infection (Shelat et al., 2021) (Hu et al., 2020).
- **Gender:** Choice experiment conducted in Copenhagen (in 2020) to study departure time preferences of people who commute by cars found that male population who lives with a spouse and children is more constrained around work and is less flexible to change in departure time (Thorhauge et al., 2020). In another research which was conducted during COVID-19 time to study trade-off between on-board crowding in trains and waiting time at platform, it was found that females are more risk averse than males (Shelat et al., 2021). In this research it is expected that gender along with living situation may have an influence on sensitivity towards schedule delay, and females are expected to be more sensitive to on-board crowd levels.
- **Income, Employment status and Education:** Respondents are asked to select their income groups, employment status and level of education. People with higher income and fixed work hours are highly likely to be constrained by work and be more sensitive to departure time change (Thorhauge et al., 2020). Behavior of populations with different employment status is also expected to differ. Students are expected to not arrive late at university. Education level affects the employment and income of people, hence behavior of people from different educational backgrounds is expected to vary.

- **Number of cars:** People with cars have an option to travel by car than by public transport in case the train is overcrowded (Pownall et al., 2008). The behavior of people with more cars is expected to be different than people without any cars. People without any cars are more bound to use trains, especially for long travel, even during COVID-19 pandemic (Jenelius & Cebecauer, 2020).

- **Living status:** In the departure time change experiment conducted in Denmark in 2020, and in another research in Denmark to develop schedule delay models it was found that household composition, especially having children can constrain a person to change departure time (Thorhauge et al., 2020) (Haustein et al., 2018). In this research sensitivity of people who live with and without family will be checked with schedule delay in MNL model. Sensitivity of people who have children will also be checked separately. In latent class models living status will be added in class membership function.

Travel and work related factors

- **Frequency of mode usage:** Ever since COVID-19 pandemic started there has been a drop in the usage of public transport and increase is usage of other private modes of transports (Jenelius & Cebecauer, 2020). The changed travel behavior may persist even after the pandemic is over. To get an idea of modal shift from the period before COVID-19 pandemic started to the period during COVID-19 people were asked to indicate their frequency of usage of popular modes of transports: bicycle, car, walk and public transport. They were also asked to indicate their expected frequency of travel in a post-pandemic scenario. These responses are collected to simply see numerically the difference in mode usage indicated by people.

- **Travel purpose and travel time:** Respondents are asked to indicate their travel purpose and travel time in trains for work/education related trips. People who travel for work or education are expected to be more sensitive to departure time change than people who travel for other purposes because they are constrained by work hours. The time multiplier of crowdedness found in several researches related to valuation of crowding has significant variations with journey purpose (Whelan & Crockett, 2009) (Z. Li & Hensher, 2011). Such experiments studied the trade-off between crowding and travel time. Although travel time has not been chosen as an attribute in this research, behavior of people can vary with the length of train journey they usually make. People who travel for longer duration in public transport are at higher risk of catching infection such as COVID-19 (Hu et al., 2020).

- **Discomfort experience due to crowding in trains:** Respondents are presented with a likert scale to rate the discomfort they perceive if the trains are crowded. This has been asked for on-board crowding and crowding during boarding/alighting for during and before COVID-19 pandemic. Crowding in trains can be experienced in different places such as stations, access/exit gates, inside vehicles and boarding/alighting (Karpouzis & Douglas, 2005). Similar to this research most of the previous researches on crowding in trains are focused on in vehicle crowding as this has been found to be most discomforting, however, boarding/alighting was rated second in the exploratory study conducted as a part of this research. The discomfort experienced due to crowding is also expected to differ from before the pandemic started to present time when the pandemic is ongoing. To measure the variation of responses (numerically) this information has been collected. Also, respondents who rate higher discomfort due to on-board crowding during the pandemic are expected to be more crowd averse.

- **Flexibility in work hours:** Flexibility in work hours is a very important factor to promote scheduled delay (Thorhauge et al., 2020). Respondents who work or go to university are asked to indicate the flexibility they have to arrive early or later at their destination. Respondents with more flexibility are expected to be less sensitive to schedule delay. Also, it would be interesting to see the number of people who had some flexibility in work hours.

- **Work from home and travel during peak hours:** The objective of this research is to find ways to manage crowds during rush hours. At the start of choice experiment, respondents are asked to assume that they are traveling during rush hour. Respondents with higher frequency of rush hour commute before COVID-19 are expected to be more comfortable with a crowded environment (H. Li et al., 2018). This information is also collected during the pandemic time case to compare the difference in rush hour commute. With a transition to work from home, and online activities, the pandemic time is a good base to attempt to reduce congestion on road and crowding in public transports, especially trains, by flattening the peak demands. When firms reopen, there is a high probability that they will have to allow staggered work hours and working from home option to maintain social distancing (Hensher, 2020). The frequency of work from home would be asked from respondents for before and during COVID-19 period. They are also asked to indicate the frequency at which they would like to continue working from home in the future when pandemic is over. The information on the proportion of people willing to work from home could be useful in making policy recommendations for companies and universities to allow for work from home options.

- **Wearing mask and registering journeys:** Respondents are asked if they would like to continue wearing masks in public transport even after the pandemic is over. As the travel behavior of people is expected to change because of COVID-19, there is a possibility that COVID-19 leaves psychological impact on travel behavior of people. The response to this question could hint if people will become more infection averse. Such questions could be used in another study about the psychological impact of COVID-19 on travel behavior. Respondents are also asked if they are willing to register their train journeys in advance to help to better predict on-board crowding in public transports (Jacob, 2020). This information could be used in making recommendations to promote such behavior of registration.

Attitude towards health and COVID-19

- **COVID-19 history:** Respondents are asked if they had COVID-19 or any of their loved ones had it. It is expected that people with some history of COVID-19 would be more sensitive to crowd levels.

- **Perception about own health:** COVID-19 affects people in different ways. It can be said that people with poor health are in higher risk groups (Stein, 2020). Respondents are asked to indicate on a likert scale if they feel that they are in good health, and if they are usually worried about their health. People with better health perception are expected to be less averse to crowd levels than people with lower health perception.

- **COVID-19 risk and fears:** It has been found that people who are less concerned about these factors are more likely to not take preventive measures of stopping the spread of COVID-19 (Sanchez & Dunning, 2021) are more optimistic about themselves of not catching COVID-19, and less optimistic about others catching it. Respondents are asked to indicate on likert scale if they are concerned about catching COVID-19, and spreading it to others. Respondents who show more concern are expected to be more crowd averse than respondents who show less concern. Responses to such questions can be used in other research for posterior analysis of latent class cluster models developed in this research.

4.3 Design of survey

In design of a choice experiment, the number of choice sets are multiplied by the number of levels in the context variable. Therefore, the total number of choice sets will be multiplied by three to develop a complete set. Ngene software is used to design the choice sets without the context variable, and then the number of choice sets obtained are multiplied by three. The code used to generate the choices can be found in Appendix B.

In a full factorial design the number of choice sets for this choice experiment would be 4*4*4,i.e., 64 without contextual variable of vaccination stage. Including the context would result in 3 times more choice sets which is 192. It would be impractical to manage and execute an experiment with 192 choice sets. Therefore the choice experiment is orthogonal in design. As per basic plan 16 (Molin, 2019b), the minimum number of rows to accommodate orthogonal design for three attributes of four level each is 16. In this design 16 rows were gives as input in Ngene. The choice sets are divided into two blocks such that the experiment is not exhaustive for each respondent. The Ngene software generates two blocks of choice sets with 8 rows in each block. When these choice sets were analysed, 3 out of 8 choice sets in each block were found to be clearly dominant and were removed. After multiplying by 3 to account for different contexts of vaccination stages, in the end, each block had 15 choice sets. So for both early and late scheduled delay, there were two blocks each with 15 choice sets. A table with all the choice sets generated in this experiment can be found in Appendix B.

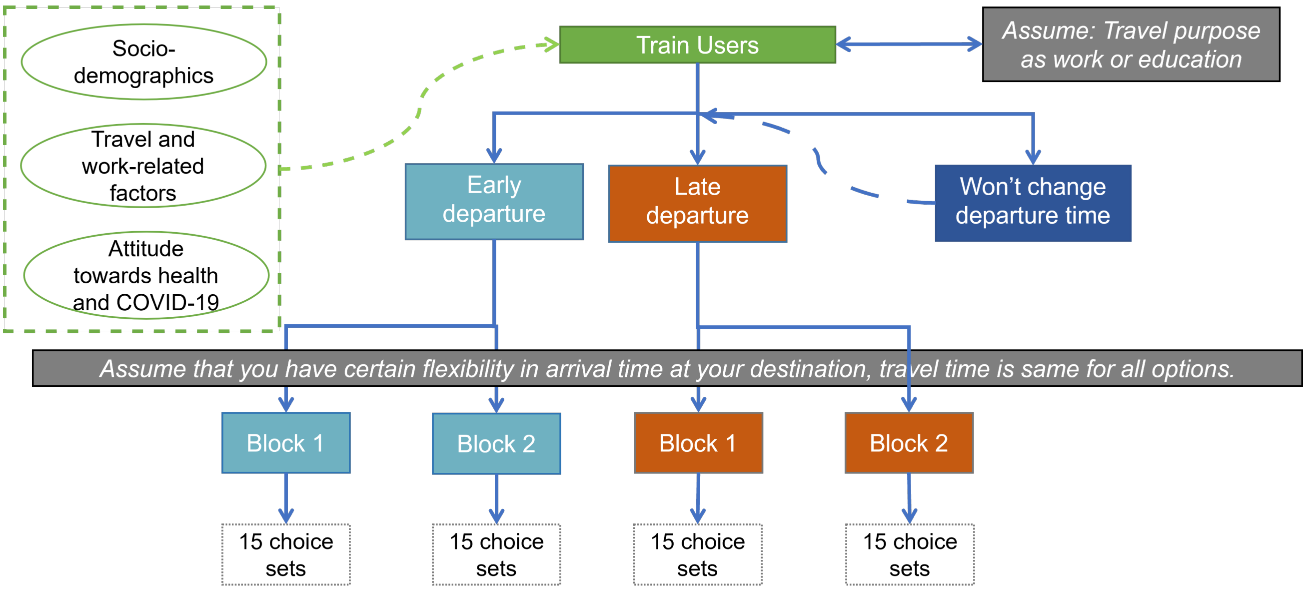


Figure 4.3: Layout of the stated choice survey

In figure 4.3 a layout of the stated choice survey is presented. *The experiment is only focused on train users in the Netherlands, and is based on a context of morning commute using trains within the Netherlands.* A respondent who is a train user in the Netherlands is defined by its socio-demographics, travel and work related factors and attitude towards health and COVID-19. The respondent is asked to assume the train travel purpose as morning commute to work or education for the choice experiment, and also to assume that work hours are flexible. They are provided with detailed information on each vaccination stage. The respondent is then asked to indicate a preference for early, late or same time departure in a scenario where more than 90% population of the Netherlands is successfully vaccinated and their usual train has 95% seats occupied. Even if a respondent selects the usual train option, they are forced to select between early or late scheduled delay. Next, the respondent is asked to assume any characteristic of trains which is not mentioned in the choice experiment to be the same as their usual train option. The choice experiment starts, and a respondent is presented with either of the two blocks of choice sets. It is assumed that all respondents select the train options based on the attributes presented in each choice set.

4.3.1 Pilot study

Pilot study for the stated choice survey is very important to see if everything is in place and general people are able to understand the survey. Feedback from the pilot study is useful in improving the survey. In this research the pilot study lasted for 1 week starting from 13th April 2021 to 20th April 2021. The distribution of the pilot survey was done using an anonymous link which was shared via social media. The survey was prepared in Qualtrics, and responses were also collected in the same platform. 20 respondents participated in the study. Everyone was able to complete the survey successfully. It was good to know that the context of vaccination stages in the choice experiment was clear to respondents which could be because the pandemic and vaccination is in process in present times and people could easily hypothesise the setting. This was confirmed with few known people who filled the survey. There were minor suggestions regarding the options in the questions related to background information, and there was one common feedback about the choice experiment. In the pilot study, each choice set consisted of two questions-

- Which train alternative would you prefer?
- Would you actually make the above mentioned choice?

The second question was added to estimate the demand of an alternative indirectly, however, respondents found this complex and tiresome to answer. In the main survey this question was removed, and it was decided to skip the opt-out question in any manner. Another change that was made was to ask respondents beforehand if they would like to depart early or late. As the experiment is unlabelled, like other stated choice experiments done in the past there were no labeled alternatives of early and later departing trains.

In the pilot the four attribute levels of departure time change included two levels of early and two levels of late departure. Some respondents pointed out that they would always like to depart early or late which was also in line with other research (Bakens et al., 2010). Also, to capture more levels of early and late simply increasing the levels of this attribute would have increased the number of choice sets. Segregating respondents into two categories of early and late was a better solution because this would allow for four levels of departure time change for early as well as late, and this would also allow to compute separately sensitivity towards each change. All these changes were made to make the survey shorter yet comprehensive.

Chapter 5

Result and Analysis

In this chapter data collected from the stated choice survey, and its processing and analysis is presented. In the first section 5.1, data collection and its processing is discussed along with individual characteristics of the respondents. Data processing is performed on the raw data collected from the survey to prepare a refined and coded data-set suitable for discrete choice modelling. Individual characteristics of the respondents are highlighted in the subsection 5.1.2. In section 5.2, Mulitnomial Logit model (MNL) model and its results are discussed. The utility specifications for MNL analysis, and selection of the attributes and background variables to derive the final MNL model is added in subsection 5.2.1. In the subsection 5.2.2, results from both early and late MNL models are discussed. Section 5.3 talks about the development of LCCM and the results obtained from this model. In the last section of this chapter (section 5.4) testing of hypotheses and conceptual model, which was presented in section 3.4, is performed. The final stated choice survey is attached in Appendix D.

5.1 Data characteristics

5.1.1 Data collection and processing

The stated choice survey was developed and circulated using Qualtrics software where a web generated anonymous link and QR code were generated and used for data collection. The data was collected between April 2021 to May 2021. Respondents were approached using social media platforms and personal contacts. Attempts were made to circulate pamphlets with QR code of the survey on train stations, although very few responses were collected by this means. In total 294 responses were collected out of which 94 responses were hardly complete and could not be used in the analysis. The responses were downloaded from Qualtrics in CSV format. Initial data processing was done in MS-Excel by filtering out less than 85% complete responses because those respondents did not complete the choice experiment part. From 200 respondents, 18 respondents said that they do not travel by train at all or did not agree to participate. A small python code was developed and used to process the remaining 182 responses to store the data in desired format in an Excel workbook. The data from the workbook was then copied into SPSS. This data included some missing responses for few individual characteristic questions and choice experiments. Respondents who did not finish the choice experiment were removed however the rest were kept as removing those respondents would have reduced the number of responses significantly. At last total 182 respondents' responses were analysed further and used in discrete choice modelling. Missing responses were replaced by 0 so that there is no effect of the missing data on the discrete choice models. For each question in the survey, the responses were coded into numeric values in SPSS. Some of the attributes such as on-board crowding, vaccination stages, gender, history with COVID-19, living status etc were effect coded. Likert scale questions and responses involving ranges in ordinal manner, such as age and income, were converted into numeric representations. In tables 5.2 and 5.3, all the attributes and background variables present in the final MNL and latent class model for scheduled early and late departure are presented.

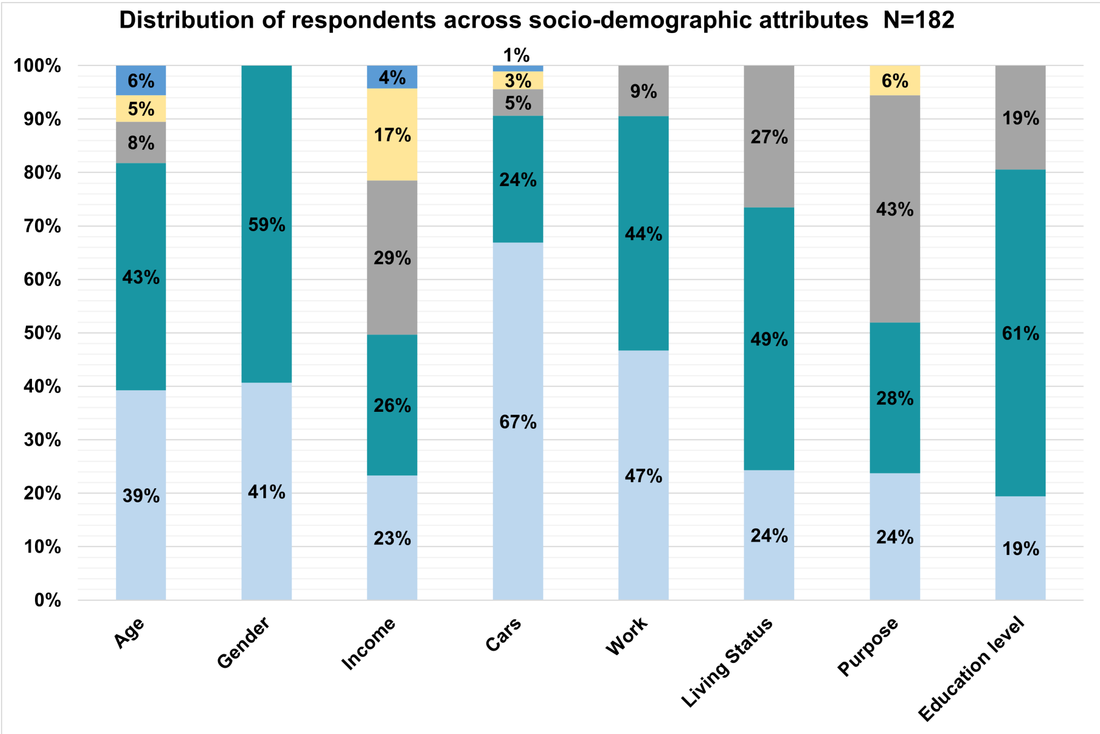
5.1.2 Respondents characteristics

In total 182 respondents completed the stated choice survey in a useful manner. These respondents vary in socio-demographic characteristics, health perceptions and travel and work related attributes. In the graph shown in figure 5.1 percentages of respondents in each category (level) of individual characteristics given in the survey are shown. Most of the population (80%) is from the age group of 18-35 years. This may be the reason that 67% of the respondents have 0 cars in their household and 80% of the population has an income less than 3500 Euros per month. Female to male ratio in the Netherlands is approximately 50-50%, however in the data collected female to male ratio is 39-51%. Entire set of respondents have at least received Bachelor level education. 47% of the population is student and 44% is employed and not a student.

Table 5.1: Comparison of socio-demographic statistics of collected data with socio demographics of the Netherlands and train travelers (CBS, ODiN, 2019)

Socio-demographic variables	Experiment	Train users in the Netherlands (2019)	Population of the Netherlands (2019)
Age			
18-25	39%	16%	10%
26-35	43%	18%	12%
36-45	8%	16%	12%
46-55	5%	17%	15%
56-65	6%	16%	13%
>65	-	17%	19%
Gender			
Female	41%	53%	50%
Male	59%	47%	50%
Education	100% high education	56% high education	
Bachelor/MBO/WO/HBO	19%	44% below university level education	
Master	62%		
PhD and higher	19%		

In table 5.1, socio-demographic characteristics of the respondents of the choice experiment are compared with socio-demographic of the population of the Netherlands and train travelers in the Netherlands. Train user data is taken from Onderweg in Nederland (ODiN) platform (CBS, ODiN, 2019) which was available for 2019 year. Also after the outbreak of COVID-19, transport use has been temporarily disrupted, therefore data from 2019 is considered in this research for representing the travel behavior of people. Similarly, data on Dutch population is also chosen from the year 2019 from the Centraal Bureau voor de Statistiek (CBS) website (CBS, 2019). It is evident from the table that the data is not representative of Dutch train travelers. Age groups 18-35 are over-represented, and other age groups are under-represented. Gender ratio is also slightly different, however, the difference (12%) is not huge. The sample collected represents highly educated people in the Netherlands which is 56% of train travelers. Although the sample is not representative, it still has significant representation of a large segment of population in the Netherlands which could be useful in study of travel behavior.



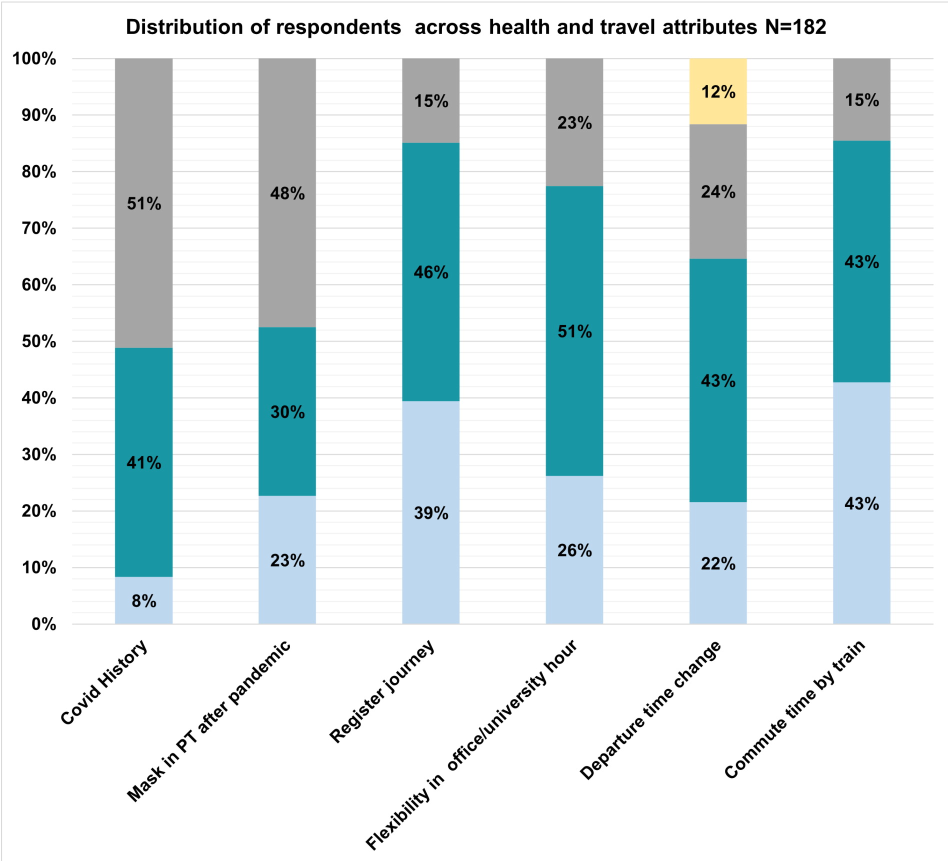
Legend					
Age (years)	18-25	26-35	36 -45	46-55	55-65
Gender	Male	Female			
Income (€/month)	<500	500-1500	1500-3500	3500-7000	>7000
Cars (nos.)	0	1	2	3	>3
Work	Student	Employed full-time	Other		
Living status	Alone	With partner/ friends / housemates	Family		
Purpose	Education	Leisure	Work	Other	
Education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

Figure 5.1: Distribution of respondents across individual characteristics:I

An article by TU Delta in 2019 also shows that changing departure time of a certain group can also considerably reduce crowding in trains during peak hours (Delta TU Delft, 2019) (subsection 3.5).

From responses gathered from health and travel and work related questions in the experiment it is known that almost 43% of the population travels by train to work. There are very few passengers (14%) who have travel time of more than 60 minutes on a train for work or education related trips. 25% of the population has stated that they live with their family, mostly partners. In Appendix B (E) two tables are added which show the variation in travel preferences and perception of respondents as reported by them. It can be noted that more people (approximately 30%) are willing to work from home at least few days a week even after the pandemic is over which could reduce traffic on roads and pressure on public transports in the Netherlands (Delta TU Delft, 2019) (Kogi, 1979). Discomfort due to crowding has drastically increased during the pandemic which is expected as crowding in confined environment such as that of public transport increases the chances of catching an infection such as COVID-19 (LUMC-COVID-19 Research Group et al., 2020) (Goscé & Johansson, 2018). A 5% drop can be seen in the everyday use of train/PT as reported by respondents, even in the scenario when the pandemic will be over. This might be a concern for train/PT operators.

In the graph shown in figure 5.2, percentage of respondents in each level of health and travel related attitudinal questions is presented. Amongst 182 respondents only 8% had COVID-19, but 41% respondents' close ones had it. 23% respondents are sure that they would like to continue wearing masks in PT travel. 39% respondents are willing to register their train journey in advance to help to mitigate crowding in PT. 46% respondents said that they may register. Such a population can be targeted and motivated to register as well. This would be helpful in predicting crowding in PT. Only 26% of the respondents have no flexibility at all in arrival time at their destination of work or education. Respondents were presented with a scenario in which they were informed beforehand that 95% seats are occupied in their usual train, and they were asked whether they would depart early, late or at the same time. Only 33% respondents chose to depart at the same time. 65% of the respondents would rather depart early than late.



Legend				
Covid History	Yes, I had COVID	No, but my close ones had it	No, I never had it, and no one close to me had it	
Mask (in PT after the pandemic)	Yes	Maybe	No	
Register journey (in advance for train travel)	Yes	Maybe	No	
Flexibility in office/work hour (reaching office/university)	No	Some	A lot	
Departure time change (Forced refers to people who first chose to not change departure time)	Early (forced)	Early	Late (Forced)	Late
Commute time by train (in minutes)	<30	30-60	>60	

Figure 5.2: Distribution of respondents across individual characteristics:II

Comparison of early and late departing respondents

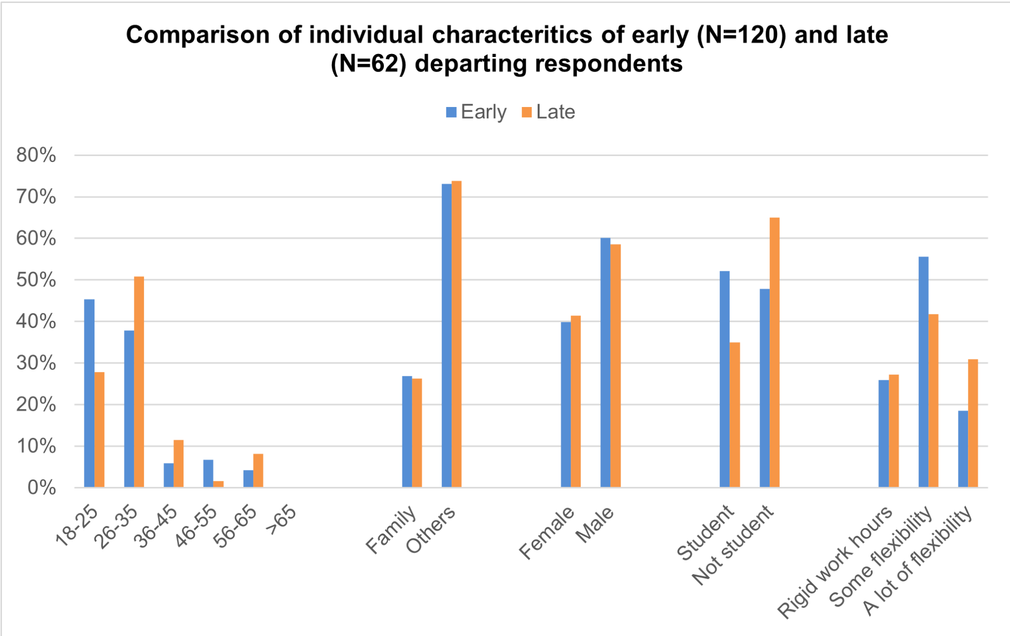


Figure 5.3: Comparison of individual characteristics of respondents who chose to depart early and late

As separate choice models are developed for the two early and late departing categories of people, a small comparison of individual characteristics of the two groups is presented here. Out of 182 respondents, 120 chose to depart early and 62 chose to depart late. Graph presented in figure 5.3 shows the distribution of respondents of each group across few socio-demographics and work/education related attributes. It can be observed that no major difference is present in socio-demographics of both the groups. The major difference seen is in the last two categories. More students choose to depart earlier than later, and people with a lot of flexibility in work hours prefer to depart later than earlier. These insights are also verified later with choice models.

5.2 Multinomial Logit model

5.2.1 Model estimation

As described in section 2.3, Multinomial Logit (MNL) models and Latent Class Choice Models (LCCM) are two discrete choice modelling techniques which are used in this research to qualitatively analyze the responses obtained from the survey. It should be noted that respondents are split into two categories based on their preference of scheduled delay as from a previous choice experiment in the Netherlands it is observed that people would either prefer to depart early or late (Bakens et al., 2010). One group of the respondents consists of people who would prefer to depart early (over late) than their usual departure time to board the train, and the other group of respondents are people who would prefer to depart late. These two categories are referred to as Scheduled Delay Early and Scheduled Delay Late respectively. In the case of the early model, the total number of respondents are 120 and there are 62 respondents for the late model. Although the parameters tested in both these categories are the same, both the models are run separately. This is based on literature review in subsection 3.3.2.

All of these models were developed in R language using the Apollo package whose codes can be found in Appendix F. The codes were referenced and adapted from a user manual of Apollo package in R (Hess & Palma, n.d.).

The choice experiment conducted as a part of this research is an unlabeled experiment (refer section 2.2) which means that both the train alternatives are not distinguishable in determining the utility. However, as the order of appearance of both the alternatives is different in choice experiments, there is a probability of having a bias towards one alternative which can be measured by adding an alternative specific constant (ASC) in the utility equation (Hensher et al., 2015). In section 2.3 it has been mentioned that the significance level used in this research to accept or reject any hypothesis is 90%. To keep a parameter in the model, it should either have p-value >0.10 or it should contribute significantly (t-ratio $>$ 1.65) in improving the goodness of fit of the model (Chorus, 2019) (Hensher et al., 2015). This ASC parameter was found to be insignificant, and did not contribute significantly in improving the fit of the model, hence ASC was removed. The unlabeled experiments allow to estimate generic parameters only (Hensher et al., 2015). The basic utility equation (for Scheduled Delay Early and Late models) without background variable effects which is used in base MNL model estimation and selection of number of classes in LCCM is:

$$\begin{aligned} V_i = \; & \beta_{CR2} * Crowd_{18i} + \beta_{CR3} * Crowd_{27i} + \beta_{CR4} * Crowd_{34i} + \beta_{fare} * Fare_i + \beta_{dep} * Dep_i \\ & + \beta_{vacstage2*crowd} * VaccStage2 * Crowdlevel_i + \beta_{vacstage3*crowd} * VaccStage3 * Crowdlevel_i \end{aligned} \tag{5.1}$$

Description of the coefficients and variables can be found in table 5.2. Crowding (on-board) is known to be a non-linear variable from literature (Whelan & Crockett, 2009) (Shelat et al., 2021). It is therefore effect-coded to capture the utility at each level. Vaccination stage is also effect-coded to test the impact of changing crowding levels with each advancing stage of vaccination, and to discover the vaccination stage at which people become less crowd averse. In subsections below results from each of the MNL and LCCM models are discussed in detail.

Table 5.2: Main effects with contextual attribute in the models

Attribute	Levels	Type of variable	Code	Coefficients
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)	-1 -1 -1 1 0 0 0 1 0 0 0 1	$-(\beta_{CR1} + \beta_{CR2} + B_{CR3})$ β_{CR1} β_{CR2} B_{CR3}
Fare discount	0% 10% 20% 40%	Scale (Numeric)		β_{fare}
Scheduled delay (early/late)	15 min 30 min 45 min 60 min	Scale (Numeric)		β_{dep}
Contextual variable				
Vaccination stage (interaction with changing crowding levels)	30-50 % 60-80% >90%	Ordinal (Effect Coded)	-1 -1 1 0 0 1	$-(\beta_{vacstage1*crowd} + \beta_{vacstage2*crowd})$ $\beta_{vacstage1*crowd}$ $\beta_{vacstage2*crowd}$ $\beta_{vacc*crowd}$ (when vaccination stage is taken as ordinal, non-coded attribute)

5.2.2 MNL model results

The MNL models for both early and late departure cases without background variables were developed using utility equation 5.1. The models were then tested with interaction effects between individual characteristics and main attributes from the choice experiment to come up with the most representative and best fitting models. After testing the early and late models separately with all the interaction effects mentioned in Appendix G, a model with more than 30 parameters was obtained. Many of the interaction terms were insignificant ($p<0.1$) and were removed one by one by testing the models with a chi-square test for 10% significance level. The final model obtained for early departure includes 11 parameters, and for late departure includes 12 parameters. The details of main effect and contextual effect attributes are presented in table 5.2. Although vaccination stages in utility specification 5.1 is effect-coded, when background variables were added in the model, the vaccination stage variable which is ordinal and not coded was found to be a better fit and more informative model. After testing the model with different parameters, following utility equations are found to best represent the MNL model for Scheduled Delay Early and Late:

Scheduled delay early

$$V_i = \beta_{CR2} * Crowd_{18i} + \beta_{CR3} * Crowd_{27i} + \beta_{CR4} * Crowd_{34i} + \beta_{fare} * Fare_i + \beta_{dep} * Dep_i + (\beta_{vacc*crowd} * Vacc + \beta_{cr*crowd} * Discom + \beta_{spreadCOV*crowd} * SpreadCOV + \beta_{cathcCOV*crowd} * CatchCOV) * Crowdlevel_i + (\beta_{stu*dep} * Student + \beta_{Gen*Dep*Liv} * Gender * Liv) * Dep_i \tag{5.2}$$

Scheduled delay late

$$V_i = \beta_{CR2} * Crowd_{18i} + \beta_{CR3} * Crowd_{27i} + \beta_{CR4} * Crowd_{34i} + \beta_{fare} * Fare_i + \beta_{dep} * Dep_i + (\beta_{vacc*crowd} * Vacc + \beta_{cr*crowd} * Discom + \beta_{spreadCOV*crowd} * SpreadCOV + \beta_{cathcCOV*crowd} * CatchCOV + \beta_{car*crowd} * Cars \beta_{Health*crowd} * HealthPercep) * Crowdlevel_i + \beta_{Gen*Dep*Liv} * Gender * Liv * Dep_i \tag{5.3}$$

In table 5.3, the background variables which were found significant in either of the two (early/late departure) models are presented. Detailed description of the background variables and other attributes can be found in section 4.1 and 4.2. In table 5.4, results from the final MNL model are presented.

Table 5.3: Background variables with significant effect in choice models

Background variable	Levels	Type of variable	Code	Coefficient
Age	18-25 26-35 36-45 46-55 56-65 >65	Ordinal	1 2 3 4 5 6	β_{Age}
Gender	Female Male	Categorical (Effect Coded)	1 -1	$\beta_{Gen*Liv*Dep}$
Flexibility in work/ education hours	No flexibility at all Some flexibility A lot of flexibility	Ordinal	1 2 3	β_{flex}
On-board crowding discomfort level before the pandemic	Not at all Slightly Uncomfortable Moderately Very	Likert Scale	1 2 3 4 5	$\beta_{Cr*Crowd}$
Student or not	No Yes	Categorical (Effect Coded)	-1 1	$\beta_{stu*Dep}$
Number of cars in a household	0 1 2 3 More than 3	Scale (Numeric)	0 1 2 3 4	$\beta_{car*Crowd}$
Living with family	No Yes	Categorical (Effect coded)	-1 1	Same as gender
Concerned about spreading COVID-19	Don't agree Somewhat disagree Neutral Somewhat agree Highly agree	Likert Scale	1 2 3 4 5	$\beta_{SpreadCOV*Crowd}$
Concerned about catching COVID-19				$\beta_{CatchCOV*Crowd}$
Good health perception				$\beta_{Health*Crowd}$

Table 5.4: Results from MNL model for early and late departure

MODEL FIT		SCHEDULED DELAY EARLY		SCHEDULED DELAY LATE	
LL(start)		-1247,69		-644.63	
LL(final)		-1013,94		-473,29	
Adj Rho-Square		0.18		0.25	
BIC		2049,89		1028,61	
AIC		2110,34		970,58	
Number of parameters		11		12	
Number of respondents		120		62	
ESTIMATED PARAMETERS					
	Variable Description	Coeff	t-ratio (p-value)	Coeff	t-ratio (p-value)
Attributes in choice sets	On-board seat occupancy (crowding level) 25% (9/36 seats occupied)	1.845	-	2.720	-
	Crowding level 50% (18/36 seats occupied)	0.702	6.52 (p<0.01)	0.912	4.29 (p<0.01)
	Crowding level 75% (27/36 seats occupied)	-0.424	-3.46 (p<0.01)	-0.614	-2.43 (p<0.02)
	Crowding level 95% (34/36 seats occupied)	-2.123	-8.84 (p<0.01)	-3.018	-5.49 (p<0.01)
	Scheduled delay (early/late)	-0.051	-12.50 (p<0.01)	-0.054	-8.35 (p<0.01)
	Discount on full fare	0.027	5.18 (p<0.01)	0.049	5.66 (p<0.01)
	Vaccination stage and on-board crowding level interaction	0.048	9.35 (p<0.01)	0.049	6.11 (p<0.01)
Background variables	Discomfort due to in-vehicle crowding before the pandemic and on-board crowding level interaction	-0.012	-3.81 (p<0.01)	-0.028	-5.76 (p<0.01)
	Student(1= Student -1= Others) and scheduled delay interaction	-0.013	-6.19 (p<0.01)	-	-
	Concern about spreading covid and on-board crowding level interaction	0.023	4.82 (p<0.01)	0.021	3.40 (p<0.01)
	Concern about catching covid and on-board crowding level interaction	-0.022	-4.76 (p<0.01)	-0.027	-4.38 (p<0.01)
	Number of cars owned and on-board crowding level interaction	-	-	0.043	5.12 (p<0.01)
	Personal health satisfaction and on-board crowding level interaction	-	-	0.012	1.73 (p<0.10)
	Females (1= Female -1 = Male) who live with family (1= Live with family -1 = Other) and scheduled delay interaction	-0.005	-2.40 (p<0.02)	-0.007	-2.32 (p<0.05)
Marginal rate of substitution	Marginal rate of substitution of fare discount offered and scheduled delay	-1.89	-	-1.27	-
	Marginal rate of substitution for scheduled delay and on-board crowding	2.22	-	3.36	-

LL and adjusted rho-square values of both the MNL models indicate that the model fit is good and the estimated model is not coincidental. As LL and rho square values compare the model fit in a relative manner, it is difficult to comment more based on these values (Chorus, 2019). All the parameters derived for main effect attributes are significant ($p<0.02$) and of expected signs. When the crowding level is <50% , it has positive utility. As crowding increases further, it causes disutility. This is depicted in the figure 5.4. It is notable that the group of people who chose to depart late show a steeper change in utility, and also have higher utility (and disutility) with changing crowd levels.

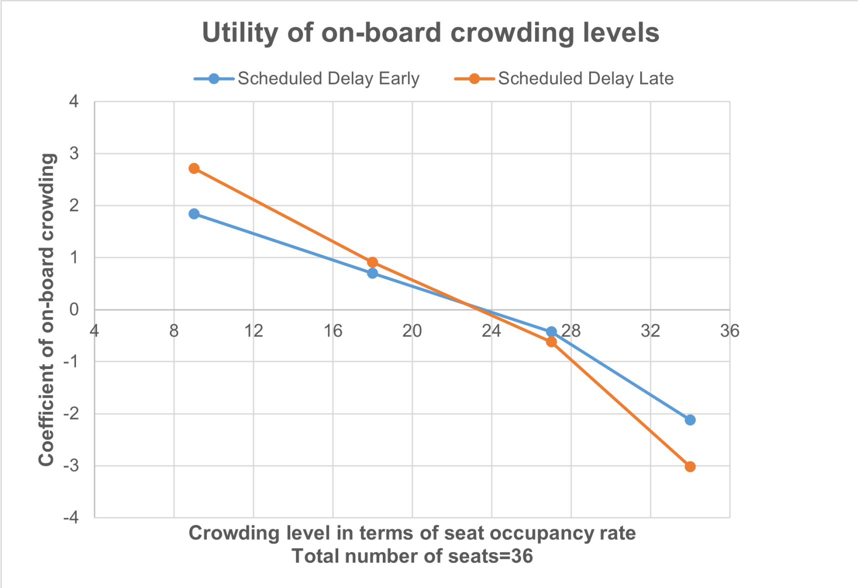


Figure 5.4: Changing utility in MNL model with increasing on-board crowd levels

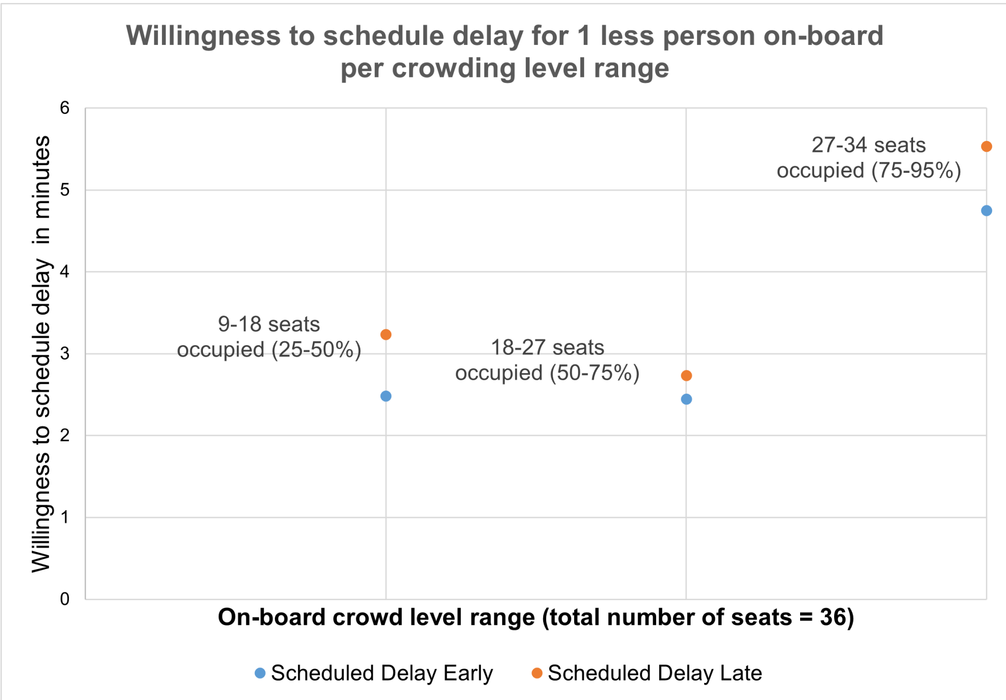


Figure 5.5: Willingness to schedule delay for one less person on-board- MNL model

In figure 5.5, the marginal rate of substitution of scheduled delay for each crowd level range is shown for Scheduled Delay Early and Late MNL models. This value is computed using equations 2.12 and 2.13 described in the subsection 2.3.3. Clearly, the group of people who chose to schedule delay late are willing to delay more than people from Scheduled Delay Early group to have one less person on-board. However, later departing people derive slightly (6%) higher disutility from scheduled delay than earlier departing people which could be because people do not want to arrive late at work/education (Thorhauge, Haustein, & Cherchi, 2016). This willingness to schedule delay is highest for crowding range 75-95% (on an average around 27-34 seats are occupied out of 36 seats in a Sprinter train carriage, subsection 4.1.1 (Expatica NL, 2021)) for both the groups, which is reasonable because the disutility of crowding is highest for this range. Results in table 5.4 show that fare discount has positive sign, which means that utility of train alternatives increases with increase in fare discount (H. Li et al., 2018). People choosing to depart late have 81% higher utility for discount on train fare than people choosing to depart early, and these people are willing to schedule delays at a lower (41% lower) offer of fare discount than early departing people. As expected, the coefficient of scheduled delay has negative sign which means that it causes disutility (Thorhauge et al., 2020) (H. Li et al., 2018) (Thorhauge et al., 2016). The parameter for interaction between vaccination stage and on-board crowding is significant ($p<0.01$) and of expected signs for both the models. There is a positive relationship between on-board crowding level and vaccination stages which indicates that at higher vaccination stages people will become less averse to on-board crowding.

Few background variables are introduced in the utility specification as interaction effects as shown in equation 5.2 and 5.3. It is interesting to see that in the MNL model for Scheduled Delay Early, the variable which represents student interaction with scheduled delay is significant ($p<0.01$) and its coefficient has a negative sign which indicates that students are less willing to depart early. Although interaction between gender and scheduled delay had no significant effect, for both early and late models female respondents who live with their family are found to be less willing to schedule delay ($p<0.05$). Respondents who indicated that they are concerned that they could spread COVID-19 to others are found to be less crowd averse which is counter-intuitive to what was expected, however, respondents who indicated that they are concerned about getting infected from COVID-19 are more averse to crowding which is as expected. Similarly, respondents who have indicated higher discomfort from on-board crowding in public transport (for during the pandemic time) are more averse to on-board crowding ($p<0.01$) which is sensible. Coefficients of interaction of personal health satisfaction with on-board crowding level and number of cars owned in interaction with on-board crowd level attribute are both significant and of positive sign in Scheduled Delay Late group of respondents. This indicates that respondents with cars are less averse to crowding in trains ($p<0.01$) which is counter-intuitive as people with cars can avoid using trains. Respondents with higher health satisfaction are also found to be less averse to on-board crowding ($p<0.10$), which is reasonable because people who find themselves in good health may also consider themselves as a lower risk group.

5.3 Latent class cluster model

To develop a latent class model in order to capture the heterogeneity in respondents' behavior, a good and sufficient number of classes need to be selected for both Scheduled Delay Late and Early models. The number of classes are selected by choosing the model with lowest BIC value, but at the same time interpretability of models, and class size are checked (Lanza et al., 2007) (Wen & Lai, 2010) (Walker & Li, 2007). None of the class sizes should be trivial, and the classes should be distinguishable and easy to label based on the heterogeneity expressed by them. More classes can make the explanation of the model more complex. Hence the final selection of number of classes is done by comparing the results of model with lowest local minima of BIC value and neighboring models with BIC value close to the local minimum value (for more details on LCCM, refer subsection 2.3.2).

Table 5.5: Results from model runs with different number of classes, without background variables

SCHEDULED DELAY EARLY					
Model Characteristics	MNL (without background variables)	2 class model	3 class model	4 class model	5 class model
LL(start)	-1247.67				
LL(final)	-1058.72	-924.27	-885.90	-848.69	-821.73
Adj.Rho-square	0.14	0.25	0.27	0.29	0.31
BIC	2169.90	1960.97	1944.21	1929.75	1935.78
AIC	2131.43	1878.53	1817.81	1759.38	1721.45
Number of parameters	7	15	23	31	39
Number of respondents	120				

SCHEDULED DELAY LATE				
Model Characteristics	MNL (without background variables)	2 class model	3 class model	4 class model
LL(start)	-644.63			
LL(final)	-513.42	-443.24	-411.56	-397.72
Adj.Rho-square	0.19	0.29	0.33	0.33
BIC	1074.68	989.01	980.36	1007.33
AIC	1040.83	916.48	869.15	857.44
Number of parameters	7	15	23	31
Number of respondents	62			

The result of model runs with different numbers of classes can be found in table 5.5. It is observed clearly from the LL, rho square, BIC and AIC values that the model fit of LCCM is better than the MNL model. All these models are run based on the same utility specifications mentioned in equation 5.1.

As a Latent Class Cluster Model (LCCM) is run after declaring the number of classes into which the respondents are split such that the classes are heterogeneous amongst each other, but homogeneous within, it is important to decide an optimum number of classes to get a good model (refer subsection 2.3.2 for more details on LCCM). Log-likelihood ratio test is not recommended to compare the models with different numbers of classes. Instead, Bayesian Information Criteria is used which puts a heavy penalty on LL value for number of parameters (Walker & Li, 2007) (Wen & Lai, 2010) (Schwarz, 1978) (refer equation 2.8). It is impractical to test all numbers of classes, therefore, the number of classes which gives a local minima of BIC value is generally preferred. It is also important that the classes are non-trivial in size, they are interpretable and it is possible to assign meaningful labels to each class (refer subsection 2.3.2).

In figure 5.6, the y-axis represents the BIC values, and x-axis represents the number of classes. *Note that in the figure number of classes = 1 represents BIC value of MNL model without background variable, as in determining number of classes for LCCM effect of background variable is not considered.* The change in BIC value can be observed as the number of classes are increasing for the Scheduled Delay Early and Late models. For Scheduled Delay Early (model with scheduled early departure), the BIC value starts decreasing as the number of classes increases up till 4 classes. For models with 5 classes BIC starts increasing again. For selection of the number of classes, the results of 3 and 4 classes are compared and it is found that the model with 3 classes explains the behavior of respondents in a reasonable manner. Later it is found that once background variables (class membership function) are added to the models with 3 and 4 classes, BIC of the model with 4 classes becomes more than the BIC of the model with 3 classes. Similarly, for the models with Scheduled Delay Late (scheduled late departure), the local minima of BIC value can be seen at 3 classes, however, as the difference between BIC value of 3 and 2 class models is very less, and the interpretation of 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. Please refer to the subsection 2.3.2 for more information on LCCM and selection of the number of classes.

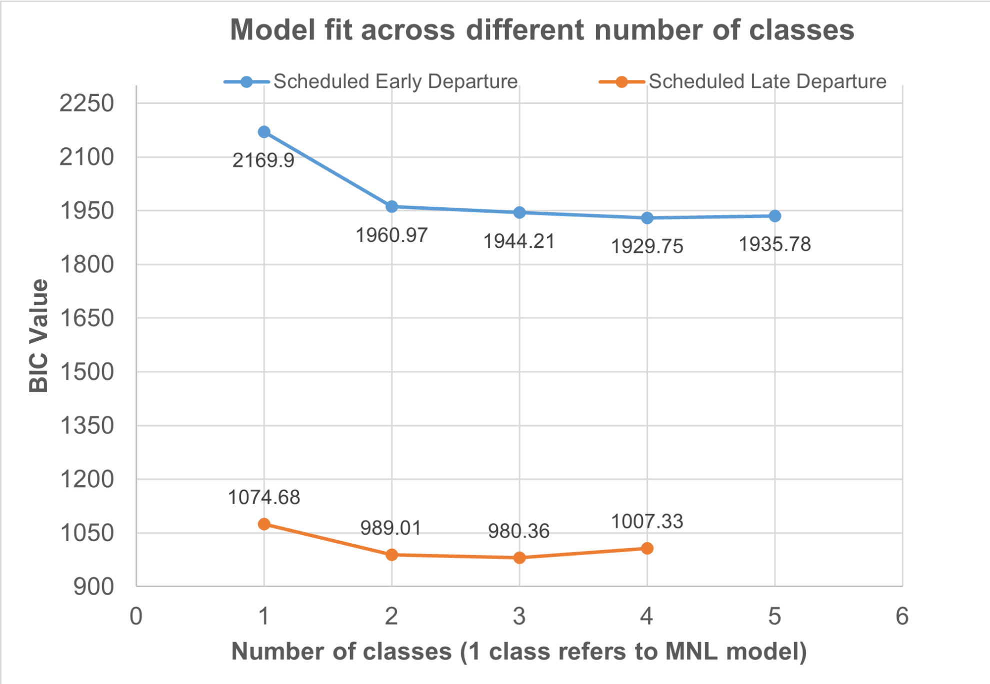


Figure 5.6: BIC value for different models run with different number of classes

5.3.1 Scheduled delay late

In table 5.7, results from 2-class LCCM 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: Crowd indifferent travelers

From results in table 5.7 it can be observed that the share of respondents belonging to this class of respondents is 54.8%. The coefficient of crowding is insignificant (p>0.10) for the two crowding levels 50% and 75% which means that this class is not affected by crowding unless the train becomes overcrowded, i.e., crowding level is 95% and around 34/36 seats are occupied. At this level, this class derives significant disutility from on-board crowding ($\beta_{CR4} = -1.381$). This class is moderately averse to scheduled delay ($\beta_{dep} = -0.065$) and would enjoy a discount on full fare ($\beta_{fare} = 0.059$). Change in behavior of respondents can be observed when vaccination stage 3 is attained, i.e., more than 90% residents of the Netherlands are vaccinated. At this stage the respondents become less averse to crowding, which validates the hypothesis that with advancing vaccination stages, people will become less crowd averse (Hypothesis 2 section 3.4.

In the class membership function two background variables were found to be significant to differentiate the behavior in two classes. In this class, respondents who have indicated more flexibility in arrival time at their work or education related destination and who are younger are over-represented. It is known from the literature review (section 3.2 (LUMC-COVID-19 Research Group et al., 2020)) conducted for this research that crowding is associated with perceived risk of catching an infection such as COVID-19, hence older people are expected to be more crowd averse. It makes sense that this class has more share of younger respondents as this class is less averse to on-board crowding in comparison with Class 2. In comparison with Class 2, the coefficient of scheduled delay is less for Class 1. It can be inferred that having more flexibility in arrival time at the destination makes this class moderately less averse to scheduled delay. Less aversion to crowds and scheduled delay also allows this class to value discounts on full fare more than Class 2 as they may choose an alternative with more discount which is available later.

Class 2: Crowd conscious travelers

The share of respondents who belong to this class is 45.2%. The behavior of respondents in this class is more in line with previous researches ((Whelan & Crockett, 2009) section 3.2) which state that crowding levels inside a vehicle has non-linear effect and disutility due to crowding starts somewhere around 80% seat occupancy rate (Tirachini et al., 2013). In this class the respondents derive high utility from train rides where they can comfortably sit alone with high chances of getting the adjacent seat vacant. At crowding level 3 (75% seats are occupied) disutility is indicated (β_{CR3}=-1.243) and it becomes very high when the train is crowded to 95%.seat occupancy (β_{CR4}= -3.868). This class of respondents are moderately averse to scheduled delay and they derive positive utility from discounts offered on full fare. At vaccination stage 3 (when more than 90% residents of the Netherlands are vaccinated), the members of this class also become less averse to crowding. Compared to Class 1, this class shows a more steep change in behavior at vaccination stage 3. This is expected because this class is more averse to crowding, and has an older age share of respondents which indicates that they are more averse to the risk of catching COVID-19.

On comparing the marginal rate of substitution of fare discount and scheduled delay for both the classes, it can be observed that respondents of Class 2 require 1.3% discount on fare for every 1 minute of scheduled delay, whereas respondents of Class 1 require 1.1% discount on fare for every 1 minute of scheduled delay. Respondents who belong to Class 2 would require approximately 16% higher discount per minute of scheduled delay compared to Class 1 respondents. However, if marginal rate of substitution of scheduled delay and on-board crowding is compared then respondents of Class 2 are willing to depart approximately 3.5 minutes late to reduce one person on-board, which is 250% more than Class 1 who are willing to delay only by approximately 1 minute.

5.3.2 Scheduled delay early

In the model where respondents have an option to depart early (Scheduled Delay Early), three heterogeneous classes were identified. The results of the model can be found in table 5.6. The naming of these three classes is done based on their sensitivity to changing on-board crowd levels, discount offered on full fare and departure time change. The description of the three classes is provided below:

Class 1: Crowd conscious and inflexible travelers

The result of the Scheduled Delay Early model (table 5.6) shows that the share of respondents belonging to Class 1 is 36%. In this class, the coefficients of parameters for less crowded trains are positive and significant ($p<0.1$), i.e., for train alternatives with crowding levels 25% and 50% the travelers show positive utility (β_{CR1}=1.792 and β_{CR2}=1.044) which decreases with increasing crowd levels. At crowding level 75% and higher, increasing disutility is observed from such train rides (β_{CR3}=-0.423 and β_{CR4}=-2.413). The hypothesis relating vaccination stages and crowd aversion holds true in this class as it is seen that the coefficient of interaction between crowd levels and vaccination stage 3 is positive and significant. Although the respondents within this class want to avoid crowded rides, they have very high disutility for scheduled delays for early departure (-0.102/minute). The effect of fare discount on such respondents and the marginal rate of substitution of fare discount for each minute of scheduled delay are found to be insignificant (p>0.1). Therefore, this class can be called as the inflexible class of respondents.

Class 2: Crowd indifferent and fare conscious travelers

As shown in table 5.6, 31.4% of respondents belong to this class. The class has an insignificant coefficient of crowding (p>0.1) unless the train becomes too crowded, i.e., at 95% crowding level the coefficient of crowd becomes significant and is of expected sign. At this level, the class derives disutility due to crowding (β_{CR4}-0.567), but this disutility is the lowest amongst the three classes identified within this model. It can be said that the respondents in this class are indifferent to crowding unless it becomes difficult for them to find an empty seat. Willingness to depart early to have one more available seat in the train is the lowest in this class (0.4 minutes). One thing that this class has in common with Class 1 is the high disutility that it obtains from scheduled delay but opposed to Class 1 this class values discount offered on train fare significantly (p<0.01). People are willing to depart early by 1 minute for approximately a 1.5% discount on train fare. With changing vaccination stages, the impact of crowding does not change significantly within this class. Therefore, it can be said that the behavior of this class will remain the same during and after the pandemic.

Class 3: Crowd conscious and flexible travelers

The respondents have 0.327 probability of belonging to Class 3. Similar to Class 1, the travelers in this class enjoy comfortable and empty train rides and derive disutility from train rides with crowding levels above 75%. This class shows the lowest disutility from scheduled delay, and hence this class can be categorized as flexible in departing early. Similar to Class 2, this class would derive positive utility from train alternatives which offer discount of train fare, but the marginal rate of substitution of fare discount and scheduled delay is found to be insignificant for this class. As vaccination stage advances, respondents of this class become less crowd averse. They are willing to depart early by 1.8 minutes for 1 freer seat in train journeys.

Only one background variable was found to have significant effect on at least one class. This variable captures whether a respondent is a student or not a student (effect coding: student =1 and others =-1). Class 2 is the fixed class, and the significant effect of background variable student (p<0.01) was found in Class 3. The coefficient has a negative sign which shows that Class 3 has less representation of students compared to other classes. As this class represents a comparatively more flexible class than other classes in terms of scheduled delay to early departure, this could mean that the students are less willing to schedule delay and depart early.

Table 5.6: Results from LCCM model for Scheduled Delay Early

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					
ESTIMATED PARAMETERS		**Class 1**		**Class 2**		**Class 3**	
Class distribution		**36%**		**31.4%**		**32.7%**	
Variable Description		**Coeff**	**t-ratio (p-value)**	**Coeff**	**t-ratio (p-value)**	**Coeff**	**t-ratio (p-value)**
Attributes in choice sets	On-board seat occupancy (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)	-0.510	-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 and on-board crowding level	-0.151	-	-0.011	-	-0.029	-
	Interaction between vaccination stage 2 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 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)
Background variables	Student (1= Student -1 = Others)	-	-	0	-	-0.964	-3.53 (p<0.01)
Marginal rate of substitution	Marginal rate of substitution of fare discount offered and scheduled delay	-3.135	-	-1.526	-	-0.651	-
	Marginal rate of substitution for scheduled delay and on-board crowding	0.42	-	0.28	-	1.76	-

Table 5.7: Results from LCCM model for Scheduled Delay Late

MODEL FIT		SCHEDULED DELAY LATE			
LL(start)		-644.63			
LL(final)		-438.65			
Adj Rho-Square		0.29			
BIC		993.49			
AIC		911.30			
Number of parameters		17			
Number of respondents		62			
ESTIMATED PARAMETERS		**Class 1**		**Class 2**	
Class distribution		**54.8%**		**45.2%**	
Variable Description		**Coeff**	**t-ratio (p-value)**	**Coeff**	**t-ratio (p-value)**
Attributes in choice sets	On-board seat occupancy (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 and on-board crowding level	-0.060	-	-0.047	-
	Interaction between vaccination stage 2 and on-board crowding level	0.013	1.14 (p>0.10)	-0.038	-1.51 (p>0.10)
	Interaction between vaccination stage 3 and on-board crowding level	0.047	3.96 (p<0.01)	0.085	4.43 (p<0.01)
Background variables	Flexibility in arrival at destination of work or education (Likert scale 1: No flexibility 3: Very flexible)	0.553	1.69 (p<0.10)	0	-
	Age (Ordinal range)	-0.786	-2.35 (p<0.02)	0	-
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	0.90	-	3.07	-

On comparing both the early and late LCCM it is observed that respondents who choose to depart early have a lower willingness to schedule delay to have one less person on board, than the respondents who choose to depart later. Willingness to schedule delay can be seen for each class and both the models in figure 5.7. Similar pattern was also observed in the MNL model for Scheduled Delay Late and Early departure when marginal rate of substitution of schedule delay for each on-board crowding level was observed. (refer figure 5.5). Crowd conscious travelers from the Scheduled Delay Late model have the highest marginal rate of substitution, whereas crowd indifferent and fare conscious travelers from Scheduled Delay Early group show the lowest value. However, this group of people can be motivated to schedule delays by offering them fare incentives.

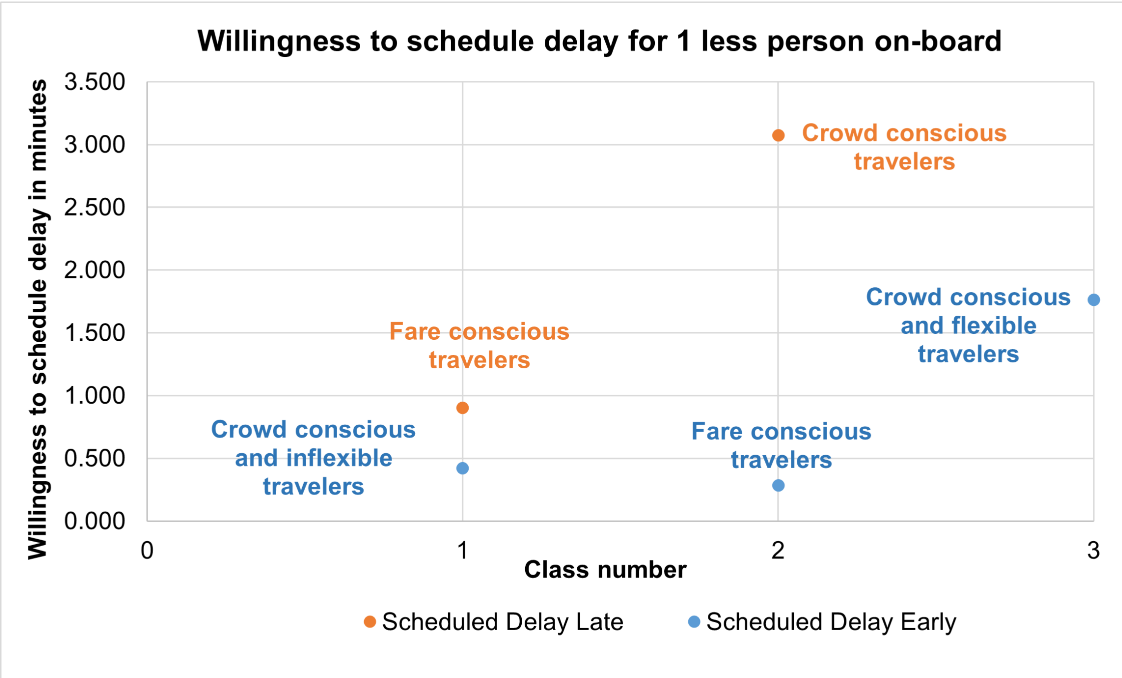


Figure 5.7: Willingness to schedule delay for one less person on-board, per class per LCCM

5.4 Conceptual model and hypotheses tests

On the basis of results of MNL model and LCCM discussed in this chapter it can be observed that the conceptual model presented in figure 3.1 in section 3.4 is valid. More research is required to validate a few hypotheses, however, some new insights are found which were not presented as hypotheses. Although the sample collected is not representative of Dutch population, all the main attributes related to train alternatives are highly significant and of expected signs, and there are some significant effects of background variables on the choices made by respondents. These results are discussed below with respect to the hypotheses added in section 3.4 (refer table 5.4 for results of MNL model, and table 5.6 and 5.7 for results of LCCMs).

Results of MNL models show that the disutility obtained from change in departure time is slightly lower for the Scheduled Delay Early group ($p<0.01$)than the Scheduled Delay Late group ($p<0.01$). However, in LCCM, highest and lowest disutility from departure time change is observed in classes of Scheduled Delay Early group ($p<0.01$ for all classes in LCCMs). Based on the MNL model *Hypothesis 1* stands true. Higher disutility due to Scheduled Delay Early can be because people want to get proper sleep. In case of late departure, being late to work/university or leaving late from office/university as one arrives late could be a few constraints in shifting departure time (Henn et al., 2011) (H. Li et al., 2018). It is also observed that more respondents chose to depart early (65%) than late which is in line with previous research (Henn et al., 2011) (Peer et al., 2016).Figure 5.4 shows taste parameter for each on-board crowd level. It is evident from this graph that people departing later are more sensitive to on-board crowding levels than people choosing to depart early. The graph shown in 5.4 also shows the non-linear utility of on-board crowding levels which proves *Hypothesis 3*, and disutility due to on-board crowding starts in the range of 50-75% seat occupancy rate for MNL models. For LCCM, each class experiences disutility at 95% crowd level. Few crowd conscious classes show behavior similar to MNL models in disutility and utility obtained from on-board crowd level. From figure 5.5 and 5.7 which shows willingness of people to schedule delay for one less person on-board in MNL model and LCCM, it can be clearly observed that people who choose to depart later are more willing to schedule delay to have lesser people on-board. Both these observations support each other. Background variable which indicates if a respondent is a student or not is found to have significant effect and of the same sign in the Scheduled Delay Early group of MNL model and LCCM. In the MNL model this variable is introduced as an interaction term with scheduled delay and the coefficient obtained is of negative sign which indicates that students are more sensitive to early departure. In LCCM for early departure this background variable is found to have significant effect and negative sign in a class where people are more flexible to schedule early departure, which means that this class has lesser representation of students.

Vaccination stages in COVID-19 pandemic are introduced as a contextual variable. This is modeled as an interaction term with on-board crowding level (refer section 4.1 and 4.1.2) to see whether people become less crowd averse (on-board crowd is referred) as more people are vaccinated in the Netherlands. In the MNL model the taste parameters of this interaction term are significant and have positive signs in both early and late models. In LCCM, vaccination stage is effect coded, and it is found that only for stage 3 in class 1 and 3 of Scheduled Delay Early and class 1 and 2 of Scheduled Delay Late models the interaction taste parameter is significant and of positive sign. This indicates that only when most (around 90%) of the people in the Netherlands are vaccinated they will become less crowd averse. This validates *Hypothesis 2*. Taste parameter of scheduled delay has negative sign in all the models and taste parameter of discount on fare has a positive sign which validates *Hypothesis 4 and 5*. *Hypothesis 6* states that gender and living status have significant effect of scheduled delay (Thorhauge et al., 2020). This is found to be true in both the MNL models as shown in table 5.4 ($p<0.05$ Scheduled Delay Late group and $p<0.02$ for Scheduled Delay Early group). Females who live with family are more sensitive to scheduled delays. However, gender and living status have no significant effect on LCCM. Gender and living status are added as interaction term with scheduled delay, and the sign of taste parameter is negative. A complication with such three order interaction term is that it can also yield some other interpretations such as females who live alone or males who live with family are willing to change departure time which does not make much sense (Hensher et al., 2015). More research is required to validate this hypothesis. *Hypothesis 7* which states that females are more sensitive to on-board crowd levels (Shelat et al., 2021) is not found to be true in this research. *Hypothesis 9* which links frequency of travel with on-board crowding level has no significant effect in any model which is contrary to previous researches (Yap et al., 2020) (Lurkin et al., 2017).

As no posterior analysis is conducted in LCCM, the effect of attitude related variables could not be tested using LCCM. The variables are tested in MNL models for Scheduled Delay Early and Late groups. It is found that the history of COVID-19 has no significant effect on utility in both the MNL models which proves wrong *Hypothesis 8a*. This could be because only 8% of respondents had COVID-19. Respondents who indicated that they are concerned that they could spread COVID-19 to others are found to be less crowd averse ($p<0.01$) which is counter-intuitive to *Hypothesis 8c*, however, respondents who indicated that they are concerned about getting infected from COVID-19 are more averse to crowding ($p<0.01$) which proves *Hypothesis 8b*. Similarly, respondents who have indicated higher discomfort from on-board crowding in public transport (for during the pandemic time) are more averse to on-board crowding ($p<0.01$) which is sensible. Coefficients of interaction of personal health satisfaction with on-board crowding level is significant and of positive sign in Scheduled Delay Late group of respondents ($p<0.1$). This indicates that respondents with higher health satisfaction are less averse to on-board crowding ($p<0.10$), which proves *Hypothesis 8d* and is reasonable because people who find themselves in good health may also consider themselves as a lower risk group.

Hypothesis 10 states that people who have flexibility in work hours are less sensitive to scheduled delay (Thorhauge et al., 2020) which is intuitive as well. Flexibility is tested as an interaction term with scheduled delay in both the MNL models and it is found to be insignificant in both models. In LCCM for Scheduled Delay Late, flexibility is significant in Class 1 ($p<0.1$) and is of positive sign. This class is also less sensitive to departure time change which supports the positive sign of taste parameter of flexibility. Significant effect of this background variable in Scheduled Delay Late model is supported by other researches which have found that arriving on time is an important factor for majority of population, and only when people have flexibility in work hours they can manage to depart late (Henn et al., 2011) (Thorhauge et al., 2020). *Hypothesis 11* which is the last hypothesis in this research states that there are heterogeneous groups of people with different preferences towards crowd level in trains, scheduled delay, fare discount and vaccination stages (Thorhauge et al., 2020) (H. Li et al., 2018) which can be validated by the discussion in this section and heterogeneous classes found from LCCM (refer section 5.3).

The real world departure time change experiment which was conducted in the Netherlands between 2012-2013 where train commuters were rewarded to schedule delay outside peak hours, β_{SDL} for morning delay late was found to be -0.02/minute and β_{SDE} for morning delay early was found to be -0.024/minute (Peer et al., 2016) (refer subsection 3.3.2 for more details). The sensitivity to departure time change found in this experiment is higher than before. In nine years the behavior of people may have changed but this difference could also be because the construct of experiment is quite different from that time. People now can avail off-peak travel discounts (NS, n.d.). Yet it is good to observe that the order of values is comparable.

Chapter 6

Conclusion and Discussion

6.1 Conclusion

The research objective of this study revolves around three key problems linked with public transports: the ever-existing problem of crowding in public transport, impact of COVID-19 pandemic on public transport ridership, and attractiveness of public transport for people. To refine the research problem and to find a solution to it, a main research question and six sub-research questions are considered. The main research question is: ***During a pandemic, for different vaccination stages in the Netherlands, to what extent people can be motivated to change departure time to avoid crowded trains?*** This question is based on extensive literature review performed in this study, and it is answered by means of sub-research questions. The main research method in this study is a stated choice experiment. The scope of this research is limited to morning train commute in the Netherlands as travel behavior and policies may vary with transport modes and from country to country. To select the attributes for choice experiment literature review is performed, which also answers the first three research questions. The last three sub-research questions and main research question are answered by analysing the responses of the survey using MNL models and LCCM. The sub-research questions and the answers found to them are discussed below:

SQ1: What is state-of-the art in Acute Respiratory Infection (ARI) transmission in public transport? A research done for BMC Public Health journal (LUMC-COVID-19 Research Group et al., 2020) in the Netherlands in 2020 found that mass gatherings can increase the transmission of viral respiratory infections such as influenza, rhinovirus and COVID-19, and social distancing has been a successful measure in controlling the spread of such infections. ***Social distancing can be termed as an antonym of crowding*** (LUMC-COVID-19 Research Group et al., 2020). Crowded and confined environments such as that of transport hubs have the potential to become a source of spread of ARIs. Different studies conducted in London such as on underground transport network during rush hours in 2018 (Goscé & Johansson, 2018), and bus and tram networks (Troko et al., 2011) when Influenza was spreading in 2008 shows a statistically significant association between ARI development and use of public transports (Troko et al., 2011) (Goscé & Johansson, 2018). An epidemiological study conducted on COVID-19 cases that travelled on high speed train across mainland China between December 2019 and March 2020, 14 days before the onset of symptoms, suggests that apart from personal hygiene, seating distance inside the trains, co-travel time with infected passengers on-board and passenger density can influence the infection risk of COVID-19 significantly (Hu et al., 2020).

SQ2: What could be the suitable indicator and measure of crowding as perceived infection risk in commuting by trains in the Netherlands? Crowding causes disutility in travel, and it is specific to public transport as a mode of travel. To measure this disutility, crowding in trains is best indicated as percentage or ratio of seats occupied (load factor) and passenger density (number of passengers standing per meter square). In metros standing capacity is more, and in trains it is more obvious to sit. In this research crowding is represented as the number of seats occupied on an average in a carriage of a train. This representation of crowding is inspired from a stated choice experiment conducted in 2020 in the Netherlands to study the trade off between on-board crowding in trains and waiting time at platforms (Shelat et al., 2021). The two most popular trains to travel within the Netherlands are a Sprinter and Intercity (Expatica NL, 2021). For this research, the layout of a Sprinter train is considered which has 36 seats in one car. To apply the disutility of crowding in transit systems it can either be translated into monetary terms or time value, but time multipliers are more popular and easy to interpret. In this research also time multipliers would be computed for on-board crowding in trains.

SQ3: What are the mitigation measures that people take to avoid crowds in train commutes? Crowding in trains affects the passengers directly. To mitigate crowding passengers may take the following measures: trading speed of train (more crowded faster Vs. less crowded but slower alternatives), changing departure times to take a more comfortable train, waiting at stations to avoid crowds in trains, switching to first class alternative or in extreme cases, changing travel mode. Amongst these measures, departure time change is a more strategic and effective measure to reduce the peak demand and overcrowding at stations and in trains. Differential fare system is a popular measure to motivate people to change departure time. In the Netherlands as well train users can avail 40% discount on train fare when they travel in off-peak hours which is 9:00 to 16:00 and 18:30 to 6:30 (NS, n.d.). Due to COVID-19 pandemic, people are advised to keep 1.5m social distance. Although in trains all seats are available for access (Dutch Railways, 2020) but if social distancing is on-board then trains would fail to meet more than 25% of normal rush hour demand (Gkiotsalitis & Cats, 2020). With a shift in departure time of people during peaks, demand can be efficiently managed.

To understand if behavior of people changes as there is an improvement in pandemic scenario, a context of advancing vaccination stages is provided in the choice experiment. Instead of providing two labeled alternatives of scheduled early and scheduled late departure, in this experiment two separate analysis are performed over respondents who choose to depart early and late at the start of the choice experiment. A conceptual model is built to understand how respondents may select an alternative in choice experiment. It is anticipated that apart from the main choice attributes and contexts, individual characteristics of respondents will affect the selection made by them. These individual characteristics are divided into three categories: Socio-demographics, travel and work related factors, and attitude towards own health and COVID-19. The analysis of responses collected from the survey answers the last three sub-research questions.

SQ4: What is the trade-off that people make between on-board crowding in train commutes and changing departure time?

SQ5 To what extent a discount offered on train fare could motivate people to change departure time? In both MNL model and LCCM, on-board crowding has been effect-coded as it is known to have non-linear effects. This is found true in this research. In MNL models the sign of taste parameter is positive for 25% and 50% seat occupancy rate. For 75% and 95% the coefficient is negative. The value of the coefficient decreases as crowding increases. Coefficient of departure time change has a negative sign and discount on fare has a positive sign. The group of people who chose to schedule delay late are willing to delay more than people from Scheduled Delay Early group to have one less person on-board. This is observed in results of MNL models as well as LCCM. From the MNL model it is observed that scheduled early group of people are willing to wait for approximately 2 minutes to have one less person on board, whereas late group of people can wait up to 3 minutes. In the LCCM of Scheduled Delay Late group of respondents, the crowd Conscious class of respondents (Class 2) enjoys empty trains and has high and increasing disutility from crowding as trains become crowded. This class is willing to depart late by approximately 3 minutes to have one less person on-board. Class 1 (Crowd Indifferent class) is only affected by crowding when it becomes overcrowded (95% seats are occupied) and they are willing to depart later by approximately 1 minutes to have one less person on-board. The disutility this class obtains from crowding is approximately 60% less than Class 2 at 95% crowd level. Both the classes obtain similar disutility from departure time change and utility from discount on fare.

Class 1 (Crowd conscious and inflexible class) and Class 2 (Crowd indifferent and fare conscious class) in LCCM for Scheduled Delay Early have very low (<1 minutes) willingness to depart later to have one less person on-board, and Class 3 (Crowd conscious and flexible class) has this willingness as approximately 1.7 minutes. Class 1 which has one of the lowest willingness to depart late to have less people on-board also has higher fare discount requirements to change departure time. This group of people is the most rigid in changing departure times. Class 2 also obtains high disutility from scheduled delay, but this class obtains the highest utility from fare discount. Their marginal rate of substitution for discount on fare and departure time change is moderate (1.5% for 1 minute delay). Similar to Class 2 of LCCM for Scheduled Delay Late, this group of people are only affected by crowding when the train gets overcrowded, and the sensitivity is still low compared to other classes. This class can be motivated by offering them discounts on fare. Class 3 (Crowd conscious and flexible travelers) in Scheduled Delay Early is the most ideal class to motivate for departure time change. They are highly sensitive to on-board crowding; they have low sensitivity (disutility) towards scheduled delay, and they are moderately sensitive (positive utility) to fare discount. The have a very low marginal rate of substitution for fare discount and scheduled delay (0.65% for 1 minute delay).

SQ6: How does the trade-off vary across different sub-groups of people? In the MNL model, background variables were introduced as interactions, and in LCCM such variables were introduced in class membership functions. From the MNL model it was found that females who live with their family are more sensitive to schedule delay (both early and late). Students who depart early are also more sensitive to departure time change. In the Scheduled Delay Early model of LCCM, it is found that less students are represented in Class 3 which is the most flexible class. This indicates that students are more sensitive to depart earlier than usual. In Scheduled Delay Late model of LCCM it was found that Class 1 which is crowd indifferent has a higher share of younger people in comparison with Class 2 which is crowd conscious, which makes sense as crowding is associated with perceived risk of catching an infection such as COVID-19, and older people are expected to be more crowd averse. Class 1 also has a higher share of people with more flexible work hours.

SQ7: What is the impact of vaccination stages on the trade-offs that people make?Coefficient of vaccination stage and on-board crowding level is found to be positive and significant in MNL models for Scheduled Delay Early and Late. It shows that as more people are vaccinated, people become less averse to on-board crowding in trains. In case of LCCM, vaccination stages are effect coded and both the models and all the classes show similar behavior for the context of vaccination stage 3, i.e., when more than 90% people are vaccinated in the Netherlands. The coefficients of interaction terms are positive and significant which indicates that people become less crowd averse at this level. Naturally, crowd conscious classes have a higher coefficient as they have higher values of crowding coefficients in comparison with crowd indifferent classes. Other vaccination stages were only found to be significant in Class 3 of Scheduled Delay Early group, and the values show the expected behavior, i.e., people become less crowd averse as more people are getting vaccinated.

Main research question: 67% people indicated in this research that they would either like to depart early or later to avoid overcrowded trains in a scenario where more than 90% people are vaccinated in the Netherlands. Only 15% of people indicated that they would not like to register train journeys in advance to help to reduce crowding in trains. And 48% of people said that they would definitely not prefer to wear masks in public transport after the pandemic. From this research it can be concluded that certain groups of people can be motivated to schedule delay by offering them proper incentives. Few groups of people may choose to change departure time to simply avoid crowds in trains, but most of the groups can be motivated to schedule delays by offering them discounts on train fare or other benefits. To allow more people to have such an option, policies such as work from home, staggered commute and flexible work hours are required in workplaces. Along with friendly policies, a system needs to be developed to predict demand and offer discounts based on the scheduled delay required.

6.2 Discussion

Managing overcrowding in public transports would not only make public transports more comfortable, it can also decrease the risk of catching ARIs such as COVID-19 while traveling. When the pandemic will be over, most of the people will become less averse to crowding, however it would still remain a disutility. Moreover, during COVID-19 pandemic, many people have shifted to other modes of transport. Some people have also indicated that they would not prefer to travel during rush hours, and few have said in this research only that they would like to continue wearing masks in public transports even after the pandemic. This indicates the necessity of crowd management in trains and other public transports, especially during rush hours, for the benefit of public transport operators and society.

The results of this research are consistent within different models in this research, and have proven some hypotheses based on previous experiments on departure time change and some which are researched for the first time in this research. Also, the values of coefficients of main attributes are within similar ranges in all the models, and are of expected sign. This supports the validity of the results. The sensitivity to departure time change found in this experiment is higher than a real-life departure time experiment conducted in 2012-2013 in the Netherlands (Peer et al., 2016) where people were offered rewards to travel outside peak hours. In nine years the behavior of people might have changed a little but this difference could also be because the construct of experiment is quite different from that time. Yet it is good to see that the order of values is comparable. From the data collected it is known that amongst the respondents who chose to delay late there is a higher proportion of respondents with more flexibility in work hours, and amongst respondents who chose to delay early there is a higher proportion of respondents who are students (refer subsection 5.1.2). In LCCM for Scheduled Delay Late, flexibility is found to be a significant background variable in class membership function, and in LCCM for Scheduled Delay Early (and also in MNL for Scheduled Delay Early) variable indicating if a respondent is a student or not is found to be significant in class membership function. People who have more flexibility in work hours can schedule delays late without the fear of being late to work. Students, although represented in a higher proportion in the Scheduled Delay Early group, are underrepresented in the class of respondents who are more flexible in scheduling delay. With online education possibilities, students may work from home a few mornings or for a few days a week.

6.2.1 Policy implications

In a report by Eurofound (Eurofound, 2012), flextime is defined as work hour flexibility, i.e., flexibility offered to employees to start and finish the work. Such a policy is said to reduce traffic congestion, improve productivity and work life balance. Another such policy is staggered work hours which is popular in Transportation Demand Management (TDM) (Zong et al., 2013). Soon workplaces will re-open in the Netherlands, but it is instructed by the government to do so by following the norm of 1.5 meters social distance, to keep people safe. Employers are instructed to allow for staggered work hours and people are encouraged to work from home as much as possible (DLA Piper, 2021) (Intyre et al., 2020). Without flextime and staggered commute, people won't have an option for scheduling delay. Such policies are important to obtain maximum benefits from policies related to fare discounts for demand management in public transports.

A policy proposal for real-time crowd management inspired from the policy proposed in the departure time change experiment conducted in Beijing in 2018 (H. Li et al., 2018) is to offer discounts on train fare in real-time based on expected overcrowding. Such a policy requires a system to predict demand during rush hours and to predict the timing of peak rush on a day to day basis, and offer this information to train passengers. To motivate people to shift departure time to reduce crowding, fare discounts can be proposed in real-time for different time windows. Offering fare discounts within peak hour will concern train operators more, as they will have to ensure that this is economically viable for them. A societal cost benefit analysis can be conducted by train operators to study if providing fare discounts is more economically beneficial for them and also in managing overcrowding, or increasing supply of trains during rush hours. To make such policies, real world experiments and pilot studies are required. Providing such real-time information on crowding level in trains without any other incentive could itself motivate certain groups of people to shift their departure time. Such a group of people are represented in a latent class group of people who are willing to depart early (Class 3: Crowd conscious and flexible travellers sub-section 5.3.2).

As discussed in section 1.1.4, there are primary and secondary stakeholders which could be affected by such policies. Railway operators in the Netherlands such as NS, Arriva, Connexxion, Keolis Nederlands, NMBS, DB Regio etc. would be directly impacted as it would affect their demand and supply. Other public transport operators such as GVB, HTM, Qbuzz, Syntuss, NS, Arriva, Connexxion, Transdev and RET may also be affected as their demand may change directly when the attractiveness of trains increases, and there can also be an indirect effect as the demand of these transport modes used for access/egress to/from train stations may change. Government authorities and policy makers would be involved in development and implementation of such policies. Companies who offer railway information through software applications such as 9292, Google Maps etc. could provide information on expected crowding level in trains in their applications. Other organizations may be involved in developing highly predictive models. ProRail, who are the infrastructure managers of train platforms, may also benefit from such policies as there will be changes in passenger demand during rush hour. Environmentalists are expected to be in support as such policies would increase the attractiveness of public transports. Medical facilities and authorities are also expected to support such models and policies as it may dampen the spread of COVID-19 infection by reducing overcrowding in train stations. Cooperation and support is required from public transport users and employees of companies which could offer flex hour/staggered commute for a successful implementation.

6.2.2 Limitations of this research

In this research the data collected from the survey is non-representative of Dutch population, even though the results from choice models are highly significant. The survey was circulated systematically, and due to a limitation on the number of responses collected, none of the respondents were removed from analysis. The limitation with number of respondents did not allow for selecting the respondents who commuted using trains in rush hours in the Netherlands before COVID-19 pandemic. Such respondents would have been better candidates for this research. Also, base alternative or opt-out alternative is not an alternative in this research, hence there is less information on demand of alternatives.

Selection bias correction is not applied in this research. Presence of sample selection bias in the data occurs when individuals (respondents) are selected non-randomly from the population. There can be other sources of selection bias as well such as there maybe respondents who already travel in off-peak hours for commute, respondents who travel in first class which is not as crowded as second class, respondents who work from home mostly or respondents who do not commute by trains, however it is not known how many, or how small of selection bias is acceptable. These respondents might be more reluctant in choosing either of the train options which ask for scheduled delay. It is good practice to assume that a model has selection bias and at later stages try to correct for the bias. The popular technique of correction of selection bias (Heckman's sample selection method) by subsampling the samples would be difficult to apply in this research as there is a limitation on the number of responses collected. Moreover, The correction of selection bias in itself is practically a complex process which needs to be addressed in future research. (Berk, 1983) (Apostolakis & Jaffry, 2006). The design of choice sets is orthogonal in this research, however, dominant choice sets are manually removed which may have introduced correlations between attributes. Another way to design choice experiments is using efficient design which minimises such correlations. As no research has been conducted before with attributes such as discount on train fare and vaccination stages in the Netherlands, without any reliable priors on taste parameters efficient design might have produced wrong results. The value of taste parameters from this research can be used as priors in other researches.

6.2.3 Recommendations

In the course of this research, several recommendations for future research were drawn which are added below:

- In this research several attitude and perception related questions were posed to respondents. A posterior analysis in LCCM including responses of such questions can give deeper insight into heterogeneity observed in the classes.
- More research is required to understand what factors determine willingness of people to depart early, late or not change departure time, and what psychological factors affect the preference of people to wear or not to wear masks in public transports after the pandemic is over.
- Another research can be conducted using Structural Equation Modelling to understand the psychological impact of COVID-19 pandemic on travel behavior of people.
- As proposed above in sub-section 6.2.1, a study of cost benefit analysis of different methods to reduce overcrowding in public transports can be performed to select the best measures.
- More research is required in understanding the effect of crowding in different locations within train stations and inside trains.
- Based on this research, a real-world experiment including other public transports can be conducted to study the impact of such policy on demand management.
- The last recommendation is to conduct an experiment to understand how people value health in making transport mode choices, and to include the risk of catching an infection as a health aspect. Such attributes in choice models can help to improve the predictability of models.

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Appendix A: Research Paper

The research paper is attached in the following pages of this report. All the figures and tables of the research paper can be found at the end of the paper.

Change in departure time to avoid crowd in trains: *A stated choice experiment study in the Netherlands in a pandemic context*

Abstract

Crowding in trains during rush hour is known to cause discomfort. After the outbreak of COVID-19 pandemic, crowding has also been highlighted as a risk factor for catching Acute Respiratory Infections (ARIs) such as COVID-19 which has affected the demand of public transport. Several countries, including the Netherlands, have differential fare systems for peak and off-peak travel, however, the problem of overcrowding in trains is still prevalent and is expected to cause more disutility than before the pandemic. To reduce peak hour rush, change in departure time has proven to be an effective measure. In this research first a review of previous experiments related to valuation of crowding and departure time change is performed. And then an exploratory study based on a stated choice experiment is conducted to understand the extent to which people can be motivated to change departure time to avoid crowded trains during rush hours by offering them real time information on on-board crowding level and a discount on train fare. Unlike previous studies, the respondents are segregated into two groups before the start of choice experiment based on their indicated preference to schedule delay early or late. To study the change in travel behavior in the pandemic time, context of different vaccination stages is provided in the choice experiment. Background information collected in the experiment is broadly categorised as: socio-demographics, travel and work related factors, and attitude towards health and COVID-19. After the responses are analysed it is found that the coefficients obtained for main attributes are highly significant, and in line with previous research. When most of the people are vaccinated in the Netherlands, they may become less averse to on-board crowding. The research also indicates that certain groups of people can be motivated to change their departure time if real-time crowding information is provided to them. Few others can be motivated by offering incentives. However it should be noticed that to allow people to change departure time, policies such as flexible work hours and staggered commute are required in workplaces.

Keywords: Public Transport, Acute Respiratory Infection, Departure Time Change, Valuation Of Crowding, Peak Off-Peak Hour, Stated Choice Experiment, Multinomial Logit, Latent Class Cluster Models

1 Introduction

Crowding causes disutility in travel, especially during rush hours when public transports could get overcrowded, and it is specific to public transport as a mode of travel. It can be defined as a state in public transport, especially trains, which can lead to mental stress, and increased risk to safety, security and health (Cox, Houdmont, & Griffiths, 2006) (Evans & Wener, 2007). Several countries, including the Netherlands have differential fare system for peak and off-peak travel (NS, n.d.), however, the problem of overcrowding in trains is still prevalent and is expected to cause more disutility than before the pandemic (Gkiotsalitis & Cats, 2020). Ever since the COVID-19 pandemic began in December 2019, crowding has also been highlighted as a source of spread of respiratory infections (LUMC-COVID-19 Research Group, Qingui, Toorop, & et. al., 2020), and it can be termed as an antonym of social-distancing (LUMC-COVID-19 Research Group et al., 2020). In a research conducted by Dutch Railways (Nederlandse Spoorwegen, NS) along with TU Delft in mid-2020, it was found that many travelers would prefer not to commute during peak hours anymore (Jacob, 2020). In the Netherlands, most of the people are expected to be vaccinated by the year 2022 (NL Times, 2021). Once the government lifts restrictions and people start traveling again, with social distancing on-board approximately only 25% of peak-hour demand could be satisfied (Gkiotsalitis & Cats, 2020) (Besinovic & Szymula, 2021). Even though social distancing is recommended by the government, train operators have allowed usage of all seats in the trains (Dutch Railways, 2020).

There is a constraint from the supply side to mitigate crowding in trains. From the demand side, passengers can shift their departure time to avoid crowded trains. Policies such as flexible work hours (Eurofound, 2012) and staggered work hours which allow people to shift their departure times help to reduce traffic congestion, improve productivity and work life balance. Soon workplaces will re-open in the Netherlands, but it is instructed by the government to do so by following the norm of 1.5 meters social distance to keep people safe. Employers are instructed to allow for staggered work hours and people are encouraged to work from home as much as possible (DLA Piper, 2021). In past few decades, change in departure time has proven to be an effective measure to reduce peak hour rush (Zong, Juan, & Jia, 2013) (Maunsell, 2007) (Pel, Bel, & Pieters, 2014) (O'Malley, 1975). It is not known if people are provided with prior or real-time information on expected crowding level in trains in the Netherlands, and if they are offered some incentive on train fare, to what extent it could motivate them to change their departure time to avoid crowded trains (H. Li, Li, Xu, Liu, & Ran, 2018), and how this behavior changes as more people get vaccinated. This is explored in this research, and it may be helpful in managing crowd in trains during and after the pandemic is over along with increasing attractiveness of trains in the Netherlands.

In section 2, a literature review of previous real life experiments, stated choice and Revealed Preference experiments that have been conducted in the past to measure the value of crowding and to study behavior related to departure time change amongst car and public transport commuters during rush hour is presented. Section 3 presents the design of the Stated Choice survey, the procedure of data collection followed and analysis of data on individual characteristics of respondents. In sections 4 the discrete choice models used to analyse the responses of the survey are explained in detail. In section 5 the results from estimated choice models are discussed. In section 6 recommendations for further research are made, and the policy implications and limitations of this research are discussed. And at the end, section 7 presents the conclusions drawn from this research.

2 Literature review

The selection of papers for literature review in this research started by using the subjective criterion of brainstorming, followed by suggestions from few experts and backward snowballing (Wee & Banister, 2016) (Jalali & Wohlin, 2012). Literature review helped with refining the scope of this research, giving an overview of work done in the past and selection of attributes and background variables for the choice experiment.

2.1 Valuation of crowding in public transport

Ever since the COVID-19 pandemic began, crowding has been highlighted as a source of spread of respiratory infections. Social distancing is termed as an antonym of crowding (LUMC-COVID-19 Research Group et al., 2020). Before theCOVID-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, Cats, & van Arem, 2020). In table 1, an overview of methodology followed in a number of experiments related to valuation of crowding which are reviewed in this study are presented. The last row of the table also shows the experiment that is conducted as a part of this research.

In 2008-2009, MVA Consultancy in the UK conducted a Stated Choice research to estimate people's "willingness to pay to reduce rail overcrowding" (Whelan & Crockett, 2009) by asking people 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, and the layout of how people are seated by considering empty seats around a passenger. It was found that time multiplier's value increased from 1 to 1.63 for seated passengers, and from 1.53 to 2.04 for passengers standing as number of passengers standing increased from 0 to 6 per meter square (Whelan & Crockett, 2009) (Z. Li & Hensher, 2011). The research recommends the computation of value of crowding as a time multiplier rather than monetary indicators, as former is easy to interpret, convert and apply for understanding influence of crowding on passenger's behaviour and benefits that could be achieved if crowding is reduced (Z. Li & Hensher, 2011).

In several researches based on Revealed Preference method (by Significance on Paris metro system (Kroes, Kouwenhoven, Debrincat, & Pauget, 2013), on Hong Kong mass transit railway (Hörcher, Graham, & Anderson, 2017), in the Netherlands for bus and trams (Yap et al., 2020)) and mix of revealed and stated preference methods (in Santiago bus, metros and trams (Batarce et al., 2015)) it was found that Stated Choice experiments often overestimate value of crowding in public transports. Usually these Revealed Preference studies are performed using Automated Fare Collection (AFC) and Automated Vehicle Location (AVL) data provided by operators of public transport. From the Revealed Preference study in 2020 in the Netherlands (Yap et al., 2020)it was found that crowding significantly impacts the route choices of passengers in public transports. 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 are occupied. Value of crowding for frequent users of public transport is higher than that of less frequent passengers, but the value of time multiplier is less than the values obtained from other SC Experiment studies such as that of MVA Consultancy (Whelan & Crockett, 2009) (Yap et al., 2020). In Stated Choice experiments, passengers tend to choose higher waiting time levels, whereas in reality they board a more crowded train with lesser waiting time. Changing departure time to avoid crowd in commuting is a more strategic and strong decision taken by passengers to avoid crowding in trains or public transports (Maunsell, 2007) (Pel et al., 2014).

In a Stated Choice experiment study conducted during COVID-19 in May 2020 in the Netherlands to find out people's willingness to wait for a less crowded trains to avoid risk of getting infected while traveling(Shelat, Cats, & Cranenburgh, 2021), people were asked to trade-off between on-board crowd levels and waiting time in contexts of ongoing infection risk and travel time. It was found using LCCM that people who belong to a more COVID conscious class have a (approximately 75%) higher value of crowding- 8.75 min per person and this value rose if there was an option to sit alone. People in higher age groups and who were females were found to be more conscious about catching COVID-19. This research also points out that government and public transport authorities need to make efforts to increase attractiveness of public transports in order to restore the demand of public transport once the pandemic is over.

Another unit of measure of disutility caused by crowding inside a vehicle is monetary value per person for per unit time of travel. In a State Choice Experiment conducted in the UK in 2008 (Lu, Fowkes, & Wardman, 2008), crowding was indicated as a probability of standing for a length of journey. Using a Multinomial Logit estimation of choice model, value of crowding was found to be 7.23 pounds per person for one hour of travel which was more than two times of value of time (in-vehicle) (Z. Li & Hensher, 2011) (Lu et al., 2008). In another SC Experiment conducted in Sydney Australia in 2005 (Douglas & Karpouzis, 2006), the attributes of two train alternatives varied in terms of on-board crowding, waiting time for the trains and in-vehicle travel time. To represent crowding in trains, respondents were presented with standing time of 'x' minutes in a crushed/uncrushed environment to get a seat which was crowded/uncrowded. Value of crowding as a time multiplier was found to be 1.17 which is in range of estimated value from 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 total cost (travel time cost and crowding cost) was found to be 9.92 AUD per person per hour. The monetary value was computed by translating time into a monetary indicator using the value of time in that region. It was observed that the relationship between load factor and total cost is non-linear. The value rises sharply as the load factor increases to 100%.

Although passengers experience disutility from crowding on platforms and access ways of train stations (stairs, elevators, check-in/check-out), very limited research is available on this. Crowding in these locations can affect waiting time valuation of passengers which is found in a Stated Choice experiment research done in Sydney in 2004 (Karpouzis & Douglas, 2005). It was found that under highly crowded situations, 1 minute of estimated waiting time on platform ranged from 1.7 to 2.5 minute of average crowding waiting time, and 1 minute of walking for access to platforms or entrance under the same circumstance ranged from 1.5 to 1.8 minute of walking under average crowding situation (Karpouzis & Douglas, 2005).

2.2 Departure time change

A very popular policy for Transportation Demand Management (TDM) is staggered work hours. This policy is known to reduce road traffic congestion as well as load 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 or flexible work hours, people may adapt their departure time to avoid rush in commute. In table 2, an overview of the departure time change experiments reviewed in this research are presented.

In a big experiment conducted in the 1970s in the Manhattan area of New York with 220,000 participants, people were asked to stagger their work hours by at least 30 minutes before or after (O'Malley, 1975). This showed a reduction in congestion at a peak time (9:00 AM) at three busiest transit subway locations by 26%. The research points out that there is a correlation between work schedules and public transport operations and demand (O'Malley, 1975). In a Stated Choice research conducted on metros in Beijing in 2018 (H. Li et al., 2018), three alternatives were presented in the survey, i.e., metro departing earlier or later than usual and metro departing at usual time (Zhu & Long, 2016). Price affects the demand, and not including fare can lead to biased results (Lurkin, Garrow, Higgins, Newman, & Schyns, 2017), hence discount offered on fare was included as an attribute in the choice experiment. Apart from these attributes, crowding inside the metro and travel time saved are the other attributes presented in the experiment. Using a Mixed Logit model it was found that the metro passengers of Beijing were more sensitive to scheduled delays late than early. This is probably because passengers are constrained at activity end (work/education). It was also found that passengers are more sensitive to fare and travel time savings and crowding levels in the metros showed insignificant effects on scheduled delays (the change in departure of passengers from usual departure time), which is contrary to previous researches, but the reason could be that people of Beijing have become accustomed to crowding which might have changed during the pandemic. Also, more frequent commuters were found to be less sensitive to crowding.

Another interesting study in Copenhagen in 2020, used state choice experiment and latent class clustering method to study departure time preferences of car commuters during morning hours using a hypothetical toll ring. The respondents were asked to fill a 24 hours trip diary. Similar to the Beijing Metro experiment, in the main choice experiment they were also presented with three alternatives. It was found that flexibility in work hours and household composition (whether or whether not someone has a child) played an important role in making a respondent sensitive to departure time change (Thorhauge, Vij, & Cherchi, 2020). Therefore, these researches suggest to explore sensitivity to departure time changes in different places, and make policies to promote this behavior by focusing on specific socio-demographic groups and problems.

In 2011, willingness to change time of travel, i.e. departure time, of rail commuters in Sydney was researched (Henn, Douglas, & Sloan, 2011). A questionnaire was given to passengers in which they were offered fare discounts along with faster train options against changing their departure time. It was found that these incentives, especially fare discount, could be effective to make people shift their timings, however, a certain group of people were unwilling to change their departure times majorly due to inflexibility in timings at their work, prior commitments. In case of early departure, getting proper sleep was a major factor for not traveling early. In case of late departure, one of the major constraints was shifting departure time from work to home-end of the trip. A significant number of people (37%) were willing to depart early by 30 minutes to avail the incentive of 30% fare discount. Comparatively, less people were willing to depart late (21%) for the same fare discount (Henn et al., 2011).

In 2009, in the Netherlands, a stated preference study was conducted where approximately 1400 Dutch train commuters were offered a choice between two passes for train travel between the Hague and Utrecht (Bakens, Knockaert, & Verhoef, 2010). One was their regular pass, the other was an 'off-peak hour pass' which was cheaper but was not valid between peak hours. Respondents were asked to indicate their pass preference and how they would adapt their journeys. It was found that departing early had less disutility than departing late, and a majority of the population which opted for off-peak hour pass would either depart early or late. Very few selected a combination of early, late and peak-hour travel. However, in 80% of choice situations, respondents chose to opt for their usual pass (Bakens et al., 2010) (Liu & Charles, 2013).

Scheduled Delay Early and Scheduled Delay Late (Peer, Knockaert, & Verhoef, 2016) (Hendrickson & Kocur, 1981) which refers to the time by which train passengers change their departure time to depart early or late respectively are popular terms used in models and experiments related to departure time change for peak avoidance. The time based differential fare system has been a successful measure in promoting travel during off-peak hours (Peer et al., 2016). Between 2012 to 2013, another experiment was conducted in the Netherlands which was carried out for months where 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 Dutch train travelers, as the participation was voluntary yet the results showed a 22% drop in peak hour travelers amongst the participants. The value of Scheduled Delay Early (SDE) was found to 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 (SDL) was found to be 5.6 Euros in the morning and 4 Euros per hour in the evening. This result shows that departing early has more disutility than departing late, however other researches show that people would rather travel early than late. Contrary to other research, this study found no relation between departure time change and on-board crowding, but this is possibly because passengers in the Revealed Preference experiment were uninformed about the crowding levels in train options. The study points out that a time based differential fare system is more cost efficient than increasing the supply during peak hours (Peer et al., 2016).

From all such research, it is inferred that people are more likely to depart early than late, and peak hour crowding can be avoided by a differential fare system. To make all this possible, there should be flexibility available to commuters to change their departure times. Government should promote policies which allow for staggered work hours (Liu & Charles, 2013), however, it is recommended to do a pilot study before implementing such policy on a wide scale (Thorhauge et al., 2020).

3 Survey design and data collection

As the research revolves around the problem of overcrowding during rush hours in trains, only train users in the Netherlands are asked to take the survey. They are asked to assume a context of morning commute to work/education using trains. Considering only train commuters during rush hour would have been more relevant but it would have compromised the number of participants in the survey. It is assumed that any train user could successfully imagine the scenarios presented in the choice experiment.

3.1 Choice experiment

Based on the factors mentioned in the literature review (section 2), three attributes and one context variable are selected for the design of choice experiment. As a context variable multiplies the number of choice sets with its number of levels (Molin, 2019c), to keep the experiment as concise as possible, four levels for each attribute are selected (Hensher, Rose, & Greene, 2015). On-board crowding level is indicated as the number of seats occupied in a train car by means of graphics and numerical information. Departure time change or scheduled delay is indicated as minutes of delay from one's usual time of departure, and fare discount is indicated as percentage of discount offered on full fare. The context of the vaccination stage has three levels which indicates the share of the fully vaccinated population in the Netherlands. The respondents are provided with details on the ongoing infection risk in each case. In table 4 different levels of attributes in the choice experiment can be seen.

Generally, people who shift their departure time (schedule delay (H. Li et al., 2018) (Thorhauge et al., 2020)) prefer to depart either late or early (Bakens et al., 2010) (Liu & Charles, 2013). Therefore, the experiment is designed to independently assess the two scheduled delays. Only two train alternatives are presented to the respondents as people are already segregated in early and later departing categories. These alternatives are unlabelled as no meaning is required to be associated with them. Both the alternatives have same attributes and same attribute levels, hence the utility equation is the same for both the train options. And as individual characteristics are also constant across both the alternatives in all choice sets, these are introduced as interaction effects. Vaccination stage is also a variable in the choice experiment, but it is a contextual information and hence it remains the same across the two alternatives in a choice set. Only the attributes which vary across all alternatives in a choice set are introduced in the utility equation as main effect (Hensher et al., 2015). This is elaborated in detail in section 4. The choice sets for the experiment are generated in Ngene and are orthogonal fractional-factorial in design as this design is practicable, manageable and it makes the estimated parameters reliable (Molin, 2019b). The orthogonal choice sets consisted of eight choice sets in each block. After removing the dominating choice sets and adding the context information the resultant experiment had fifteen choice sets in each block. An example of a choice set is shown in figure 1.

3.2 Background information

In the decision to schedule delay, apart from socio-demographic characteristics such as income, gender, employment, age etc., attitude, lifestyle, travel mode preferences and travel characteristics are also found to be influencing factors in choice making (Haustein, Thorhauge, & Cherchi, 2018) (Thorhauge et al., 2020). Factors such as living with family and children constrain a person in changing departure time as this decision is linked with activities or schedules of other family members, especially of 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). Attempts are being made to link mode choices to health related individual factors(Boniface, Scantlebury, Watkins, & Mindell, 2015), and health indicators such as BMI (Body Mass Index) have been used previously to study such relationships (Barbour, Zhang, & Mannering, 2019). As this research is linked with the COVID-19 pandemic, some background information is 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 is divided into three broad categories: *Socio-demographics, Travel and work related factors, Attitude 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 circulated using social media platforms and used for data collection. The data was collected between April 2021 to May 2021 when the Netherlands was in partial lockdown phase and vaccination had started. After data processing and removing incomplete responses where the choice experiment was incomplete,a total 120 respondents were processed further in the scheduled delay early group and 62 respondents were processed further in the Scheduled Delay Late group (N=182). In graphs shown in figure 2 and 3 distribution of respondents across different background variables is illustrated. In table 3, socio-demographic characteristics of respondents are compared with data on train travelers within the Netherlands (CBS, ODiN, 2019) and data on population of the Netherlands (CBS, 2019). The data of the year 2019 is chosen for comparison as that is the year just before the pandemic began. Although the sample is not representative of Dutch population who travel by train, it is still a significant representation of a large segment of population in the Netherlands which could be useful in study of travel behavior. An article by TU Delta in 2019 also shows that changing departure time of a certain group can also considerably reduce crowding in trains during peak hours (Delta TU Delft, 2019). Entire set of respondents have at least received Bachelor level education. 47% of the population is student and 44% is employed and not a student. In this experiment only train travellers within the Netherlands are considered as the scenarios in the experiment would be of at least some relevance to them.

From the data collected on travel and health related factors it was observed that approximately 30% respondents say that they are willing to work from home at least few days a week even after the pandemic is over, which could reduce traffic on roads and pressure on public transports in the

Netherlands (Delta TU Delft, 2019) (KOGI, 1979). Respondents have indicated a higher level of discomfort due to crowding during the pandemic than before the pandemic which is expected as crowding in confined environment such as that of public transport increases the chances of catching an infection such as COVID-19 (LUMC-COVID-19 Research Group et al., 2020) (Goscé & Johansson, 2018). A 5% drop can be seen in the everyday use of train/PT as reported by respondents, even in the scenario when the pandemic will be over. This might be a concern for train/PT operators.

Amongst 182 respondents only 8% have been diagnosed with COVID-19, but 41% respondents' close ones had it. 23% respondents have surely indicated that they would like to continue wearing masks in PT travel. 39% respondents are willing to register their train journey in advance to help to mitigate crowding in PT. 46% respondents said that they may register. Such a population can be targeted and motivated to register as well. This would be helpful in predicting crowding in PT. Only 26% of the respondents have no flexibility at all in arrival time at their destination of work or education. Respondents were presented with a scenario in which they were informed beforehand that 95% seats are occupied in their usual train, and they were asked whether they would depart early, late or at the same time. Only 33% respondents chose to depart at the same time. Overall, 65% of the respondents would rather depart early than late.

4 Model estimation

To analyze the choices made by respondents in the Stated Choice survey of this research, discrete choice models based on random utility maximization principle were used here which simplifies the complexity of true behavior to the form of a model (McFadden, 1999). In this study a MNL (Multinomial Logit) model is developed initially to set a comparison for LCCM (Latent Class Cluster Model). A standard MNL model fails to capture heterogeneity across individuals, and if heterogeneity exists in the data, then MNL models can give biased results (Wen & Lai, 2010). To capture the heterogeneity in the data set collected, latent class cluster models (LCCM) are a popular choice, and have been successfully used before in departure time change experiments (Thorhauge et al., 2020). The basic utility equation (deterministic part of scheduled delay early and late models) without background variable effects which is used in base MNL model estimation and selection of number of classes in LCCM is:

$$\begin{aligned} V_i = \; & \beta_{CR2} * Crowd_{18i} + \beta_{CR3} * Crowd_{27i} + \beta_{CR4} * Crowd_{34i} + \beta_{fare} * Fare_i + \beta_{dep} * Dep_i \\ & + \beta_{vacstage2*crowd} * VaccStage2 * Crowdlevel_i + \beta_{vacstage3*crowd} * VaccStage3 * Crowdlevel_i \end{aligned} \tag{1}$$

Here 'i' represents the train alternative. Details on the levels of all these attributes can be found in table 4. The ASC parameter was found to be insignificant, and did not contribute significantly in improving the fit of the model, hence ASC was removed from model specifications.

4.1 Multinomial Logit Model

Multinomial Logit models are one of the simplest and most extensively used random utility models (Ben-Akiva & Lerman, 2018) (Bierlaire, 1998). In MNL models the probability of a respondent 'r' to choose an alternative 'i' is computed as:

$$P_{ir} = e^{V_i} / \sum_{i=1}^{I} V_{ir} \tag{2}$$

Here 'I' represents a set of all alternatives in the choice experiment which is two in this study. As the experiment conducted in this research is unlabeled, there is no meaning of alternative labels (Hensher et al., 2015), hence there is no meaning of the probability of choosing an alternative. After testing the utility equation for both the models of scheduled delay early and later with different interaction terms and attributes, the utility specification obtained for each case is: **Scheduled delay early**

$$\begin{aligned} V_i = \; & \beta_{CR2} * Crowd_{18i} + \beta_{CR3} * Crowd_{27i} + \beta_{CR4} * Crowd_{34i} + \beta_{fare} * Fare_i + \beta_{dep} * Dep_i \\ & + (\beta_{vacc*crowd} * Vacc + \beta_{cr*crowd} * Discom + \beta_{spreadCOV*crowd} * SpreadCOV + \\ & \beta_{cathcCOV*crowd} * CatchCOV) * Crowdlevel_i + (\beta_{stu*dep} * Student + \beta_{Gen*Dep*Liv} * Gender * Liv) * Dep_i \end{aligned} \tag{3}$$

Scheduled Delay Late

$$V_i = \beta_{CR2} * Crowd_{18i} + \beta_{CR3} * Crowd_{27i} + \beta_{CR4} * Crowd_{34i} + \beta_{fare} * Fare_i + \beta_{dep} * Dep_i$$
$$+(\beta_{vacc*crowd}*Vacc+\beta_{cr*crowd}*Discom+\beta_{spreadCOV*crowd}*SpreadCOV+\beta_{cathcCOV*crowd}*CatchCOV+$$
$$\beta_{car*crowd} * Cars\beta_{Health*crowd} * HealthPercep) * Crowdlevel_i + \beta_{Gen*Dep*Liv} * Gender * Liv * Dep_i \quad (4)$$

The description of each variable can be found in table 5. For this research a 10% significance level (t-ratio >1.65) is chosen to decide whether a parameter has a significant effect on the model or not. A high threshold of p-value is selected in this research so that at least the sign of background variables which may be lost because of a very high threshold is captured (Yap, Correia, & van Arem, 2015). The significant taste parameters are simply kept in the model, however, the decision to keep or remove an insignificant parameter in utility specification is taken by Log-likelihood (LL) ratio test in which log-likelihood of models with and without the insignificant taste parameter is compared using a chi-square significant test. Note that this test is only possible when models can be nested (Chorus, 2019).

4.2 Latent Class Choice Model

The LCCM divides 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). In development of LCCM, generally an underlying MNL model specification is used (Equation 1). The first step is to select the number of classes and then the final model with the selected number of classes is developed. A class membership function is also added to the selected model to allow for the effect of background variables in the model (Hess, 2014). To select the optimum number of classes first the the models with different number of classes are compared with each other in terms of Bayesian Information Criteria (BIC (Schwarz, 1978)). Number of classes where the local minima of BIC lies is generally selected, however in this study the number of classes are also selected by ensuring that the classes are non-trivial in size, and they are interpretable with assigned meaningful labels. BIC is preferred here over AIC as it imposes a more stringent penalty on the number of parameters (Walker & Li, 2007) (Wen & Lai, 2010). Along with this criteria, The probability of an individual 'r' to select an alternative 'i', whose probability of belonging to class 's' is π_{rs}), is given in equation 5. β_s represents the taste parameter vector for a class 's' and 'S' represents a set of all classes (Shelat et al., 2021) (Hess, 2014):

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

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

Here γ_{sk} and z_k are class membership coefficients.

4.3 Marginal rate of substitution

In this research, to analyse preferences, two marginal rates of substitution are computed. First is between scheduled delay and discount on fare, and the other one is between on-board crowding level and scheduled delay. It is known that on-board crowding has non-linear effect on utility function (Whelan & Crockett, 2009) (Shelat et al., 2021), that is why on-boarding crowding is effect coded, which results in different taste parameters for each level of on-board crowding. To compute the marginal rate of substitution for on-board crowding and departure time change following process is followed (Shelat et al., 2021):

$$\beta_{crowd:g \rightarrow g+1} = (\beta_{crowd:g} - \beta_{crowd:g+1})/(x_g - x_{g+1}) \tag{7}$$

$$MR'_{g \rightarrow g+1} = \beta_{crowd:g+1} * (x_g - x_{g+1})/\beta_{delay} \tag{8}$$

$$MR' = (\sum_g MR'_{g \rightarrow g+1} * (x_{g+1} - x_g))/(\sum_g (x_{g+1} - x_g)) \tag{9}$$

$crowd : g \rightarrow g+1$ indicates the change in crowd level from 'g' to 'g+1'. MR' is the marginal rate of substitution of crowd and scheduled delay for the effect coded part of the utility equation. The overall marginal rate of change of crowd and scheduled delay is obtained as a sum of marginal rate of effect coded part (MR') and interaction part.

5 Result of models

5.1 MNL model

The results from the MNL model for scheduled delay early and late can be found in table 6. Log-likelihood (LL) and adjusted rho-square values of both the MNL models indicate that the model fit is good and the estimated model is not coincidental. As LL and rho square values compare the model fit in a relative manner, it is difficult to comment more on the model based on these values (Chorus, 2019).

All the parameters derived for main effect attributes are significant ($p<0.02$) and of expected signs. When the crowding level is $<=50\%$, it has positive utility. It is notable that the group of people who chose to depart late show a steeper change in utility, and also have higher utility (and disutility) with changing crowd levels. Clearly, the group of people who chose to schedule delay late are willing to delay more than people from Scheduled Delay Early group to have one less person on-board. However, later departing people derive slightly (6%) higher disutility from scheduled delay than earlier departing people which could be because people do not want to arrive late at work/education (Thorhauge, Haustein, & Cherchi, 2016), whereas people who choose to depart early may have a limitation on how early they can depart because of sleep schedule (Henn et al., 2011). The parameter for interaction between vaccination stage and on-board crowding is significant ($p<0.01$) and of expected signs for both the models. There is a positive relationship between on-board crowding level and vaccination stages which indicates that at higher vaccination stages people will become less averse to on-board crowding.

Few background variables are introduced in the utility specification as interaction effects to improve the model fit (refer equation 3 and 4 and table). Variable which represents student interaction with scheduled delay is significant ($p<0.01$) in scheduled delay early group, and its coefficient has a negative sign which indicates that students are less willing to depart early. Female respondents who live with their family are found to be less willing to schedule delay ($p<0.05$) in both the models. Respondents who indicated that they are concerned that they could spread COVID-19 to others are found to be less crowd averse which is counter-intuitive to what was expected, however, respondents who indicated that they are concerned about getting infected from COVID-19 are more averse to crowding which is as expected. Similarly, respondents who have indicated higher discomfort from on-board crowding in public transport (for during the pandemic time) are more averse to on-board crowding ($p<0.01$) which is sensible. Coefficient of interaction between number of cars owned and on-board crowding level is found to be positive and significant ($p<0.01$) in schedule delay late group of people which is counter-intuitive as people with cars can avoid using trains. This could be an anomaly because of less representation of people having cars in their household in the sample. Respondents with higher health satisfaction are found to be less averse to on-board crowding ($p<0.10$) in the Scheduled Delay Late group of people, which is reasonable because people who find themselves in good health may also consider themselves in a lower risk group.

The real world departure time change experiment which was conducted in the Netherlands between 2012-2013 where train commuters were rewarded to schedule delay outside peak hours, β_{SDL} for morning delay late was estimated to be -0.02/minute and β_{SDE} for morning delay early was -0.024/minute (Peer et al., 2016) (refer section 2 for more details). The sensitivity to departure time change found in this experiment is higher than before. In nine years the behavior of people might have changed a little but this difference could also be because the construct of experiment is quite different from that time. In this experiment there is no reward to travel outside peak hours. People now get off-peak travel discounts (NS, n.d.). Yet it is good to observe that the order of values is comparable.

5.2 LCCM: Scheduled Delay Late

In table 8, results from 2-class LCCM 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: Crowd indifferent travelers From results in table 8 it can be observed that the share of respondents belonging to this class is 54.8%. The coefficient of crowding is insignificant (p>0.10) for the two crowding levels 50% and 75% which means that this class is not affected by crowding unless the train becomes overcrowded, i.e., crowding level is 95% and around 34/36 seats are occupied. At this level, the class derives significant disutility from on-board crowding ($\beta_{CR4} = -1.381$). This class is moderately averse to scheduled delay ($\beta_{dep} = -0.065$) and would enjoy a discount on full fare ($\beta_{fare} = 0.059$). Change in behavior of respondents can be observed when vaccination stage 3 is attained, i.e., more than 90% residents of the Netherlands are vaccinated. At this stage the respondents become less averse to crowding.

In the class membership function two background variables were found to be significant to differentiate the behavior in two classes. In this class, respondents who have indicated more flexibility in arrival time at their work or education are over represented. Crowding is associated with perceived risk of catching an infection such as COVID-19 (LUMC-COVID-19 Research Group et al., 2020), hence older people are expected to be more crowd averse. It makes sense that this class has more share of younger respondents as this class is less averse to on-board crowding in comparison with Class 2. In comparison with Class 2, the coefficient of scheduled delay is less for Class 1. It can be inferred that having more flexibility in arrival time at the destination makes this class moderately less averse to scheduled delay. Less aversion to crowds and scheduled delays also allows this class to value discounts on full fare more than Class 2 as they may choose an alternative with more discount which is available later.

Class 2: Crowd conscious travelers The share of respondents who belong to this class is 45.2%. The behavior of respondents in this class is more in line with previous researches (Whelan & Crockett, 2009) which state that crowding levels inside a vehicle has non-linear effect and disutility due to crowding starts somewhere around 80% seat occupancy rate (Tirachini, Hensher, & Rose, 2013). In this class the respondents derive high utility from train rides where they can comfortably sit alone with high chances of getting the adjacent seat vacant. At crowding level 3 (75% seats are occupied) disutility is indicated (β_{CR3}=-1.243) and it becomes very high when the train is crowded to 95%.seat occupancy (β_{CR4}= -3.868). This class of respondents are moderately averse to scheduled delay and they derive positive utility from discounts offered on full fare. At vaccination stage 3 (when more than 90% residents of the Netherlands are vaccinated), the members of this class also become less averse to crowding. Compared to Class 1, this class shows a more steep change in behavior at vaccination stage 3. This is expected because this class is more averse to crowding, and has a higher share of older people which indicates that they are more averse to the risk of catching COVID-19.

On comparing the marginal rate of substitution of fare discount and scheduled delay for both the classes, it can be observed that respondents who belong to Class 2 would require approximately 16% higher discount per minute of scheduled delay compared to Class 1 respondents. However, if marginal rate of substitution of scheduled delay and on-board crowding is compared then respondents of Class 2 are willing to depart approximately 3.5 minutes late to reduce one person on-board, which is 250% more than Class 1 who are willing to delay only by approximately 1 minute.

5.3 LCCM: Scheduled delay early

In the model where respondents have an option to depart early (scheduled delay early), three heterogeneous classes are identified. The results of the model can be found in table 7. The naming of these three classes is done based on their sensitivity to changing on-board crowd levels, discount offered on full fare and scheduled delays. The description of the three classes is provided below:

Class 1: Crowd conscious and inflexible travelers This class has a share of 36%, and the coefficients of parameters for less crowded trains (crowding level not more than 50%) are positive and significant (p<0.1) (β_{CR1}=1.792 and β_{CR2}=1.044). At crowding level 75% and higher, increasing disutility is observed (β_{CR3}=-0.423 and β_{CR4}=-2.413). Coefficient of interaction between crowd levels and vaccination stage 3 is positive and significant. Although the respondents within this class want to avoid crowded rides, they have very high disutility for scheduled delays for early departure (-0.102/minute). The effect of fare discount on such respondents and the marginal rate of substitution of fare discount for each minute of scheduled delay are found to be insignificant ($p>0.1$). Therefore, this class can be called as the inflexible class of respondents.

Class 2: Crowd indifferent and fare conscious travelers As shown in table 7, 31.4% of respondents belong to this class. Only when the train becomes too crowded, i.e., at 95% crowding level, the coefficient of crowd becomes significant and is of expected sign. At this level, the class derives disutility due to crowding (β_{CR4}-0.567), but this disutility is the lowest amongst the three classes identified within this model. It can be said that the respondents in this class are indifferent to crowding unless it becomes difficult for them to find an empty seat. Willingness to depart early to have one more available seat in the train is also the lowest in this class (0.4 minutes). One thing that this class has in common with Class 1 is the high disutility that it obtains from scheduled delay, but opposed to Class 1 this class values discount offered on train fare significantly ($p<0.01$). People are willing to depart early by 1 minute for approximately a 1.5% discount on train fare. With changing vaccination stages, the impact of crowding does not change significantly within this class. Therefore, it can be said that the behavior of this class will remain the same during and after the pandemic.

Class 3: Crowd conscious and flexible travelers The respondents have 0.327 probability of belonging to Class 3. Similar to Class 1, the travelers in this class enjoy comfortable and empty train rides and derive disutility from train rides with crowding levels above 75%. This class shows the lowest disutility from scheduled delay, and hence this class can be categorized as flexible in departing early. Similar to Class 2, this class would derive positive utility from train alternatives which offer discount of train fare, but the marginal rate of substitution of fare discount and scheduled delay is found to be insignificant for this class. They are willing to depart early by 1.8 minutes for 1 freer seat in train journeys. As vaccination stage advances, respondents of this class become less crowd averse.

Only one background variable is found to have significant effect on at least one class. This variable captures whether a respondent is a student or not a student (effect coding: student =1 and others =-1). Class 2 is the fixed class, and the significant effect of background variable student ($p<0.01$) was found in Class 3. The coefficient has a negative sign which shows that Class 3 has less representation of students compared to other classes. As this class represents a comparatively more flexible class than other classes in terms of scheduled delay for early departure, this could mean that the students are less willing to schedule delay to depart early.

On comparing both the early and late LCCM it is observed that respondents who choose to depart early have a lower willingness to schedule delay to have one less person on board, than the respondents who choose to depart later. This is also depicted from the graph shown in figure 4. Similar pattern is also observed in the MNL model for Scheduled Delay Late and Early departure. Crowd conscious travelers from the Scheduled Delay Late model have the highest marginal rate of substitution between on-board crowding and schedule delay, whereas crowd indifferent and fare conscious travelers from Scheduled Delay Early group show the lowest value. However, this group of people can be motivated to schedule delays by offering them fare incentives.

6 Discussion

Soon workplaces will re-open in the Netherlands, but it is instructed by the government to do so by following the norm of 1.5 meters social distance to keep people safe. Employers are instructed to allow for staggered work hours and people are encouraged to work from home as much as possible (DLA Piper, 2021). Without flextime and staggered commute, people won't 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 societal cost benefit analysis can be conducted by train operators to study if providing fare discounts is more economically beneficial for them and also in managing overcrowding, or increasing supply of trains during rush hours. A policy proposal for real-time crowd management inspired from the policy proposed in the departure time change experiment conducted in Beijing in 2018 (H. Li et al., 2018) is to offer discounts on train fare in real-time based on expected overcrowding. Such a policy requires a system to predict demand during rush hours and to predict the timing of peak rush on a day to day basis, and offer this information to train passengers. To motivate people to shift departure time to reduce crowding, fare discounts can be proposed in real-time for different time windows. To make such policies, real world experiments and pilot studies are required. Providing such real-time information on crowding level in trains without any other incentive could itself motivate certain groups of people to shift their departure time. Such a group of people are represented in a latent class group of people who are willing to depart early (Class 3: Crowd conscious and flexible travellers subsection 5.3).

Managing overcrowding in public transports would not only make public transports more comfortable and attractive, it can also decrease the risk of catching ARIs such as COVID-19 while traveling.

Such policies are 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. Other public transport operators such as GVB, HTM, Qbuzz, Syntuss, NS, Arriva, Connexxion, Transdev and RET may also be affected as their demand would change directly as the attractiveness of trains may increase, and indirectly as the demand of these transport modes used for access/egress to/from train stations may change. Government authorities and policy makers would be involved in development and implementation of such policies. Companies who offer railway information through software applications such as 9292, Google Maps etc. could provide information on expected crowding level in trains in their applications. Other organizations may be involved in developing highly predictive models. ProRail, who are the infrastructure managers of train platforms, may also benefit from such policies as there will be changes in passenger demand during rush hour. Environmentalists are expected to be in support as such policies would increase the attractiveness of public transports. Medical facilities and authorities are also expected to support such models and policies as it may dampen the spread of COVID-19 infection by reducing overcrowding in train stations. Cooperation and support is required from public transport users and employees of companies which offer flex hour/staggered commute for a successful implementation.

Limitations and recommendations: One of the limitations to this research is that the data collected from the survey is non-representative of Dutch population, however the results show a high significance level which indicates 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 are a simplified version of reality, and to develop such simplified yet informative models assumptions are made. In this research, it is assumed that when people change departure time, they would either like to depart early or later than usual. Selection bias correction is not applied in this research as it is in itself a complex process. It is recommended to perform a posterior analysis to understand how attitude related factors influence the probability of an individual to belong to a class in LCCM. Another research can be conducted to understand the psychological impact of COVID-19 pandemic on travel behavior of people. The last recommendation is to conduct an experiment to understand how people value health in making transport mode choices, and to include the risk of catching an infection as a health aspect. Such attributes in choice models can help to improve the predictability of models.

7 Conclusion

Since a few decades, several experiments have been conducted to measure the disutility of crowding and to mitigate it. The best indicator of crowding in trains is found to be percentage or ratio of seats occupied (load factor) and passenger density (number of passengers standing per meter square). To apply the disutility of crowding in transit systems it can either be translated into monetary terms or time value, but time multipliers are more popular and easy to interpret (Z. Li & Hensher, 2011). To mitigate crowding, 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 is conducted in the Netherlands to understand the extent to which people can be motivated to change departure time to avoid crowded trains with an incentive of discount on train fare. This study is performed in a hypothetical context of increasing vaccination stages.

65% people indicated in the survey that they would like to depart earlier than later in a post-pandemic scenario. Similar to previous experiments, the disutility obtained from Scheduled Delay Early is found to be less than Scheduled Delay Late (Bakens et al., 2010), but group of people who chose to schedule delay late are willing to delay more than people from Scheduled Delay Early group to have one less person on-board. This may be because people have difficulty in being too early due to their sleep schedule (Henn et al., 2011). On-board crowding level is found to have non-linear effect (Douglas & Karpouzis, 2006) (Shelat et al., 2021) and disutility starts at 75% seat occupancy rate which is at 5% lower level than stated in other research (Tirachini et al., 2013). It could be said the COVID-19 pandemic made people in the Netherlands more crowd sensitive than before the pandemic.

Nearly all the classes in LCCM of Scheduled Delay Early and Late groups have the same share of respondents. In LCCM of Scheduled Delay Late group of respondents, two heterogeneous classes are found: Crowd Conscious class (Class 2) which enjoys empty trains and has high and increasing disutility from crowding as trains become crowded, and Crowd Indifferent class (Class 1) which is only affected by crowding when it becomes overcrowded (more than 95% seats are occupied). Class 1 (Crowd Conscious and Inflexible class) of Scheduled Delay Early group is the most rigid class to motivate to change departure times. Class 2 (Crowd indifferent and fare conscious travelers) obtains high disutility from scheduled delay similar to Class 1, but this class obtains the highest utility from fare discount. This class can be motivated to schedule delays by offering them discounts on fare. Class 3 (Crowd conscious and flexible travelers) in Scheduled Delay Early groups is the most ideal class to motivate for departure time change. They are highly sensitive to on-board crowding; they have low sensitivity (disutility) towards scheduled delay, and they are moderately sensitive (positive utility) to fare discount.

In the Scheduled Delay Early model of LCCM, it is found that less students are represented in Class 3 which is the most flexible class. This indicates that students are more sensitive to depart earlier than usual. In Scheduled Delay Late model of LCCM it was found that Class 1 which is crowd indifferent has a higher share of younger people in comparison with Class 2 which is crowd conscious, which makes sense as crowding is associated with perceived risk of catching an infection such as COVID-19, and older people are expected to be more crowd averse. Class 1 also has a higher share of people with more flexible work hours. Coefficient of vaccination stage and on-board crowding level is found to be positive and significant in MNL models for Scheduled Delay Early and Late groups, and in both LCCM (except for Class 2 of Scheduled Delay Early group) the coefficient of vaccination stage 3 is found to be positive and significant. It shows that as more people are vaccinated, people become less averse to on-board crowding in trains. Background variables such as gender, frequency of using trains which were found significant in previous researches (Shelat et al., 2021) (H. Li et al., 2018) (Peftitsi, Jenelius, & Cats, 2020) (Whelan & Crockett, 2009) have no effect in LCCM estimated in this research. It could be because COVID-19 pandemic has changed travel behavior. Disutility of scheduled delay has increased in comparison with a previous real life experiment conducted in the Netherlands (Peer et al., 2016) which could be because nine years back there was no peak and off-peak based fare deferential system, and people who participated in the experiment were rewarded, however, it is good to observe that the coefficients are in a comparable range.

The data collected on background information in the survey indicates that 67% respondents would either like to depart early or later to avoid overcrowded trains in a scenario where more than 90% people are vaccinated in the Netherlands. Only 15% of people would not like to register train journeys in advance to help to reduce crowding in trains. And 48% of people indicated that they would definitely not prefer to wear masks in public transport after the pandemic. From this research it can be concluded that few groups of people may choose to change departure time to simply avoid crowds in trains if they are provided with prior information on crowding level in trains, but most of the groups can be motivated to schedule delays by offering them discounts on train fare or other benefits. To allow more people to have such an option, policies such as work from home, staggered commute and flexible work hours are required in workplaces. Along with friendly policies, a system needs to be developed to predict demand and offer discounts based on the scheduled delay required.

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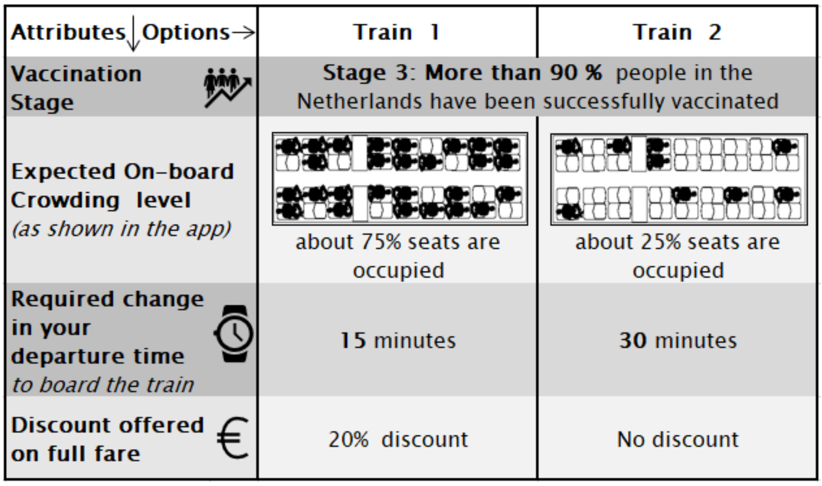
Tables and figures



Attributes↓ Options→	Train 1	Train 2
Vaccination Stage	**Stage 3: More than 90 %** people in the Netherlands have been successfully vaccinated	
Expected On-board Crowding level *(as shown in the app)*	about 75% seats are occupied	about 25% seats are occupied
Required change in your departure time *to board the train*	15 minutes	30 minutes
Discount offered on full fare	20% discount	No discount

Figure 1: Example of a choice set from choice experiment of this research

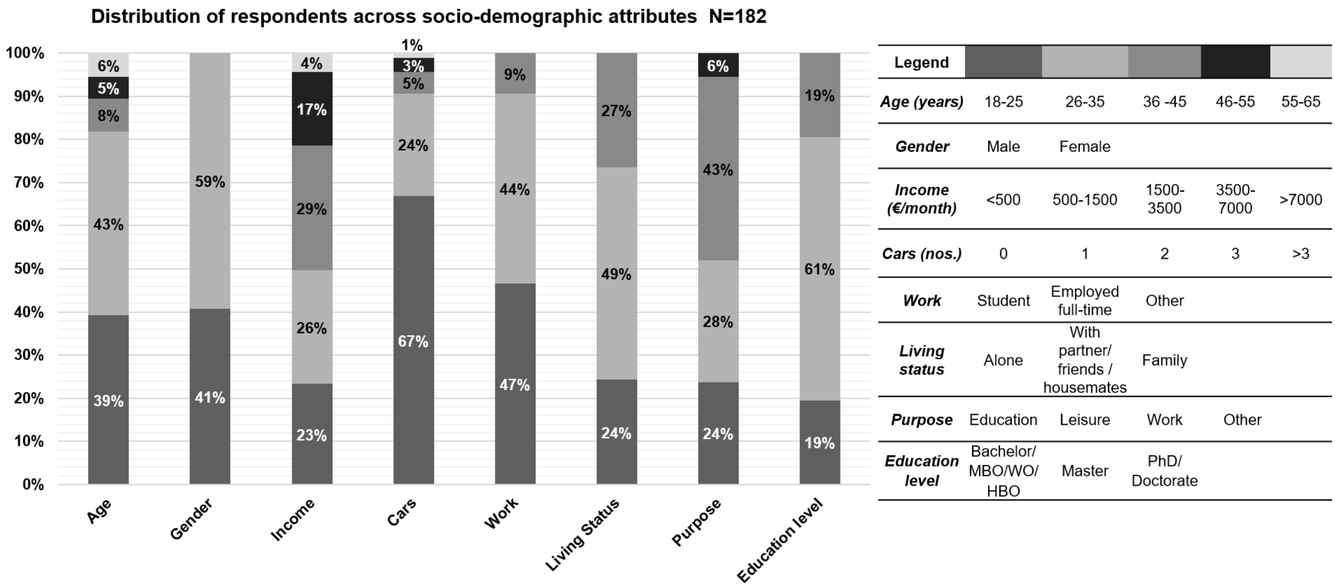


Figure 2: Background characteristics of data collected in the survey I

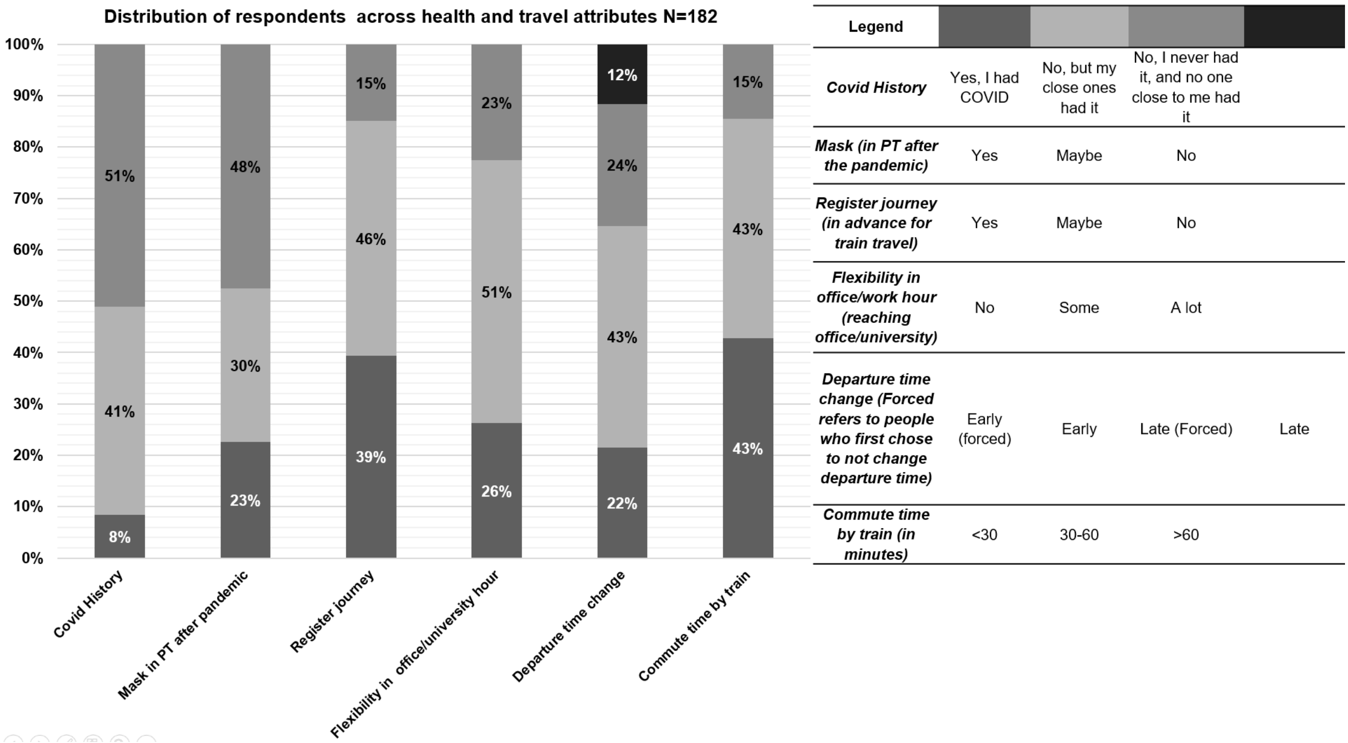


Figure 3: Background characteristics of data collected in the survey II

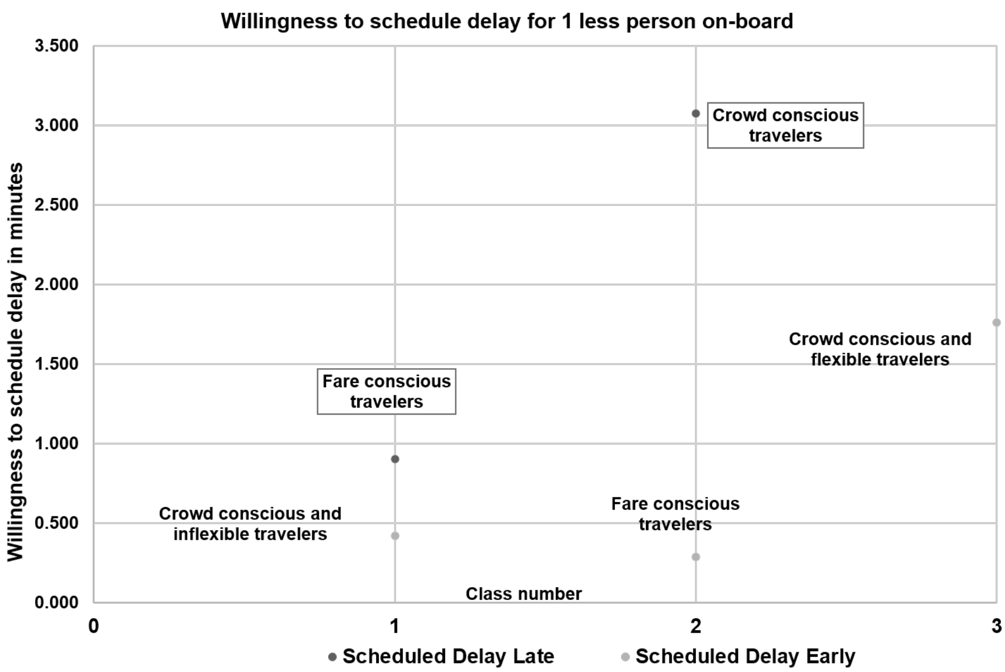


Figure 4: Willingness to schedule delay for one less person on-board- LCCM model

Table 1: Valuation of crowding experiments (Karpouzis & Douglas, 2005)(Douglas & Karpouzis, 2006)(Lu et al., 2008)(Whelan & Crockett, 2009)(Batarce et al., 2015) (Hörcher et al., 2017)(Yap et al., 2020)(Shelat et al., 2021)

S. No.	Research title	Crowding location	Indicator of crowding	Method	Trade-off for crowding	Value of crowding (measurement)
1	*Estimating the Passenger Cost of Station Crowding (2005), Sydney*	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 (2006), Sydney*	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 (2008), UK*	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 (2009), UK*	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 (2015), Santiago*	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 (2017), Hong Kong*	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 (2018), the Hague*	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 [Working paper]. (2020), the Netherlands*	In-Vehicle (Train)	Number of seats occupied	SP	Waiting time and crowding levels in different contexts of infection risk	Waiting time multiplier
9	*Departure time change to avoid crowd in trains -A stated choice experiment study in the Netherlands with a pandemic context(2021, Master thesis)*	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

Table 2: Departure Time Change Experiments (O'Malley, 1975)(Bakens et al., 2010)(Henn et al., 2011)(H. Li et al., 2018)(Peer et al., 2016)(Thorhauge et al., 2020)

S. No.	Research title	Method	Alternatives and attributes	Findings
1.	*Transportation Research Board Special Report (1975), Manhattan, New York*	Experiment with 220,000 people	Staggered commute with at least 30 minutes early or later departure in the morning	Reduced congestion at busiest subways by 26%
2.	*Rewarding Off-Peak Railway Commuting: A Choice Experiment (2010), the Netherlands*	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 (2011), Sydney*	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 (2016), the Netherlands*	RP Experiment between 2012 to 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% 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 (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. Affect of crowding was insignificant.
5.	*Heterogeneity in departure time preferences, flexibility and schedule constraints (2020), Copenhagen*	SP Experiment on Car users with 24 hours trip diary as responses	Departing on-time, later or earlier using a hypothetical toll ring. Cost of the toll ring varied with departure time.	People are constrained by household composition and flexibility at workplace in changing departure time.
6.	*Departure time change to avoid crowd in trains -A stated choice experiment study in the Netherlands with a pandemic context (2021, Master thesis)*	Respondents divided into early and late group. SP Experiment with unlabeled train alternatives	Two unlabeled train alternatives in same context of vaccination stage and which vary in: scheduled delay, on-board crowd levels and discount on full fare	Expectations: Fare discount and prior information on crowding level in trains can motivate some people to schedule delay. Heterogeneity expected in respondents.

Table 3: Comparison of socio-demographic statistics of collected data with socio demographics of the Netherlands and train travelers (CBS, ODiN, 2019)

Background Variable	Data collected (N=182)	Train users in the Netherlands (2019)	Population of the Netherlands (2019)
Age			
18-25	39%	16%	10%
26-35	43%	18%	12%
36-45	8%	16%	12%
46-55	5%	17%	15%
56-65	6%	16%	13%
>65	-	17%	19%
Gender			
Female	41%	53%	50%
Male	59%	47%	50%
Education	100% high education	56% high education 44% below university level education	-
Bachelor/MBO/WO/HBO	19%		
Master	62%		
PhD and higher	19%		

Table 4: Main effects with contextual attribute in the models

Attribute	Levels	Type of variable	Code	Coefficients
		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)	-1 -1 -1 1 0 0 0 1 0 0 0 1	$-(\beta_{CR1} + \beta_{CR2} + B_{CR3})$ β_{CR1} β_{CR2} B_{CR3}
Fare discount	0% 10% 20% 40%	Scale (Numeric)		β_{fare}
Scheduled delay (early/late)	15 min 30 min 45 min 60 min	Scale (Numeric)		β_{dep}
		Contextual variable		
Vaccination stage (interaction with changing crowding levels)	30-50 % 60-80% >90%	Ordinal (Effect Coded)	-1 -1 1 0 0 1	$-(\beta_{vacstage1*crowd} + \beta_{vacstage2*crowd})$ $\beta_{vacstage1*crowd}$ $\beta_{vacstage2*crowd}$ $\beta_{vacc*crowd}$ (when vaccination stage is taken as ordinal, non-coded attribute)

Table 5: Background variables with significant effect in choice models

Background variable	Levels	Type of variable	Code	Coefficient
Age	18-25 26-35 36-45 46-55 56-65 >65	Ordinal	1 2 3 4 5 6	β_{Age}
Gender	Female Male	Categorical (Effect Coded)	1 -1	$\beta_{Gen*Liv*Dep}$
Flexibility in work/ education hours	No flexibility at all Some flexibility A lot of flexibility	Ordinal	1 2 3	β_{flex}
On-board crowding discomfort level before the pandemic	Not at all Slightly Uncomfortable Moderately Very	Likert Scale	1 2 3 4 5	$\beta_{Cr*Crowd}$
Student or not	No Yes	Categorical (Effect Coded)	-1 1	$\beta_{stu*Dep}$
Number of cars in a household	0 1 2 3 More than 3	Scale (Numeric)	0 1 2 3 4	$\beta_{car*Crowd}$
Living with family	No Yes	Categorical (Effect coded)	-1 1	Same as gender
Concerned about spreading COVID-19	Don't agree Somewhat disagree Neutral Somewhat agree Highly agree	Likert Scale	1 2 3 4 5	$\beta_{SpreadCOV*Crowd}$
Concerned about catching COVID-19				$\beta_{CatchCOV*Crowd}$
Good health perception				$\beta_{Health*Crowd}$

Table 6: Results from MNL model for early and late departure

MODEL FIT		SCHEDULED DELAY EARLY		SCHEDULED DELAY LATE	
LL(start)		-1247,69		-644.63	
LL(final)		-1013,94		-473,29	
Adj Rho-Square		0.18		0.25	
BIC		2049,89		1028,61	
AIC		2110,34		970,58	
Number of parameters		11		12	
Number of respondents		120		62	
ESTIMATED PARAMETERS					
	Variable Description	Coeff	t-ratio (p-value)	Coeff	t-ratio (p-value)
Attributes in choice sets	On-board seat occupancy (crowding level) 25% (9/36 seats occupied)	1.845	-	2.720	-
	Crowding level 50% (18/36 seats occupied)	0.702	6.52 (p<0.01)	0.912	4.29 (p<0.01)
	Crowding level 75% (27/36 seats occupied)	-0.424	-3.46 (p<0.01)	-0.614	-2.43 (p<0.02)
	Crowding level 95% (34/36 seats occupied)	-2.123	-8.84 (p<0.01)	-3.018	-5.49 (p<0.01)
	Scheduled delay (early/late)	-0.051	-12.50 (p<0.01)	-0.054	-8.35 (p<0.01)
	Discount on full fare	0.027	5.18 (p<0.01)	0.049	5.66 (p<0.01)
	Vaccination stage and on-board crowding level interaction	0.048	9.35 (p<0.01)	0.049	6.11 (p<0.01)
Background variables	Discomfort due to in-vehicle crowding before the pandemic and on-board crowding level interaction	-0.012	-3.81 (p<0.01)	-0.028	-5.76 (p<0.01)
	Student(1= Student -1= Others) and scheduled delay interaction	-0.013	-6.19 (p<0.01)	-	-
	Concern about spreading covid and on-board crowding level interaction	0.023	4.82 (p<0.01)	0.021	3.40 (p<0.01)
	Concern about catching covid and on-board crowding level interaction	-0.022	-4.76 (p<0.01)	-0.027	-4.38 (p<0.01)
	Number of cars owned and on-board crowding level interaction	-	-	0.043	5.12 (p<0.01)
	Personal health satisfaction and on-board crowding level interaction	-	-	0.012	1.73 (p<0.10)
	Females (1= Female -1 = Male) who live with family (1= Live with family -1 = Other) and scheduled delay interaction	-0.005	-2.40 (p<0.02)	-0.007	-2.32 (p<0.05)
Marginal rate of substitution	Marginal rate of substitution of fare discount offered and scheduled delay	-1.89	-	-1.27	-
	Marginal rate of substitution for scheduled delay and on-board crowding	2.22	-	3.36	-

Table 7: Results from LCCM model for scheduled delay early

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					
ESTIMATED PARAMETERS		**Class 1**		**Class 2**		**Class 3**	
Class distribution		**36%**		**31.4%**		**32.7%**	
Variable Description		**Coeff**	**t-ratio (p-value)**	**Coeff**	**t-ratio (p-value)**	**Coeff**	**t-ratio (p-value)**
Attributes in choice sets	On-board seat occupancy (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)	-0.510	-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 and on-board crowding level	-0.151	-	-0.011	-	-0.029	-
	Interaction between vaccination stage 2 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 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)
Background variables	Student (1= Student -1 = Others)	-	-	0	-	-0.964	-3.53 (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	-

Table 8: Results from LCCM model for scheduled delay late

MODEL FIT		SCHEDULED DELAY LATE			
LL(start)		-644.63			
LL(final)		-438.65			
Adj Rho-Square		0.29			
BIC		993.49			
AIC		911.30			
Number of parameters		17			
Number of respondents		62			
ESTIMATED PARAMETERS		**Class 1**		**Class 2**	
Class distribution		**54.8%**		**45.2%**	
Variable Description		**Coeff**	**t-ratio (p-value)**	**Coeff**	**t-ratio (p-value)**
Attributes in choice sets	On-board seat occupancy (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 and on-board crowding level	-0.060	-	-0.047	-
	Interaction between vaccination stage 2 and on-board crowding level	0.013	1.14 (p>0.10)	-0.038	-1.51 (p>0.10)
	Interaction between vaccination stage 3 and on-board crowding level	0.047	3.96 (p<0.01)	0.085	4.43 (p<0.01)
Background variables	Flexibility in arrival at destination of work or education (Likert scale 1: No flexibility 3: Very flexible)	0.553	1.69 (p<0.10)	0	-
	Age (Ordinal range)	-0.786	-2.35 (p<0.02)	0	-
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	0.90	-	3.07	-

Appendix B

The code developed in Ngene to generate orthogonal choice sets in two blocks is included below:

```
?Late
design
;alts = T1, T2
;orth = seq
;rows = 16
;block = 2
;model:
U(T1) = b0 + b1*crowd[25,50,75,95] + b2*dep[30,45,15,60]+ b3*fare[0,10,20,40] /
U(T2) = b1*crowd + b2*dep + b3*fare
$
```

Figure B.1: Ngene code to generate orthogonal choice sets for choice experiment

Choice set	T1 Crowd level	T1 Scheduled delay	T1 Fare discount	T2 Crowd level	T2 Scheduled delay	T2 Fare discount	Block
1	75	15	20	25	30	0	1
3	75	45	0	50	30	20	1
4	25	30	10	50	60	10	1
2	50	60	0	75	45	0	1
3	50	30	40	75	15	40	1
4	95	15	10	95	45	40	1
5	95	45	20	95	15	10	1
14	25	60	40	25	60	20	1
1	95	15	0	50	60	0	2
2	50	30	20	95	15	0	2
3	75	45	10	95	45	20	2
4	25	60	20	75	15	20	2
12	50	60	10	50	30	40	2
5	95	45	40	25	60	40	2
15	75	15	40	75	45	10	2
16	25	30	0	25	30	10	2

Table B.1: Orthogonal choice sets generated by Ngene in two blocsk

As the alternatives are unlabeled, the utility equation of both the alternatives is the same. Minimum number of rows are kept 16 (selected from basic plan (Molin, 2019b)) so that the choice sets generated can measure taste parameters for interaction effects also in choice modelling. All the choice sets generated are presented in table B.1. The highlighted ones are clearly dominant and are removed from the experiment presented to respondents. The remaining choice sets are presented three times with different context of vaccination stages. To reduce bias, the choice sets are presented randomly.

Appendix C

Individual characteristics	Levels	Type of background information
Travel time in train for education/work related trips (if a person travels by train for such trips)	< 30 minutes 30-60 minutes >60 minutes	Travel and work
Travel purpose	Work Education Leisure Other	Travel and work
Frequency of travel using different modes (before, during and post COVID-19)	Never Less than once a month Few days a month Few days a week Almost everyday	Travel and work
Discomfort due to in-vehicle crowding and crowding in boarding/alighting (before and during the pandemic)	Not at all Slightly Uncomfortable Moderately Very	Travel and work
Flexibility of arrival time at work/education destination before COVID-19	No flexibility Some flexibility A lot of flexibility	Travel and work
Train travel frequency during peak hour before and during the pandemic	Not at all Only when necessary Few days a month Few days a week Almost everyday	Travel and work
Work from home frequency (before, during and after the pandemic)		Travel and work
Continue wearing mask in PT after the pandemic is over?	Yes Maybe No	Travel and work
Register train journeys in advance to reduce on-board crowding?		Travel and work
Covid history	Never had COVID-19, and no one close to me had it Never had COVID-19 but people close to me had it Yes, I had COVID-19	Attitude towards health and COVID-19
I am in excellent physical health (health perception)	Don't agree Somewhat disagree Neutral Somewhat agree Highly agree	Attitude towards health and COVID-19
I am generally worried about my health		Attitude towards health and COVID-19
Stress of catching COVID		Attitude towards health and COVID-19
Concern about spreading COVID		Attitude towards health and COVID-19

Table C.1: Background information collected from survey I

Individual characteristics	Levels	Type of background information
Age	18-25 26-35 36-45 46-55 56-65 66-75 >75	Socio-demographic
Income	500 €/month 500-1500 €/ month 1500-3500 €/ month 3500-7000 €/ month >7000 €/ month	Socio-demographic
Education level	Primary Education Diploma/Secondary School/HAVO MBO Bachelor WO/HBO Master WO/HBO PhD/Doctorate	Socio-demographic
Employment status	Student with no job Student with work Employed full time Employed part-time unemployed	Socio-demographic
Number of cars in a household	0 1 2 3 >3	Socio-demographic
Living status (with family or not)	Alone With friends/flatmates With family	Socio-demographic
Household composition (if family) - With grandparents; with partner; With parents; with siblings; With children < 12 years of age; 13-18 years of age; >18 years of age	Yes No	Socio-demographic
Gender	Female Male	Socio-demographic

Table C.2: Background information collected from survey II

Appendix D

The final survey circulated amongst people in the Netherlands has been attached in the following pages. It should be noted that the survey is provided here simply for reference, hence only one choice set is

Informed Consent

WELCOME!.
You are being invited to participate in a research survey related to travel choices of people within the Netherlands. This will take you approximately 10-12 minutes to complete. The data will be used for academic research only. Your participation in this study is entirely voluntary and you can withdraw at any time. We believe there are no known risks associated with this research study. To the best of our ability your answers in this study will remain confidential. We will minimize any risks by maintaining anonymity by not asking questions on identity and storing the data in TU Delft approved storage which will be accessible only to the researchers involved in the study.

Jyotsna Singh
J.Singh-8@student.tudelft.nl

- I agree to participate and I am above 18 years of age.
- I agree to participate but I never travel by trains within the Netherlands.
- No, I don't agree/ I am under 18 years of age.

A) Travel and mode choice

A) Travel Choices. In this section you will answer questions related to your travel within the Netherlands.

A.1. Before the outbreak of COVID-19 pandemic, how frequently did you use the following modes, for travel within the Netherlands?

	Never	Less than once a month	Few days a month	Few days a week	Almost everyday
Bicycle	○	○	○	○	○
Cars	○	○	○	○	○
Trains/Public Transports	○	○	○	○	○
Walk	○	○	○	○	○

A.2. What is your usual travel purpose for the train trips mentioned above?

- Work/Business
- Education

shown in this document.

- Leisure
- Other

A.2.1. For education/work travel purpose, what is your usual travel time inside trains?

- <30 min
- 30-60 min
- >60 min
- I don't travel by train for work or education

A.3. During COVID-19 pandemic, how frequently are you using the following modes to travel within the Netherlands?

	Never	Less than once a month	Few days a month	Few days a week	Almost everyday
Bicycles	○	○	○	○	○
Cars	○	○	○	○	○
Trains/Public Transports	○	○	○	○	○
Walk	○	○	○	○	○

A.4. After the COVID-19 pandemic gets over, what is your expected travel frequency using the following modes to travel within the Netherlands?

	Never	Less than once a month	Few days a month	Few days a week	Almost everyday
Bicycles	○	○	○	○	○
Cars	○	○	○	○	○
Trains/Public Transports	○	○	○	○	○
Walk	○	○	○	○	○

A.5. After the COVID-19 pandemic is over, would you prefer to continue wearing mask while travelling in public transport?

- Yes, I would prefer.
- Maybe or maybe not, depends upon the environment and surroundings.
- No, I would not prefer.

A.6. How uncomfortable do you feel, because of crowding inside trains and train stations, while travelling in the Netherlands?

	Not at all	Slightly Uncomfortable	Moderately Uncomfortable	Uncomfortable	Very Uncomfortable
In-vehicle crowding before COVID-19 pandemic	○	○	○	○	○
In-vehicle crowding during the pandemic.	○	○	○	○	○

	Not at all	Slightly Uncomfortable	Moderately Uncomfortable	Uncomfortable	Very Uncomfortable
Crowding in boarding/alighting trains before the pandemic	◯	◯	◯	◯	◯
Crowding in boarding/alighting trains during the pandemic	◯	◯	◯	◯	◯

A.7. Are you willing to register your train journeys in advance, to help train operators predict crowding better in train stations and inside trains?

◯ Yes, I am willing to register.
◯ Maybe I will.
◯ No, I am unwilling to register.

A.8. Which of the following statements best defines your employment status?

◯ I am a student and I work part-time.
◯ I am a student and I don't work part-time.
◯ I am employed full-time
◯ I am currently unemployed
◯ I work part-time.

A.8.1. When not working from home, how much flexibility in timings do you have for arrival at your destination of work/education related trips?

◯ I always have to reach on a particular time.
◯ I have some flexibility.
◯ I have a lot of flexibility. I can decide my own arrival time.
◯ I don't make work or education related trips.

A.9. Please select the most agreeable option related work/education from home, and travel statements given below.

	Not at all	Only when necessary	Few days a month	Few days a week	Almost everyday
I used to study/work from home even before COVID-19 pandemic started.	◯	◯	◯	◯	◯
During the pandemic, I have been studying/working from home.	◯	◯	◯	◯	◯
After the pandemic is over I would like to continue working/studying from home.	◯	◯	◯	◯	◯
Before the pandemic started, I used to travel by train during peak hours.	◯	◯	◯	◯	◯

	Not at all	Only when necessary	Few days a month	Few days a week	Almost everyday
During the pandemic, I travel by train during peak hours.	○	○	○	○	○

B) General Information

B) Choice Experiment. In this section you will make choices for train trip options presented in different scenarios.

Imagine-

- You have to travel by train for work/education during morning peak hours
- You use an OV-chipkaart and you pay your train fare. Ignore any existing special card or offers.
- There is flexibility in terms of arrival time at your destination, and there is an option to check the expected crowding levels in trains using a mobile app.
- For Vaccination Stage 1, when 30-50 % residents of the Netherlands are vaccinated with all doses, assume the ongoing rate of spread of infection is Level 3 out of 4, .i.e., roughly 8000 cases per day (similar to present time).
- For Vaccination Stage 2, when 50 - 80 % residents of the Netherlands are vaccinated, assume the ongoing rate of spread of infection is Level 2 (Moderate), .i.e, roughly 2000 cases per day (similar to last summer).
- For Stage 1 and 2, assume that government has relaxed restrictions. You can go to office/university or work from home. There are some restrictions related to social distancing, sanitising and wearing mask indoor and in public transports.
- For Vaccination Stage 3, i.e., when more than 90% residents are vaccinated in the Netherlands, assume the rate of spread of infection is almost negligible, and all the restrictions are removed.

B.1.
Now imagine you have to make the trip explained above when more than 90 % people are vaccinated in the Netherlands (Vaccination Stage 3). A day before your trip, you get an alert on your app that the option of train available at your usual departure time ,i.e., your usual train, is expected to be overcrowded (almost 95% seats are occupied and standing capacity with social distancing of <1m is available), and you have also known this from your experience.
How will you adapt your departure time in this scenario?

*Note: This scenario and your answer to this question would be valid in the following choice set questions as well.

○ I will depart early to catch an early train.

○ I will depart late to catch a later train.

- ○ I will not change my departure time, and board the usual train.

B.1.1. If you have to shift your departure time due to capacity constraints in trains, which option would you prefer?

- ○ I will depart early to catch an early train.
- ○ I will depart late to catch a later train.

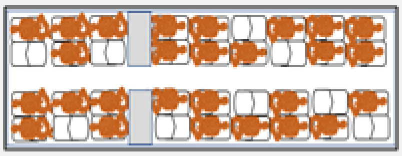
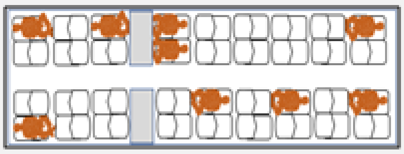
B) Train choice experiment

B.2. Choice Experiment with early train departure options-

Now, for each choice set -

- Assume you are only looking for earlier than usual train options on your mobile app, for your trip to workplace or university.
- Select the train option that you would prefer based on on-board crowding levels, discount offered on full-fare and the change in your departure time (from home) required to catch those train options in different hypothetical contexts of vaccination stages .
- If any characteristic of train alternatives is not mentioned, assume that all the train alternatives share the same characteristic as your usual train. For e.g., same travel time.

B.2) Choice Set 1.

Attributes↓ Options→	**Train 1**	**Train 2**
Vaccination Stage	**Stage 2: About 60-80 %** people in the Netherlands have been successfully vaccinated	
Expected On-board Crowding level *(as shown in the app)*	 about 75% seats are occupied	 about 25% seats are occupied
Required change in your departure time *to board the train*	**15** minutes	**30** minutes
Discount offered on full fare	20% discount	No discount

From the above two train options, which one do you prefer?

Train 1	Train 2
○	○

C) This section contains questions related to your health.

C) Health&COVID-19:. This section consists of questions related to your health and perceived risk of COVID-19 infection.

C.1. Have you been exposed to COVID-19 before?

- Yes, I was/am infected with COVID-19.
- No, I have never been tested positive with COVID-19, but my close family member / roommate / friend had it.
- No, I have never been tested positive with COVID-19, and no person close to me ever had it.

C.2. Please select the most agreeable option for the health related statements presented below.

	I don't agree.	I somewhat disagree	Neutral	I somewhat agree	Yes, I strongly agree.
I am in excellent physical health.	○	○	○	○	○
I am usually worried about my physical health.	○	○	○	○	○
I am concerned that I could catch COVID-19.	○	○	○	○	○
I am concerned that I could spread COVID-19 to others.	○	○	○	○	○

D) This section contains questions related to your socio-demographics.

D)Socio-Demographic:. This section consists of questions related to your socio-demographics.

D.1. Which age group do you belong to?

- 18-25 years
- 26 to 35 years
- 36 to 45 years
- 46 to 55 years
- 56 to 65 years
- 66 to 75 years
- > 75 years

D.2. Please select your individual gross monthly income group.

- <500 €/month
- 500-1500 €/ month
- 1500-3500 €/ month
- 3500-7000 €/ month
- >7000 €/ month

- Prefer not to say

D.3. From the options below, please select your highest level of education.

**If you are currently enrolled in a course/program, you may select its qualification.*

- Primary Education
- Diploma/Secondary School/HAVO
- MBO
- Bachelor WO/HBO
- Master WO/HBO
- PhD/Doctorate

D.4. How many cars do you have in your household?

- 0
- 1
- 2
- 3
- More than 3

D.5. Please select your province of residence within the Netherlands.

D.6. Which category best defines your household composition?

- I live alone.
- I live with my family.
- I live with my friends/housemates/partner.

D.7. Please select your gender.

- Male
- Female
- Let me type..
- Prefer not to say

D.7.1. My gender is-

D.8. Answer the following questions related to your household composition:

	Yes	No
My partner lives with me.	○	○
My parents/grandparents live with me.	○	○
I have children under the age of 12 years and they live with me.	○	○
I have children between the age group of 13 to 18 years, and they live with me.	○	○
I have children of more than 18 years of age, and they live with me.	○	○
I live with my siblings.	○	○

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Appendix E

Table E.1: Results from stated choice survey (N=182): I

	Before the pandemic	During the pandemic	After the pandemic gets over
Work From Home frequency			
Not at all (1)	28%	3%	13%
Only when necessary (2)	31%	2%	13%
Few days a month (3)	26%	4%	24%
Few days a week (4)	14%	8%	44%
Almost everyday (5)	2%	82%	7%
Bicycle use frequency			
Not at all (1)	5%	6%	5%
Less than once a month(2)	2%	8%	2%
Few days a month (3)	6%	16%	6%
Few days a week (4)	15%	40%	24%
Almost everyday (5)	73%	29%	63%
Car use frequency			
Not at all (1)	33%	42%	34%
Less than once a month(2)	32%	22%	29%
Few days a month (3)	22%	25%	25%
Few days a week (4)	11%	11%	9%
Almost everyday (5)	2%	1%	2%
Trains/PT use frequency			
Not at all (1)	1%	20%	3%
Less than once a month(2)	11%	35%	10%
Few days a month (3)	35%	31%	37%
Few days a week (4)	34%	13%	36%
Almost everyday (5)	20%	2%	15%
Walk frequency			
Not at all (1)	4%	3%	4%
Less than once a month(2)	3%	2%	2%
Few days a month (3)	7%	9%	5%
Few days a week (4)	27%	29%	29%
Almost everyday (5)	59%	57%	60%

Table E.2: Results from stated choice survey (N=182): II

	Before the pandemic	During the pandemic
Travel by train during peak hours		
Not at all (1)	12%	48%
Only when necessary (2)	27%	31%
Few days a month (3)	19%	10%
Few days a week (4)	23%	7%
Almost everyday (5)	20%	3%
Discomfort due to on-board crowding		
Not at all (1)	25%	11%
Slightly uncomfortable (2)	37%	8%
Uncomfortable (3)	10%	29%
Moderately uncomfortable (4)	26%	16%
Very uncomfortable (5)	3%	35%
Discomfort due to crowding in boarding/alighting		
Not at all (1)	35%	11%
Slightly uncomfortable (2)	29%	17%
Uncomfortable (3)	10%	20%
Moderately uncomfortable (4)	21%	21%
Very uncomfortable (5)	5%	31%

Appendix F

The code for MNL and LCCM models developed in R using a user manual of Apollo (Hess & Palma, n.d.) to generate the results of these discrete choice models can be found in the following pages.

```
## MNL Code for Late Departure
### Clear memory
rm(list = ls())
### Load Apollo library
library(apollo)
### Initialise code
apollo_initialise()
### Set core controls
apollo_control = list(
  modelName  ="MNL Late Departure",
  modelDescr ="MNL Results for Late model",
  indivID    ="ID"
)
#### LOAD DATA
database = read.delim("CodedResults2406.dat",header=TRUE)
database = subset(database,database$TrainChoice!=0&(DepChange==2|ForcedDepChange==2))
### Vector of parameters, including any that are kept fixed in estimation
apollo_beta=c(BETA_CR_1 = 0,
            BETA_CR_2 = 0,
            BETA_CR_3 = 0,
            BETA_DT   = 0,
            BETA_FA   = 0,
            B_CAR     = 0,
            B_CR      = 0,
            B_COSP    = 0,
            B_COST    = 0,
            B_PH      = 0,
            B_GenLiv  = 0,
            BETA_VCr  = 0)
### Vector with names (in quotes) of parameters to be kept fixed at their starting value in apollo_beta, use apollo_beta_fixed = c() if none
apollo_fixed = c()
#### GROUP AND VALIDATE INPUTS
apollo_inputs = apollo_validateInputs()
#### DEFINE MODEL AND LIKELIHOOD FUNCTION
apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate"){
  ### Attach inputs and detach after function exit
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))
  ### Create list of probabilities P
  P = list()
  ### List of utilities: these must use the same names as in mnl_settings, order is irrelevant
  V = list()
  V[['Train1']]  =  B_GenLiv*Gender*Liv_1*DepTime1 +  Crowd1*(B_CR*CrowdInVehDC + B_COSP*SpreadCovid + B_COST*CatchCovid +
B_PH*ExcPH ) + B_CAR*Cars*Crowd1 +  Cr1_1*BETA_CR_1 + Cr1_2*BETA_CR_2 + Cr1_3*BETA_CR_3 + Fare1*BETA_FA + DepTime1*BETA_DT
+ VaccStage*Crowd1*BETA_VCr
  V[['Train2']]  = B_GenLiv*Gender*Liv_1*DepTime2 + Crowd2*(B_CAR*Cars + B_CR*CrowdInVehDC + B_COSP*SpreadCovid +
B_COST*CatchCovid + B_PH*ExcPH ) +  Cr2_1*BETA_CR_1 + Cr2_2*BETA_CR_2 + Cr2_3*BETA_CR_3 + Fare2*BETA_FA + DepTime2*BETA_DT +
VaccStage*Crowd2*BETA_VCr
 ### Define settings for MNL model component
  mnl_settings = list(
    alternatives  = c(Train1=1, Train2=2),
    avail         = list(Train1=1, Train2=1),
    choiceVar     = TrainChoice,
    V             = V
  )
  ### Compute probabilities using MNL model
  P[['model']] = apollo_mnl(mnl_settings, functionality)
  ### Take product across observation for same individual
  P = apollo_panelProd(P, apollo_inputs, functionality)
  ### Prepare and return outputs of function
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)
}
#### MODEL ESTIMATION
model = apollo_estimate(apollo_beta, apollo_fixed, apollo_probabilities, apollo_inputs)
#### MODEL OUTPUTS
apollo_modelOutput(model,modelOutput_settings=list(printPVal=TRUE))
apollo_saveOutput(model)
```

LCCM CODE FOR EARLY DEPARTURE

```
# ################################################################# #
#### LOAD LIBRARY AND DEFINE CORE SETTINGS                       ####
# ################################################################# #
### Clear memory
rm(list = ls())
### Load Apollo library
library(apollo)
### Initialise code
apollo_initialise()
apollo_control = list(
  modelName  ="LCCM Early departure",
  modelDescr ="LC model with early departure and covariates",
  indivID    ="ID",
  nCores     = 3
)
# ################################################################# #
#### LOAD DATA AND APPLY ANY TRANSFORMATIONS                     ####
# ################################################################# #
database = read.delim("CodedResults2406.dat",header=TRUE)
database = subset(database,database$TrainChoice!=0&(DepChange==1|ForcedDepChange==1))
# ################################################################# #
#### DEFINE MODEL PARAMETERS                                     ####
# ################################################################# #
### Vector of parameters, including any that are kept fixed in estimation
apollo_beta = c(BETA_CR_1a = 0,
        BETA_CR_2a = 0,
        BETA_CR_3a = 0,
        BETA_DTa   = 0,
        BETA_FAa   = 0,
        BETA_CR_1b = 0,
        BETA_CR_2b = 0,
        BETA_CR_3b = 0,
        BETA_DTb   = 0,
        BETA_FAb   = 0,
        BETA_CR_1c = 0,
        BETA_CR_2c = 0,
        BETA_CR_3c = 0,
        BETA_DTc   = 0,
        BETA_FAc   = 0,
        B_VACr1a   = 0,
        B_VACr1b   = 0,
        B_VACr1c   = 0,
        B_VACr2a   = 0,
        B_VACr2b   = 0,
        B_VACr2c   = 0,
        gamma_st3a = 0,
        gamma_st3b = 0,
        gamma_st3c = 0,
        delta_a    = 0,
        delta_b    = 0,
        delta_c    = 0)
### Vector with names (in quotes) of parameters to be kept fixed at their starting value in apollo_beta, use apollo_beta_fixed = c() if none
apollo_fixed = c("delta_b","gamma_st3b")
# ################################################################# #
#### DEFINE LATENT CLASS COMPONENTS                              ####
# #################################################################
apollo_lcPars=function(apollo_beta, apollo_inputs){
  lcpars = list()
  lcpars[["BETA_CR_1"]] = list(BETA_CR_1a, BETA_CR_1b, BETA_CR_1c )
  lcpars[["BETA_CR_2"]] = list(BETA_CR_2a, BETA_CR_2b, BETA_CR_2c )
  lcpars[["BETA_CR_3"]] = list(BETA_CR_3a, BETA_CR_3b, BETA_CR_3c)
  lcpars[["BETA_DT"]] = list(BETA_DTa, BETA_DTb, BETA_DTc)
  lcpars[["BETA_FA"]] = list(BETA_FAa, BETA_FAb, BETA_FAc)
  lcpars[["B_VACr1"]] = list(B_VACr1a, B_VACr1b, B_VACr1c)
  lcpars[["B_VACr2"]] = list(B_VACr2a, B_VACr2b, B_VACr2c)
  V=list()
  V[["class_a"]] = delta_a  + gamma_st3a*Student_1
```

```
  V[["class_b"]] = delta_b +gamma_st3b*Student_1
  V[["class_c"]] = delta_c    + gamma_st3c*Student_1


  mnl_settings = list(
    alternatives = c(class_a=1, class_b=2, class_c=3),
    avail        = 1,
    choiceVar    = NA,
    V            = V
  )
  lcpars[["pi_values"]] = apollo_mnl(mnl_settings, functionality="raw")
  lcpars[["pi_values"]] = apollo_firstRow(lcpars[["pi_values"]], apollo_inputs)
  return(lcpars)
}
# ################################################################# #
#### GROUP AND VALIDATE INPUTS                                  ####
# ################################################################# #
apollo_inputs = apollo_validateInputs()
# ################################################################# #
#### DEFINE MODEL AND LIKELIHOOD FUNCTION                       ####
# ################################################################# #
apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate"){
  ### Attach inputs and detach after function exit
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))
  ### Create list of probabilities P
  P = list()
  ### Define settings for MNL model component that are generic across classes
  mnl_settings = list(
    alternatives  = c(Train1=1, Train2=2),
    avail         = list(Train1=1, Train2=1),
    choiceVar     = TrainChoice
    )
  ### Loop over classes
  s=1
  while(s<=3){
    ### Compute class-specific utilities
    V=list()
    V[['Train1']]  = B_VACr1[[s]]*Crowd1*Vacc_1 +B_VACr2[[s]]*Crowd1*Vacc_2  +Cr1_1*BETA_CR_1[[s]] + Cr1_2*BETA_CR_2[[s]] + 
Cr1_3*BETA_CR_3[[s]] + Fare1*BETA_FA[[s]] + DepTime1*BETA_DT[[s]]
    V[['Train2']]  = B_VACr1[[s]]*Crowd2*Vacc_1  + B_VACr2[[s]]*Crowd2*Vacc_2 +Cr2_1*BETA_CR_1[[s]] + Cr2_2*BETA_CR_2[[s]] + 
Cr2_3*BETA_CR_3[[s]] + Fare2*BETA_FA[[s]] + DepTime2*BETA_DT[[s]]
    mnl_settings$V = V
    mnl_settings$componentName = paste0("Class_",s)
    ### Compute within-class choice probabilities using MNL model
    P[[paste0("Class_",s)]] = apollo_mnl(mnl_settings, functionality)
    ### Take product across observation for same individual
    P[[paste0("Class_",s)]] = apollo_panelProd(P[[paste0("Class_",s)]], apollo_inputs ,functionality)
    s=s+1}
  ### Compute latent class model probabilities
  lc_settings   = list(inClassProb = P, classProb=pi_values)
  P[["model"]] = apollo_lc(lc_settings, apollo_inputs, functionality)
  ### Prepare and return outputs of function
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)
}
# ################################################################# #
#### MODEL ESTIMATION                                           ####
# ################################################################# #
### Estimate model
model = apollo_estimate(apollo_beta, apollo_fixed,
                        apollo_probabilities, apollo_inputs,
                        estimate_settings=list(writeIter=FALSE))
### Show output in screen
apollo_modelOutput(model)
### Save output to file(s)
apollo_saveOutput(model)
```

Appendix G

In the table shown below, all the interactions which were tested in selection of best and most representative MNL models for both scheduled early and late departure are presented.

Individual characteristics	Interactions with	Crowd levels	Fare discount	Scheduled delay	Type of variable
Travel time in train for education/work		√			Travel
Frequency of travel using PT before the pandemic		√		√	Travel
Discomfort due to in-vehicle crowding during pandemic		√		√	Attitudinal
Student or not			√	√	Socio-demographic
Flexibility of arrival time at work/education destination				√	Travel
Train travel frequency during peak hour before pandemic		√	√	√	Travel
Covid history		√			Attitudinal
Health perception		√			Attitudinal
Health concern		√			Attitudinal
Stress of catching COVID		√			Attitudinal
Concern about spreading COVID		√			Attitudinal
Age		√	√	√	Socio-demographic
Income		√	√	√	Socio-demographic
Number of cars in a household		√			Socio-demographic
Living status (with family or not)				√	Socio-demographic
Gender		√	√	√	Socio-demographic