Travel behaviour during unplanned train disruptions

Considering changed behaviour due to the COVID-19 pandemic

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by

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Preface

Dear reader,

This thesis, which I have been working on for the past eight months, is the final step in obtaining my master's degree in Transport, Infrastructure and Logistics at Delft University of Technology. Starting out with a bachelor in Applied Physics six years ago I am still surprised how I ended up here but glad that I made the choice to switch study directions. During this project I learned a lot about this topic, new methodologies and mostly about myself. I am very grateful for the opportunity to carry out my project in cooperation with NS which was my ambition since starting this master's degree.

Without help from family, supervisors at the TU Delft and NS carrying out this project would not have been possible. I would like to thank my graduation committee for guiding me during this project and also for giving much appreciated feedback. I would like to thank the chair of the committee, Eric Molin, for helping me make the big decisions during this graduation project and for reminding me to sometimes take a step back and zoom out. I would like to thank Niels van Oort for making me keep in mind why I am executing this project, always giving positive and helpful feedback and remind me to critically think about the results and possible implications. As well as for helping me expand my network by inviting me to conferences and asking me to give a presentation at the Smart Public Transport Lab. I would like to thank Nejc Geržinič for the help with creating my stated choice experiment and the choice modelling. I really appreciated the extensive feedback and feedback sessions which always gave me lots of new ideas and helped to move forward in the project.

I would also like to thank my supervisors from NS, Heleen van Beek and Menno de Bruyn. Heleen, thank you for helping me start up the project and introducing me to NS. You made me feel very welcome and I appreciated all the conversations that we had which helped scope the project and focus on the relevant factors for NS. Thank you Menno for taking over the supervisor role and providing new insights every time we talked and helping to reach people within NS for whom the results might also be interesting therefore maximizing the impact of my work. Also a big thank you to the colleagues from Team Modelontwikkeling at NS. You made me feel welcome and also provided me with a lot of feedback throughout the project. Lastly, I want to thank all of my family and fellow students for their support. I am very grateful to have you all by my side.

This is now officially the end of my study period at the TU Delft. I will miss studying at the campus but I am also excited to see what is ahead and continue learning.

J.E.B. Bickel
Delft, September 2022

Summary

In March 2020 the COVID-19 pandemic started in the Netherlands resulting in an enormous decrease of train passengers due to government restrictions but also train travellers' attitudes towards travelling by train during the pandemic. Two years later travellers are coming back to the train but still less travellers are seen than in 2019. To keep regular train travellers in the train and also attract new train passengers it is required that the level of service remains high. During disruptions this level of service can still be improved. Unplanned public transport disruptions are common and can lead to delays and crowding in stations. Possible control strategies such as extending trains or providing accurate information could therefore be applied to better accommodate passengers during disruptions. For control strategies requiring a change in rolling stock to be applied it is necessary to have a prediction of passenger flows during disruptions. These predictions are difficult to make based on smartcard data since it is difficult to assign passengers to trains based on their check-ins and check-outs during disruptions. Therefore this study focusses on trying to predict passenger flows for different groups of train travellers and investigate which factors influence their behaviour. Unique in this study is that the expected changes in travel behaviour due to the COVID-19 pandemic including the resulting rise of teleworking and aversion of crowding are taken into account. This study contributes to science by exploring the effects of the COVID-19 pandemic on travel behaviour during disruptions and also to policy making and providing recommendations for applying control strategies. This study aims to answer the following research question:

How do different groups of train travellers travel during unplanned rail disruptions in the Dutch train network in the aftermath of the COVID-19 pandemic and what factors influence their travel behaviour?

First, literature is studied to examine which factors influenced travel behaviour during disruptions before the COVID-19 pandemic. Then again by studying literature with the addition of the COVID-19 studies performed jointly by NS and TU Delft changes in travel behaviour and perceptions due to the COVID-19 pandemic are investigated.

A stated choice experiment is conducted by sending an online questionnaire to members of the NS panel who commute to work by train. The previously executed literature review provides relevant factors and attributes that are included in the stated choice experiment. In the stated choice experiment it is assumed that respondents are travelling to their work and a disruption occurs either upon arriving at the origin train station or during the train trip at an intermediate station. For each disruption scenario respondents could make one choice among the following travel options; wait for the disruption to be over and continue on the original route, reroute by train or return back home. The disruption is specified in terms of expected length of disruption, additional travel time on reroute, additional transfers on reroute, crowding on platforms and several other factors. In the questionnaire additional questions are asked about normal travel behaviour, respondents' working situations, perception of COVID-19, experience with disruptions and attitude towards provided information.

The online questionnaire was available for response between the 7th and 13th of June in 2022 and 815 valid responses were received. At the time, there were no COVID-19 measures active in the Netherlands. The answers respondents gave to the different disruptions scenarios shows that travel behaviour during disruptions is mostly influenced by the disruption length and the moment during the journey when the disruption is discovered or occurs. For a disruption length of 30 minutes waiting for the disruption to be over is the dominant alternative in the stated choice experiment. While for longer disruptions the percentage of choosing to wait in the stated choice experiment quickly drops to approximately 10% for disruptions lengths of 60 minutes. The figure below also shows that when the disruption is discovered during the train journey the respondents are less likely to return home.

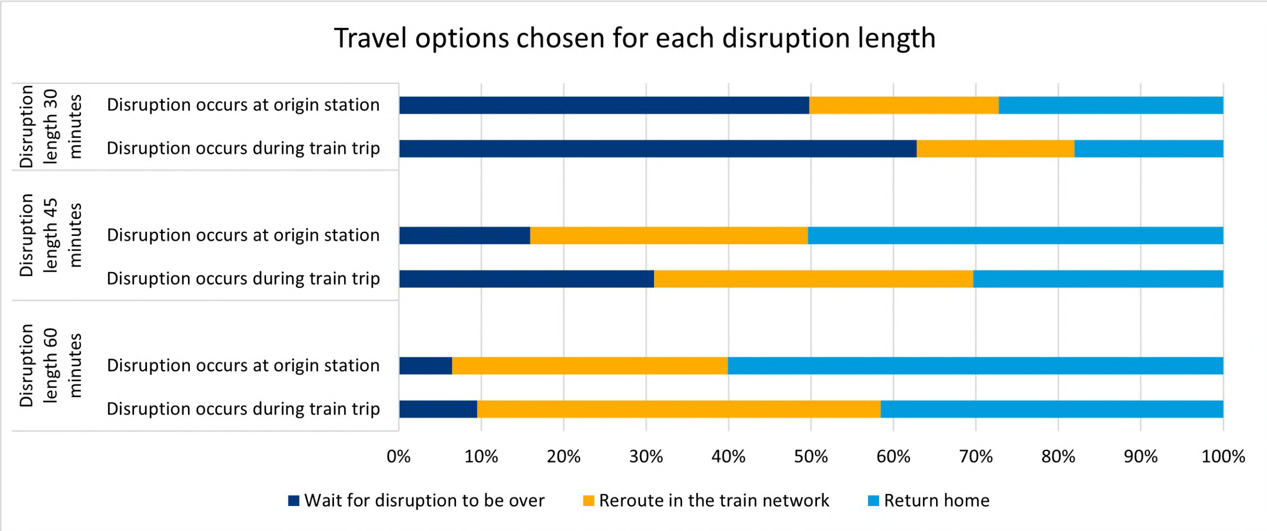

Figure 1: Choice overview for the different disruption lengths and disruption scenarios in the stated choice experiment.

Questions about COVID-19 were also answered by respondents and compared to previous research conducted on COVID-19 by NS and TU Delft. Compared to previously executed studies the attitude towards COVID-19 seems to follow the trend of people getting less afraid of the virus. In April of 2020 only 35% of train travellers indicated that they enjoyed travelling by train which has increased to almost 80% in this current study. Avoiding of crowded places is still done by roughly 45% of train travellers but this value has already decreased drastically since September 2020 when roughly 85% of train travellers indicated they avoided crowded places. With the decreasing awareness of COVID-19 over time the role of crowding might also become less important over time.

A multinomial logit (MNL) model is estimated to predict choices between the three travel alternatives when applying a certain disruption scenario. Sociodemographics are added to this model as interactions to test if people with different characteristics have different taste parameters. A latent class choice model is estimated afterwards to capture heterogeneity among train travellers assuming that each traveller has their own preferences and not all travellers are equally sensitive to all attributes.

All tested attributes except for respondents' usual travel time in the train are significant and therefore have an effect on the choices made by respondents. Increasing 'disruption length', 'additional travel time on reroute', 'additional number of transfers on reroute', 'travel time in train to return back to origin station', 'waiting time', 'access time' and 'crowding' all negatively influence the choice for the corresponding travel option. The access time has the potential to have the largest influence since the access time used respondent's own input and had a maximum value of 85 minutes. The second largest influence comes from the disruption length followed by the additional travel time on the rerouting option. Crowding on the platform as an indication of crowding in the train can also have a large impact but only when the crowding is extreme (Fruin level F). For the number of additional transfers, one additional transfer does not have much of an influence but two additional transfers on the rerouting option has a large negative impact.

When adding the sociodemographic characteristics as interactions to the MNL model the following results are found:

- Teleworkers are more likely to return home during a disruption than people who cannot work from home. When comparing the share of people returning home to findings from literature, the share of this travel option has increased and is larger than before the COVID-19 pandemic. On top of that, teleworkers are more sensitive to additional travel time than people who have to arrive at their workplace.
- Train travellers who have to arrive at their workplace are more sensitive to access time and moderate crowding. They are less sensitive to additional travel time, disruption length, extreme crowding, two additional transfers and waiting time compared to people who do not have to arrive at the workplace.

- Train travellers with a negative attitude towards teleworking are less likely to return home than people with a positive attitude towards teleworking.
- Train travellers who do not feel to travel by train because of the crowding and avoid crowded places are more sensitive to extreme crowding. The effects are however not as large as expected indicating that during a disruption crowding might not be a leading factor for decision-making. An explanation could be that commuters are already used to crowding and therefore during disruptions avoiding crowding is not a relevant factor.
- Train travellers who do not trust information about the disruption provided by NS are more likely to return home or reroute.
- Train travellers who start their journey at a small station with less facilities are more sensitive to waiting time.

By estimating the latent class choice model heterogeneity is captured by distinguishing four discrete classes. These classes are specified as 'Trade-off teleworkers' (39%), 'Sceptic returners' (20%), 'Trusting workplace travellers' (18%) and 'Endless waiters' (23%). Figure 2 shows the classes with their corresponding characteristics.

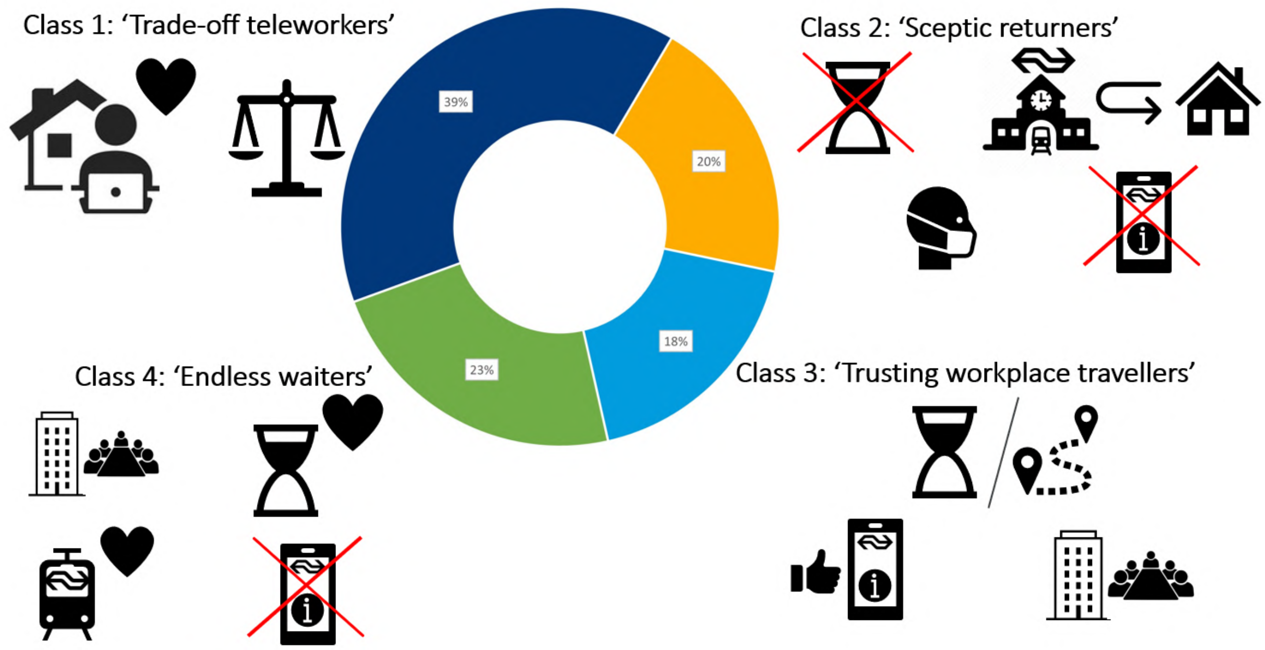

Figure 2: The latent classes characterized in terms of class size, preferred travel option and corresponding characteristics.

The 'Trade-off teleworkers' is the largest class and is mainly characterized by the preference to trade-off all attributes. This class therefore does not have a preferred travel option. For this class all attributes except for access times are significant. The train travellers in this class are more likely to have the possibility to work from home and have a positive attitude towards teleworking. The ability to telework adds an additional travel possibility, returning home, compared to people who cannot work from home thus decreasing equity between people who can and cannot work from home. People belonging to this class are likely to not have to arrive at their workplace. The attribute levels and therefore also the specification of the disruption scenario have a large impact on the travel behaviour of this class. Train travellers in the age group 35-44 years old are more likely to belong to this class.

The 'Sceptic returners' have a very averse attitude towards waiting. For shorter disruptions they are likely to return home and this is enforced by longer disruption lengths. People belonging to this class are likely to be afraid of getting infected with COVID-19, do not feel free to travel by train because of the crowding, continue to wear a facemask and dislike travelling by train. This class is sensitive to crowding and would rather travel 15 additional minutes in the train to avoid crowding. This class is also sceptic towards travel information provided by NS. Train travellers belonging to this class are likely to be teleworkers and can therefore easily return home.

The ’Trusting workplace travellers’ class consists of train travellers who have to arrive at their workplace and are not likely to be able to work from home. This class has a large initial preference for rerouting which might be caused by their trust in provided information and willingness to follow advice from travel apps. They are less experienced travellers which might be why they trust information and follow advice. Even though rerouting is the preferred option this class is very sensitive to additional travel time which might be caused by this class having to arrive at their workplace on time. When the additional travel time increases this class is more likely to wait for the disruption to be over.

The ’Endless waiters’ is the only class that is not sensitive to the disruption length meaning that their travel behaviour is not influenced by the length of a disruption. This class has a preference for waiting for the disruption to be over in each possible disruption scenario. Similar to the previous class the train travellers in this class are likely to have to arrive at their workplace and cannot work from home. If they can work from home it is likely that their attitude towards teleworking is negative which might explain why they would not return home. Train travellers in this class like to travel by train, normally travel by train for over 60 minutes, are in the age group 18-34 years old and do not trust the prognosis on the disruption length provided by NS. This last characteristic is unexpected since distrusting information on the prognosis was expected to result in rerouting or returning home and not waiting for the disruption to be over.

To see how different control strategies influence travel behaviour disruption scenarios are specified and then altered to represent a control strategy. Applying a control strategy such as extending trains or increasing the frequency of rerouting trains could lead to more people rerouting instead of returning home which would increase the revenue for NS. It should be noted that this could again lead to more crowding since less people return home but this is not taken into account. The tested control strategies are extending rerouting trains to avoid crowding and doubling the frequency of rerouting trains. Doubling the frequency of the trains and therefore reducing crowding due to increasing capacity has a more positive effect on the number of people rerouting than extending the rerouting trains. Applying the control strategies also shows that the ’Sceptic returners’ and ’Endless waiters’ classes are difficult to influence since they have defined preferences for returning and waiting respectively. Making rerouting more attractive barely has an effect on these two classes. The ’Trade-off teleworkers’ and ’Trusting workplace travellers’ can however be influenced by making rerouting more attractive. The larger share of rerouting is mostly caused by changing travel choices of these two classes. The question however is if the induced demand on the rerouting option is beneficial. By not applying the control measures, people who cannot telework are affected more than the people who can telework since they have the option to return home and avoid the crowding. This however does reduce demand on the rerouting options. When applying control strategies rerouting trains become less crowded which is a benefit for the people who were already on that train and for people who cannot work from home and have to reroute due to a disruption. Another downside of applying control strategies is that rolling stock plans have to be changed and that more staff is required to run the service which might be problematic due to the recent staff shortage.

This study has provided the first piece of the puzzle for predicting passenger flows during disruptions. Insight is gained in different groups of travellers and what their preferred travel options are including the factors that influence their behaviour. The results of this study are currently used in a tool created by NS for adapting rolling stock plannings during disruptions. This shows the relevance of this study for the operations side of rolling stock planning. It is recommended to expend the model used in this tool to incorporate more factors such as disruption length, rerouting possibilities and possibly crowding.

Based on the results from the model estimation and questions asked in the online questionnaire several recommendations can be made. First of all it is recommended to improve information provision during disruptions since approximately 50% of respondents indicated that they do not trust the prognosis of the disruption length provided by NS. Respondents also commented that rerouting advice often is not given during disruptions and this is especially useful for less experienced travellers. It is therefore recommended to provide information on rerouting options during disruptions and also being more transparent about the situation even if it is not clear yet what is happening. On top of that, asking train drivers and train conductors to help passengers at stations during disruptions might help to be more visible for the passengers and increase the trust in the provided information.
At this moment in time control strategies cannot be applied yet during disruptions while this study shows that

applying them might lead to a reduction in crowding on rerouting trains which is beneficial especially for travellers that do not have the option to telework. Therefore it is recommended to try and become more flexible in planning rolling stock. Not only is it helpful during disruptions but the pandemic has also resulted in less busy workdays and flexibility in rolling stock then might also decrease costs.
It is recommended that the estimated model is validated using smartcard data. This however does involve creating a tool or technique which can accurately assign passengers to a train based on their check-ins and check-outs even during a disruption. This is not an easy task since smartcard data is often less accurate during disruptions and check-in and check-outs more difficult to interpret.

This study has led to multiple directions for further research. In this study only behaviour of commuters was investigated but it is also interesting to investigate how students and people who travel for leisure purposes behave during a disruption. This is also necessary to improve passenger flow predictions. The same study can also be executed for longer disruptions where bus replacement services are deployed or shorter trips where other forms of public transport have the potential to replace the train trip. This study was performed three months after the last COVID-19 restrictions in the Netherlands were dropped. Over time, assuming other pandemics do not rise up, perception of crowding and teleworking might change again making it interesting to see if these changes are permanent or subject to change.

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1 Introduction

Railway systems have the potential to reduce the contribution of transport systems to climate change (Givoni et al., 2009). Especially when private car users and airplane travellers switch to travelling by train. In the Netherlands the number of kilometres travelled by train increased by 14% between 2010 and 2018 (Rijksoverheid, 2020). For the Dutch Railways (NS) this increase was 22% which is explained by a quality improvement of the offered services such as increased frequency, connections between trains and network expansion. In the same period, the travelled kilometres by private cars increased by 7.9% (Rijksoverheid, 2022c). Private car users often have the perception that travelling by public transport takes more time than it does in reality (van Exel & Rietveld, 2009). If their perception about travel time in public transport would be more in line with their perception of car travel time about two out of three car users would consider public transport as an alternative. It should be noted that for short trips the car is usually faster but for longer trips public transport could be a viable alternative. Car users can be attracted to public transport if the image and levels of service of public transport are improved. However, if the public transport service is unreliable people are more likely to switch to the car (Beirão & Cabral, 2007). Therefore it is important that train services are reliable to capture car users and make transportation more sustainable.

Service reliability in public transport has a large impact on passenger satisfaction (Soza-Parra et al., 2019). Public transport services are often perceived as unreliable by passengers and in concessions passenger impacts of service unreliability do not receive enough attention (van Oort, 2014). Unplanned public transport disruptions can lead to delays and crowding in stations and vehicles which causes anxiety for passengers (Cheng, 2010). These sudden disruptions force passengers to instantaneously shift their travel strategies and often switch to less familiar alternatives (Drabicki et al., 2021). Control strategies can help to mitigate crowding and also improve regularity of the public transport vehicle trips (Nuzzolo & Comi, 2016). Information such as the vehicle occupancy rate and the number of travellers waiting at stops are important inputs for such control strategy applications by public transport operators. An example of a control strategy is to extend trains on alternative routes which are expected to become more crowded during disruptions. Other practices are deadheading and short-turning which entails skipping stops with low demand and performing shorter cycles to increase frequency respectively (Canca et al., 2012). To apply the control strategies information on travel behaviour during unplanned disruption is required to predict passenger flows as input for the models.

In March of 2020 the COVID-19 pandemic began in the Netherlands and government restrictions regarding travelling and working from home changed people's lives and behaviour. A longitudinal study by NS and the Delft University of Technology investigating travel behaviour during the COVID-19 pandemic found that 20% of all respondents expect to travel less by train after the COVID-19 pandemic is over (van Hagen, de Bruyn, et al., 2021b). The main reason being that people expect to work more from home, 46% of respondents who expect to travel less gave this as a reason. A study by de Haas et al. (2020) found that of the people who worked from home during the pandemic, 27% expect to work more from home after the COVID-19 pandemic than before. If people will follow their intentions, it can be stated that the pandemic has changed people's travel behaviour. Due to this change people might also respond differently in disrupted train situations. Because teleworking has become more popular, people might cancel their trip and return back home after finding out about the disruption. It is expected that this behaviour will be more common than before the start of the COVID-19 pandemic. Crowding in vehicles might also have a larger impact on passenger's comfort than before the pandemic since larger crowds are associated with more risk of infection. Therefore this study will concentrate on what decisions people make during unplanned rail disruptions but considering the possibly changed travel behaviour due to the COVID-19 pandemic. The next sections will describe the problem statement and why it is valuable to conduct this study.

1.1. Problem statement

For train operators, it is important to know how many passengers cancel their trip or reroute in the train network to apply appropriate control strategies during unplanned disruptions to better accommodate passengers. Currently, redistribution of train carriages is not yet executed because of uncertainty in passenger flows and also because adding a carriage to one train often means removing a carriage from another train. Different decisions on control strategies can only be made if passenger flows can be accurately predicted. The Dutch Railways (NS) can predict passenger flows very well in normal situations and use the predicted passenger flows to evaluate their timetables with their self developed model TRENO. Passenger flows can also be predicted well during maintenance works or other pre-planned disruptions because travel options are known in advance by both passengers and NS. It is more difficult to predict passenger flows during unplanned disruptions because travellers make different decisions in a short time instance and information can be lacking especially in the beginning phase of the disruption. After conducting a preliminary literature review on the topic of travel behaviour during unplanned disruptions it can be concluded that, to the best knowledge of the author, the influences of the COVID-19 pandemic on travel behaviour have not been taken into account yet. The decisions that people make during unplanned disruptions and the factors they are based on in the aftermath of the COVID-19 pandemic are unknown. Without this information the prediction of passenger flows is not accurate and control strategies cannot be applied successfully.

1.2. Research question

When looking at the problem statement defined in Section 1.1 this study aims to answer the question what kind of decisions train travellers make during unplanned disruptions and on what factors their decisions are based including changed behaviour due to the COVID-19 pandemic and rise of teleworking. This information will provide NS and other train operators with the tools to make better predictions of passenger flows and also adapt their control strategy during unplanned disruptions accordingly. It is also relevant for science since it is expected that travel behaviour has changed due to the COVID-19 pandemic and this is not yet studied in the context of disruptions. It is hypothesised that the ability to telework will increase the share of travellers returning home and awareness of COVID-19 to lead to an aversion of crowding. This study aims to fill multiple research gaps which are found based on the performed literature review. This extensive review can be found in Chapter 3. Factors such as the rise of teleworking and crowding in vehicles are investigated to incorporate behavioural changes due to the COVID-19 pandemic. The option of rerouting in the robust Dutch national train network is also investigated to provide information on the number of passengers that would reroute in certain disruption scenarios. The main research question for this study is defined as:

How do different groups of train travellers travel during unplanned rail disruptions in the Dutch train network in the aftermath of the COVID-19 pandemic and what factors influence their travel behaviour?

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

1. Which factors influenced travel behaviour during unplanned disruptions before the COVID-19 pandemic?
2. Which factors related to travel behaviour became more relevant to train travellers during the COVID-19 pandemic?
3. What decisions do train travellers make during unplanned rail disruptions in the aftermath of the COVID-19 pandemic and which factors influence the travel behaviour?
4. Which factors influence the behaviour of different train traveller groups during unplanned disruptions in the aftermath of the COVID-19 pandemic?

The first sub-question focuses on previous literature on which the research gap is based in order to investigate which factors influence travel decisions during unplanned disruptions. This information is also used to determine the attributes and context variables that will be part of the stated preference survey which will be conducted in this study. The answer to the second sub-question is again used as input for the stated preference survey by examining how the pandemic has influenced travel behaviour in public transport. This behaviour could last even after the pandemic and should therefore be considered in the study. The information from the first and second sub-question is combined to help answer the third sub-question. The third question focuses on the decisions that people would make during unplanned disruptions while weighing context variables and attributes in a stated choice experiment which are inspired by literature. The last sub-question investigates the responses of the stated choice experiment and tries to find different groups of people which each respond in a certain way to unplanned disruptions. The following section explains which methodologies are used to answer the posed sub-questions and why. The results of the research aim to give a better insight in travel behaviour during unplanned disruptions. In the reflection at the end of the study policy recommendations are given to NS based on the analyzed results from the stated choice experiment. Recommendations for future research are also given.

1.3. Relevance

The scientific relevance of this study is that travel behaviour during unplanned disruptions is studied in the context of the aftermath of the COVID-19 pandemic which is expected to have changed people's travel behaviour. To the best of the author's knowledge the effect of the pandemic on travel decisions during unplanned disruptions has not yet been investigated. This study will contribute to science because some of the effects of the pandemic are expected to be lasting and travel behaviour has also changed with it. Therefore it is necessary to look at travel behaviour during unplanned disruptions while assuming that travel behaviour in normal conditions has also changed. The study is also relevant for public transport providers. With this knowledge passenger flows might become better predictable during unplanned disruptions in a robust rail network. Control strategies can then be applied during the disruptions to reduce crowding and better accommodate passengers. Reducing crowding in the vehicles and a better management of disruptions increases passenger satisfaction which might ultimately lead to more public transport users which is relevant for public transport operators and policy makers.

1.4. Thesis outline

In the next chapter of the report the methodologies applied to answer the research question are explained. An extensive literature review is performed in Chapter 3. The literature review provides the input for the design of a conceptual framework which is discussed in the same chapter. In the second part of the report the design of the stated choice experiment is explained in Chapter 4 and descriptive statistics after gathering the data in Chapter 5. Discrete choice modelling will then be applied to create a choice model which aims to help answering the main research question in Chapter 6. Applications of the results are discussed in Chapter 7. Finally, conclusions, discussions and recommendations are discussed in Chapter 8. The outline of the report is visually displayed in Figure 1.1.

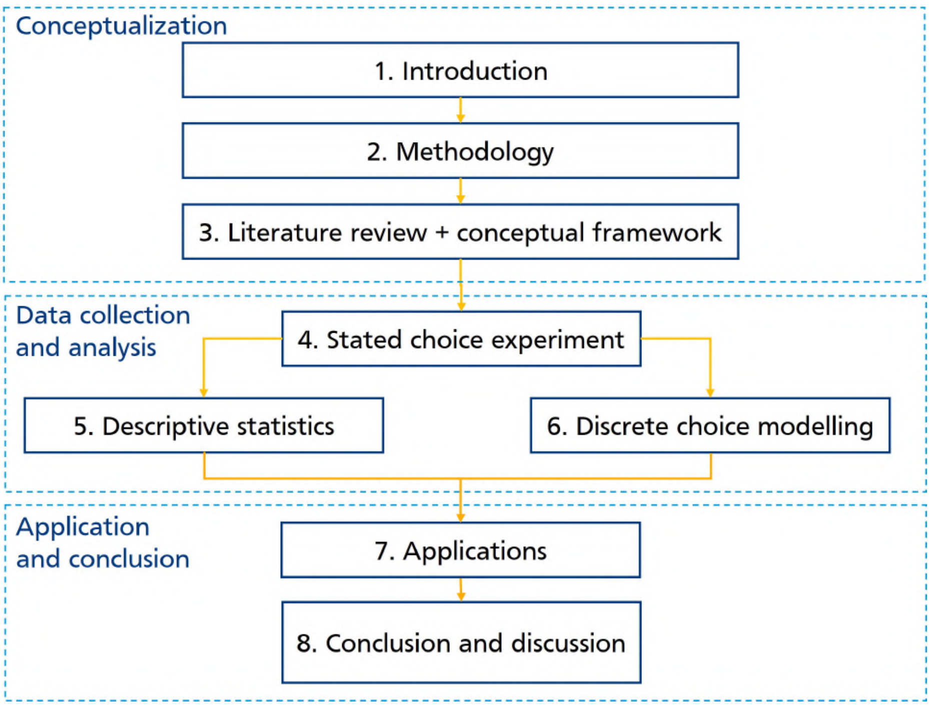

Figure 1.1: Thesis outline with the conceptualization, data collection and analysis and conclusions.

2 Methodology

This chapter focuses on explaining the methodologies that will be used in this study to answer the main research question. For each methodology the principles are explained and also why they are used to answer the sub-research questions. Table 2.1 gives an oversight of the research questions as proposed in Section 1.2 with the chosen methodology to answer the question.

Table 2.1: The main research question and sub-questions with the proposed methodology.

How do different groups of train travellers travel during unplanned rail disruptions in the Dutch train network in the aftermath of the COVID-19 pandemic and what factors influence their travel behaviour?	
Sub-question	**Methodology**
1. Which factors influenced travel behaviour during unplanned disruptions before the COVID-19 pandemic?	Literature review
2. Which factors related to travel behaviour became more relevant to train travellers during the COVID-19 pandemic?	Literature review Data from NS panel longitudinal study
3. What decisions do train travellers make during unplanned rail disruptions in the aftermath of the COVID-19 pandemic and which factors influence the travel behaviour?	Stated preference survey
4. Which factors influence the behaviour of different train traveller groups during unplanned disruptions in the aftermath of the COVID-19 pandemic?	Latent class choice models

2.1. Literature review

A literature review on studies investigating travel behaviour during unplanned disruptions is performed to give an overview of the state-of-the-art research, find the research gaps and also answer the first two sub-questions. The review aims to answer the questions which factors influence travel behaviour during disruptions before the COVID-19 pandemic and which factors related to general travel behaviour became more important during the COVID-19 pandemic. Literature reviews can also be useful for identifying relevant methodologies and discovering variables that might be important for research (Randolph, 2009). The relevant variables are especially important for setting up the stated preference experiment. The literature can be used to find relevant attributes and context variables. After the survey is conducted and the data analysis is executed, the literature can also be used to compare the results with. An integrative review approach is used since it has the aim to critique, synthesize and assess the literature with the aim of creating a conceptualization (Snyder, 2019). The created conceptualization gives an overview of all possible factors influencing travel behaviour during disruptions in the aftermath of the COVID-19 pandemic based on which the stated choice experiment can be designed.

2.2. Stated choice experiment

In order to answer the question what choices train travellers make during disruptions data has to be gathered. As a train operator company, NS has a lot of data on passengers including tap in and tap out data from the OV-chipkaart (smartcard) (Nijënstein & Bussink, 2015). Using this data to reveal the decisions that people make during unplanned disruptions would be a form of revealed preference research. Revealed preference is often preferred over stated preference because the respondents' stated preferences may not be their actual preferences (Wardman, 1988). The reason that for this study revealed preference methods are not used is that the impact of changes in external factors (such as information provision, length of disruption etc.) can rarely be evaluated with revealed preferences methods (Kroes & Sheldon, 1988). It is also not known what choice alternatives the passengers considered. Stated choice experiments are used to study the choices people make in an environment controlled by the experimenter (Louviere & Woodworth, 1983). The experimenter designs the experiment and therefore can decide on attributes, attribute levels and context variables which is an advantage of stated choice experiments. The goal is to determine the influence of different attributes on the choices that respondents make during the experiment (ChoiceMetrics, 2021). For each choice task the respondent is shown a context and different alternatives between which they should choose. Each alternative has certain attributes with different levels. A drawback of stated preference experiments is that respondents claim they would make a certain decision but their behaviour can be different in real life (Kroes & Sheldon, 1988). Another disadvantage is that predictions of the shares of travel options can only be made for the investigated attribute level ranges. The decision is made to focus on decisions that passengers make during unplanned disruptions but especially which factors influence those decisions. Data on past disruptions and the circumstances surrounding those disruptions is not readily available for use within NS and therefore conducting a revealed preference study to investigate which factors influence travel decisions during unplanned disruptions is not feasible for this study. Because using revealed preference it is much more difficult to investigate which factors influence travel decisions during unplanned disruptions, a stated choice experiment is conducted in the form of a survey to collect data on what decisions people would make during unplanned disruptions under different circumstances.

There are three main steps that are taken when designing the stated choice experiment; model specification, experimental design and creating the questionnaire (ChoiceMetrics, 2021). For each of these steps the choices that have to be made in this study are discussed. Which choices are made for each step is elaborated upon in Chapter 4. The stated choice experiment is designed using the Ngene software (ChoiceMetrics, 2021).

2.3. Discrete choice modelling

Once data is gathered using the stated choice experiment described prior, the choices respondents make are used to estimate parameters of discrete choice models. The discrete choice models are used to answer the question what factors influence the travel behaviour of different train traveller groups and what decisions they are likely to make. Discrete choice models aim to describe or predict a choice between a discrete number of alternatives (McFadden et al., 1973). The main elements which influence the choice-making are; the decision maker, the alternatives, the attributes belonging to the alternatives and the decision rule (Ben-Akiva et al., 1985). The Random Utility Maximization (RUM) decision-rule assumes that each alternative has a certain utility U and the decision maker n chooses the alternative i from their choice set C_n which has the highest utility for them (Ben-Akiva et al., 1985).

$$U_{in} > U_{jn}, \qquad j \neq i, j \in C_n \tag{2.1}$$

The utility U_{in} of alternative i consists of the systematic utility V_i and a random component ϵ_{in} and can mathematically be written as:

$$U_{in} = V_i + \varepsilon_{in}, \qquad \forall i \in C_n \tag{2.2}$$

The systematic utility consists of the levels of the attributes k (x_{ik}) which are embedded in each alternative i multiplied by a weight factor β_{ik}. This weight factor captures the taste preference and is added to β_i, the alternative specific constant (ASC).

$$V_{in} = \beta_i + \sum_k \beta_{ik} x_{ikn} \tag{2.3}$$

The random component represents all that cannot be captured by the systematic utility such as taste heterogeneity. The random components are independently and identically Gumbel distributed (i.i.d.) which leads to the multinomial logit (MNL) model (Koppelman, 2007).

2.3.1. Multinomial logit models

The multinomial logit model describes the probability that alternative i is chosen from a set of alternatives J. The model is mathematically described as:

$$P_{in} = \frac{e^{V_{in}}}{\sum_{i'=1}^{J} e^{V_{i'n}}} \tag{2.4}$$

One of the advantages of the MNL model is that it is closed form and therefore has a small computation time. Though simple and elegant, the MNL model also has shortcomings. One of them being the assumption of independence from irrelevant alternatives (IIA) (Greene & Hensher, 2003). Observed taste heterogeneity can be investigated by interacting the attributes with individual characteristics (Bansal et al., 2018). However, capturing unobserved taste heterogeneity requires a different model. When estimating the β parameters it is assumed that all individuals have the same taste parameters. Unobserved taste heterogeneity cannot be captured with the MNL model but can be captured using either the mixed logit model or latent class choice models. The mixed multinomial model introduced by McFadden & Train (2000) started to tackle this problem by providing a continuous distribution of parameters. A disadvantage of this model compared to the MNL model is that it loses its closed form. Another model able to capture taste heterogeneity is the latent class choice model. For the application of this model it is assumed that the population can be split into a finite, discrete number of groups based on a combination of characteristics (Matyas & Kamargianni, 2021). Traits within the classes are homogeneous but differ between the classes (Coogan et al., 2011). This classification into subgroups makes the latent class choice model more flexible than the mixed logit model and can help with interpretation of the results (Hess et al., 2008). Since research question number four focuses on behaviour of different traveller groups latent class choice models are estimated in this study.

2.3.2. Latent class choice models

A latent class choice model probabilistically assigns an individual to the discrete mixture of classes (Shelat et al., 2021). Since each class has their own choice model it is possible to create a completely different choice model structure for each class, for example a mixed logit model or nested logit for some classes and a regular MNL model for the other classes. In this study it is chosen to estimate regular MNL models for all the classes. The formula below shows the probability that a decision maker n who belongs to class s chooses alternative i. It consists of the sum over all the classes of the class membership probability π_{ns} multiplied by the probability of choosing alternative i for class s, P_{in}.

$$P_{in} = \sum_{s=1}^{S} \pi_{ns} P_{in}(\boldsymbol{\beta_s}) \tag{2.5}$$

The previously mentioned approach assumes that all choices of each respondents provide the same amount of information while it is especially important to look at the probability of their choice sequences. This panel effect is accounted for by applying the formula below. It describes the likelihood of observing a sequence of T choices for decision maker n.

$$L_{in} = \sum_{s=1}^{S} \pi_{ns} \prod_{t=1}^{T} P_{in_t}(\boldsymbol{\beta_s}) \tag{2.6}$$

The large advantage of latent class choice models is that sociodemographic and other relevant characteristics can be added to the class membership function π_{ns} to explain class membership. In the formula below the γ parameters indicate the influence of characteristics such as sociodemographics on class membership.

$$\pi_{ns} = \frac{e^{\delta_s + \sum\limits_k \gamma_{ks} z_{kn}}}{\sum_{s'=1}^{S} e^{\delta_{s'} + \sum\limits_{k'} \gamma_{k's'} z_{k'n}}} \tag{2.7}$$

All parameters (β_s, δ_s and γ_{ks}) are estimated simultaneously using the PythonBiogeme package created by Michel Bierlaire (Bierlaire, 2020).

2.3.3. Analyzing model fit

The fit of the different models is investigated using different measures. For the latent class choice models McFadden's rho-square and the Bayesian Information Criterion (BIC) are used to analyze the fit. The rho-square is used to calculate the percentage of explained variability. It is calculated by dividing the final log-likelihood of the model $LL(\beta)$ by the null log-likelihood $LL(0)$ and subtracting this value from one. The rho-square is therefore a value between zero and one.

$$\rho^2 = 1 - \frac{LL(\beta)}{LL(0)} \tag{2.8}$$

The BIC is based on the final likelihood of the model L, the number of observations n and number of parameters k (Gideon et al., 1978).

$$BIC = k \ln n - 2 \ln L \tag{2.9}$$

Adding additional parameters to a model may lead to over-fitting but the BIC introduces a penalty for introducing a free parameter. Therefore it is a good measure to evaluate if a parameter gives additional value to the model. A limitation of the BIC is that it can only be used if the sample size is much larger than the number of estimated parameters. Since a large sample of respondents can be approached through the NS panel this is not expected to be a problem. The aim is to maximize the rho-square and minimize the BIC values.

2.4. Conclusion

Summary

- A literature review is performed to define research gap, give overview of state-of-the-art research and define factors that might influence travel behaviour during disruptions.
- A stated choice experiment in the form of an online survey is used to gather data on which choices train travellers would make in different disruptions scenarios.
- Discrete choice modelling is used to analyze the gathered data.

In this chapter the research questions are coupled to the applied methodologies. First, a literature review is performed to identify the research gaps, give an overview of state-of-the-art research. The literature review also performs as a tool to define factors that influence travel behaviour during disruptions before the COVID-19 pandemic and identify changes in normal travel behaviour due to the COVID-19 pandemic. Data on which choices train travellers would make during disruptions is gathered using a stated choice experiment. A stated choice experiment is chosen since the study focusses on discovering the factors that influence behaviour which is difficult to investigate using revealed preference research. Discrete choice modelling is applied to estimate choice models which aim to describe and predict choice behaviour. First a basic MNL model is estimated after which potential heterogeneity is captured by estimating latent class choice models to discover different groups of train travellers.

3 Literature review and conceptual framework

In this chapter the literature review is presented which deals with two different topics. The first part of the review focuses on travel behaviour during unplanned disruptions before the COVID-19 pandemic. The second part of the review looks at how the COVID-19 pandemic has changed travel behaviour. The review aims to answer the first two research questions and also to gather information on which factors are important to take into account in the stated choice experiment.

3.1. Methodology

Because the literature review analyses two different topics the relevant papers are found using different search queries. The methodology for this literature review consists of four consecutive steps. First, the search engine Scopus and Google Scholar are used to find relevant papers for both topics. The papers on the topic of travel behaviour during unplanned disruptions are found using different search queries and are shown in Table 3.1. Different search queries are used to capture all public transport modes. The resulting queries make sure that literature is found which specifically looks at unplanned disruptions in public transport with a focus on travel behaviour. The search was performed on January 31st 2022. For the second topic on travel behaviour during and after the COVID-19 pandemic the search queries ”travel behaviour” AND ”COVID-19” are used. Since it is a recent topic, social media websites such as LinkedIn are also used to find relevant articles and master theses. The Delft University of Technology also wrote conference papers with NS on travel behaviour during COVID-19 which cannot be found with the conventional scientific search engines but are added to this review for additional information. This search was conducted on March 1st 2022.

Table 3.1: Search queries for literature review.

Concept groups	unplanned disruption; travel behaviour; public transport
Keywords	Unplanned disruption; unplanned disturbance Public transport; train Travel behaviour; behaviour
Truncation	(disruption) AND (public transport) AND (travel behaviour)

The second step consists of filtering the found papers based on language. English and Dutch are chosen as possible languages for the papers. During the third step, the abstracts of the remaining papers are read to see if the papers are significant for the literature review focused on travel behaviour during disruptions in public transport and on travel behaviour during and after the COVID-19 pandemic. The fourth and final step is downloading all of the papers and emitting the papers that are not accessible to fully read. The references of the final papers are reviewed to find other papers that might add more information relevant to the topic. This method of searching for papers is called forward snowballing.

3.2. Travel behaviour during unplanned disruptions before COVID-19 pandemic

This section of the literature review deals with the topic of travel behaviour during unplanned disruptions in a pre-pandemic context. It aims to answer the first research question and also provide factors that are important when creating a realistic stated choice experiment and simulating an unplanned disruption scenario.

When entering the search queries as defined in Table 3.1 into Scopus and Google Scholar, 35 papers are found. All of these papers are written in English and therefore none of the papers are emitted based on the language criterion. The abstracts of these papers are read and 27 papers are removed from the review after this step. The main purpose for removing papers is because they focus on the vehicles during disruptions instead of the behaviour of passengers. A large number of the found papers also defines COVID-19 as an unplanned disruption which is not the type of service disruption that is meant in this case of a train network. One paper is not available for download. Nine papers are found by forward snowballing. This results in a total of seventeen papers to be reviewed. An overview of the reviewed papers can be found in Table 3.2. The table shows the focus area of the reviewed papers, the transport modes that are disrupted, the methodology that is used and also the location of the study.

Table 3.2: Overview of reviewed papers and their focus area, disrupted mode of transport, methodology and location of research.

Citation	Focus area	Disrupted mode	Methodology	Location
Fukasawa et al. (2012)	Impact of information during train delays	Train	SP survey	Japan
Guiver (2013)	Role of social networks to increase resilience during disruptions	No specific mode	Online RP survey	Iceland and England
Bai & Kattan (2014)	Behavioural responses to real-time on-route information	Light rail	SP survey with multinomial logit models	Calgary, Canada
Pender et al. (2014)	Social media use during disruption	No specific mode	Literature review	x
Teng & Liu (2015)	Assign passenger flow under section disruption in urban rail transit	Metro	Passenger behaviour and SP survey with multinomial logit model	Shanghai, China
Lin et al. (2016)	Future research directions	No specific mode	Literature review	x
Currie & Muir (2017)	Passenger behaviours, perceptions and priorities during unplanned disruptions	Train	Online RP survey	Melbourne, Australia
Lin (2017)	Mode choice during disruption	Metro and light rail	RP-SP survey	Toronto, Canada
Hua & Ong (2018)	Information contagion during train service disruption	Train	Information contagion model with dynamic user equilibrium	Singapore
Lin et al. (2018)	Mode choice during disruption	Metro	RP-SP survey with multinomial logit model	Toronto, Canada
Nguyen-Phuoc et al. (2018)	Behavioural reactions of PT users during PT service withdrawal	No specific mode	RP-SP online questionnaire with multinomial logit model	Melbourne, Australia
Adelé et al. (2019)	Behaviour service disruption that has just occurred and the options people consider	Suburban train	RP questionnaire and diary study with cluster analysis	Île-de-France
Rahimi et al. (2019)	Waiting tolerance during unplanned disruptions	Bus and train	Interval-censored accelerated failure time models	Chicago, US
Auld et al. (2020)	Individual trade-offs between different modes and travel plan modification strategies	Bus and train	Online SP intercept survey based on actual trip	Chicago, US
Li et al. (2020)	Factors that affect mode shift and travel plan choice behaviour	Metro	SP survey with nested logit model	Guangzhou, China
Rahimi et al. (2020)	Behaviour during unplanned service disruption and what factors affect their behaviour	Bus and train	RP-SP survey with mixed logit model	Chicago, US
Drabicki et al. (2021)	How PT users adapt travel behaviour and what sources of information they use	No specific mode	SP-RP survey	Krakow, Poland

Studying travel behaviour during unplanned disruptions is, to the best of the author's knowledge, a recent research topic among the identified papers with the first paper published in 2012. From 2017 onwards the topic has received more attention with multiple published papers per year. When looking at the locations where research has been conducted especially the US, China, Canada and Australia are well represented with a total of ten out of seventeen papers. Two out of the seventeen reviewed papers are literature reviews which have no exact location of research. Europe enters the list three times with research conducted in Poland, France, Iceland and England. The disrupted modes that the papers focus on differ but most of them focus on rail systems such as light rail, metro and train. There are also studies with no specific disrupted mode of transport. Either because the study was a literature review where all sorts of modes of transport were investigated or because the study used revealed preference and respondents experienced disruptions with different modes of transport. Figure 3.1 shows the modes of transport which were disrupted in the reviewed papers. If a paper reviewed multiple modes, a count is added to both modes of transport. This literature review first discusses the methodologies used to conduct research in Section 3.2.1 which helps identifying useful methodologies for this current study and also helps understanding how the studies are executed before diving deeper into the results. The network structure of the investigated locations and transport modes will be discussed in Section 3.2.2 which can then be compared with the Dutch train network to find similarities and differences. The travel options during disruptions and the information that passengers prefer are investigated in Section 3.2.3 and Section 3.2.4. This information will be useful when thinking about factors that will have to be considered in the stated choice experiment.

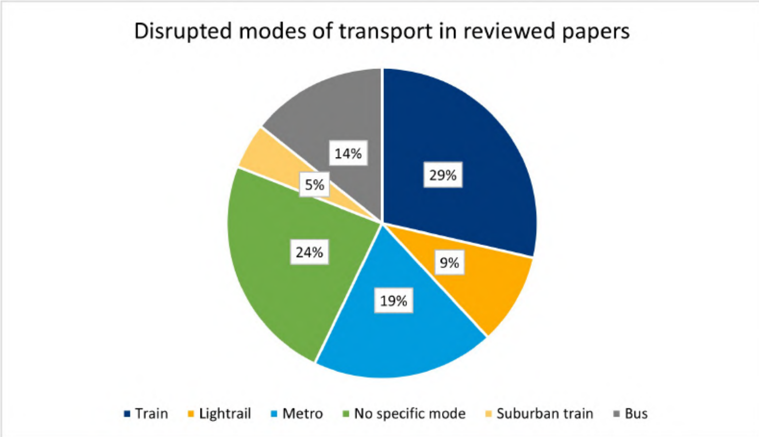

Figure 3.1: Pie chart of types of transport modes which were disrupted in reviewed papers.

3.2.1. Methodology

The reviewed papers mostly used questionnaires and surveys as a method of data collection. Five out of seventeen papers used stated preference questions to investigate behaviour (Auld et al. (2020); Bai & Kattan (2014); Fukasawa et al. (2012); Li et al. (2020); Teng & Liu (2015)). The first identified paper on the topic of travel behaviour during disruptions used stated preference questions to investigate the influence of information during disruptions on train choice behaviour (Fukasawa et al., 2012). The spreading of this information during disruptions was still not common so revealed preference was not suited. The study by Auld et al. (2020) used stated preference questions since hypothetical situations were created using actual trips made by travellers and could therefore vary attributes in the experiment. A similar reason was named in the study by Teng & Liu (2015) which varied crowding in and expected speed of shuttle buses replacing a disrupted urban rail service. Li et al. (2020) mentions that the occurrence time of disruptions is irregular and when disruptions occur passengers are reluctant to answer questions as reasons for stated preference questions. Revealed preference studies study actual behaviour that respondents executed during disruptions and was used in three out of seventeen reviewed papers (Adelé et al. (2019); Currie & Muir (2017); Guiver (2013)). Real disruptions and people's reactions were investigated in the study by Guiver (2013) which focused on the role of social networks during disruptions. Revealed preference was used for the experiment because the disruptions were very large and memorable (volcanic eruption, bridge closures and extreme winter weather). Bus replacement during a rail disruption is also deemed as memorable and therefore opinions were asked on behaviour during real disruptions in the study by Currie & Muir (2017). A new approach was developed by Pnevmatikou et al. (2015) which combined both stated and revealed preference and was used by five out of seventeen papers (Drabicki et al. (2021); Lin (2017); Lin et al. (2018); Nguyen-Phuoc et al. (2018); Rahimi et al. (2019); Rahimi et al. (2020)). This new method performed better than the SP-only or RP-only models (Lin et al., 2018). The method is based on intercepting respondents while they are waiting in transit stations (Rahimi et al., 2020). They provide more accurate information because the memory effect is reduced. For statistical modelling the multinomial logit model was often used (Bai & Kattan, 2014, Lin et al., 2018, Nguyen-Phuoc et al., 2018, Teng & Liu, 2015). A nested logit model was used in the study by Li et al. (2020) to create a structure with two levels namely the mode shift choice and the travel plan choice corresponding to the mode shift. A random parameter multinomial logit model eliminates the limitations of the multinomial logit model since it allows random taste variations, relaxes the independence of irrelevant alternatives assumptions and allows for potential correlation in unobserved factors over time and was therefore used by Rahimi et al. (2020). Adelé et al. (2019) used hierarchical clustering to obtain eight different suburban train behaviour profiles.

3.2.2. Network structure comparison

In the reviewed papers different modes of transport have been investigated in different cities around the world. The network topology can make an impact on the ability to reroute within the same network when a disruption occurs. The networks investigated in papers which only looked at one mode of transport are discussed in this section to see if rerouting within the network of the disrupted mode of transport is a feasible option since in the Dutch train network it often is an option. The Canadian networks from the light rail in Calgary and the metro in Toronto are shown in Figure 3.2. The networks have a transversal character and are designed in such a way that rerouting is hardly possible due to the lack of loops in the structure. Rerouting in the same network was also not taken into account as a travel option in the study by Bai & Kattan (2014) which investigated travel behaviour during disruptions in Calgary.

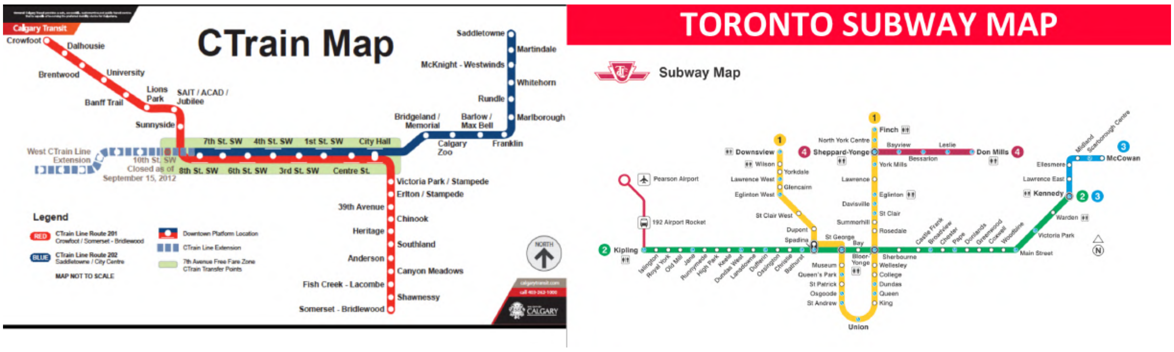

Figure 3.2: Left: map of Calgary light rail network (Calgary Transit, n.d.).
Right: map of Toronto metro network (Around the Metro, 2017).

Figure 3.3 shows the networks of the train in Melbourne and the metro in Shanghai. Both are radial networks with a strong focus on a city centre. The network of Melbourne provides little rerouting options if a disruption occurs in the radials. The network also contains only one loop leading to a small amount of travel options and long travel times between different radials. Rerouting was not taken into account in the study by Nguyen-Phuoc et al. (2018) which investigated travel behaviour in Melbourne. The metro network in Shanghai also has a radial structure but provides more travel options especially in the area within the circle line. However, when a disruption occurs in the radials there are hardly any travel options within the same network. The loop around the centre provides more rerouting options and was also considered as an option in the study by Teng & Liu (2015).

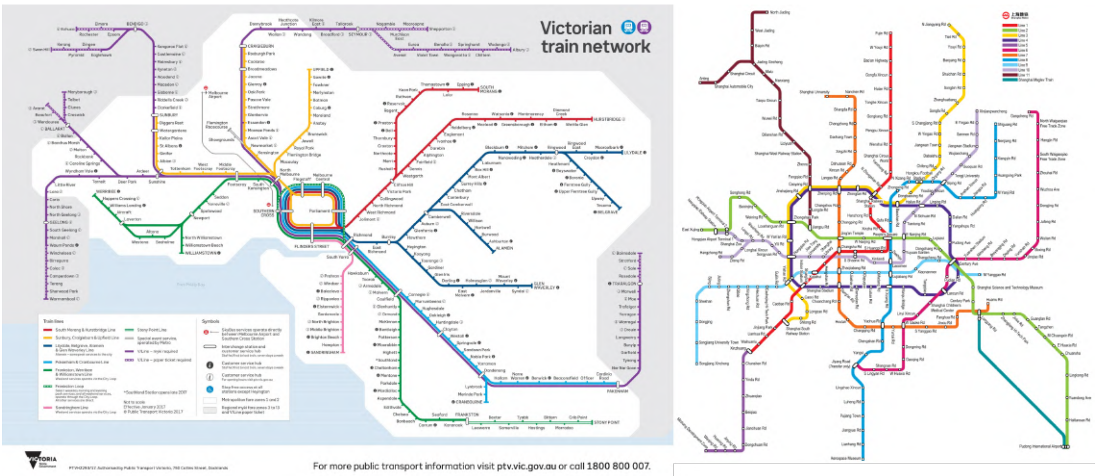

Figure 3.3: Left: map of Melbourne train network (Public Transport Victoria, 2017).
Right: map of Shanghai metro network (China Discovery, 2022).

The metro network in Guangzhou and the train network in Île-de-France have a less clear network structure as can be seen in Figure 3.4. The network in Île-de-France seems to have a radial structure with the centre in Paris but contains much more loops than the Melbourne network discussed before. The loops provide a great number of alternative routes in case of a disruption. However, the study by Adelé et al. (2019) looked at suburban train travellers who often travel from the ends of the radials were there are no rerouting options within the network. The network in Guangzhou has multiple crossing lines and loops in the network which provide many rerouting options. In the case study by Li et al. (2020) one piece of infrastructure was disrupted and one alternative route within the network was given as a travel option.

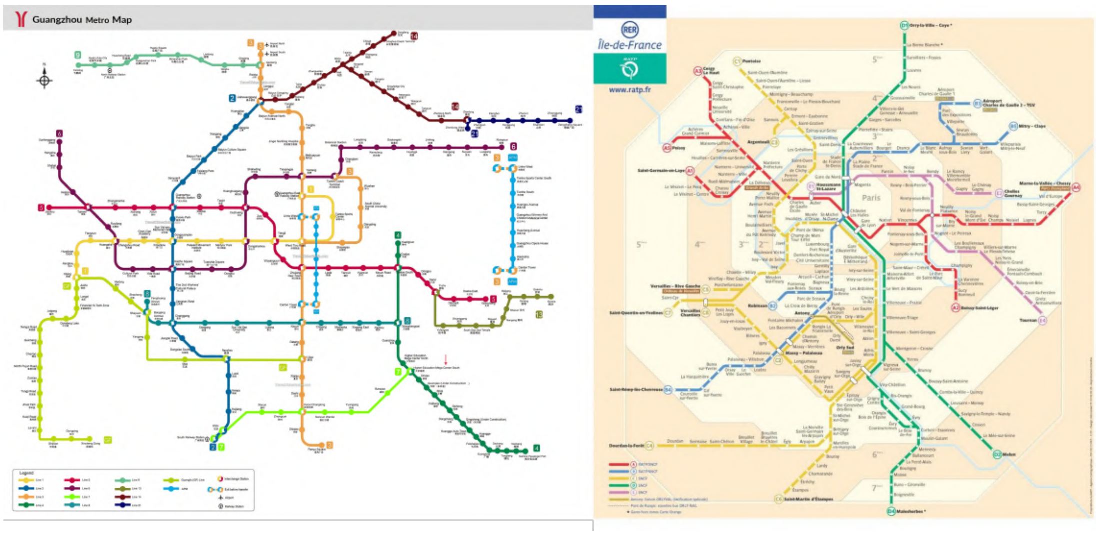

Figure 3.4: Left: map of Guangzhou metro network (Travel China Guide, 2022).
Right: map of Île-de-France suburban train network (RATP, n.d.).

3.2.3. Travel options during disruptions

Passengers can make several decisions when exploring travel behaviour during disruptions. The options that were discussed in the reviewed papers are: waiting for the disrupted service to resume, changing the route but still travelling with the same mode of transport, waiting for a replacement shuttle, change destination station or departure time, switch to a different mode of transport and cancel the trip. The factors contributing to public transport users choosing a certain option will be discussed in this section.

Waiting for disrupted service to resume

Lin et al. (2018) found that about two-thirds of investigated passengers reported waiting for the metro services to continue and travel to their destination on the original route. It should however be noted that not all reported disruptions were major. A stated preference survey by Auld et al. (2020) found that about 49% of respondents would wait for the services to resume or the shuttle that replaces the service. The revealed preference study and travel diaries by Adelé et al. (2019) showed that about 10.3% of respondents waited for the service to resume on the outbound journey and 16.8% of respondents on the return journey during disruptions lasting more than 30 minutes on the Transilien network in France. If passengers experienced time constraints the waiting time before changing route was lower than for respondents without time constraints. This result was also found in the studies by Drabicki et al. (2021) and Rahimi et al. (2019). People executing a time-critical trip waited more than 10 minutes in only 20% of the cases (Drabicki et al., 2021). The study by Rahimi et al. (2019) primarily focused on waiting tolerance during disruptions and at what point in time people start thinking about changing their route. Factors that were found to increase waiting tolerance were: transit users trust information from the public transport operator, transit users selected public transport to avoid traffic congestion, people have a lack of other alternatives, people use public transport often, increasing trip distance, increasing age and passengers who are already used to waiting will stay in the station for a longer time. The finding that people with increasing age will wait longer for services to resume is confirmed by the study by Drabicki et al. (2021) where 29% of all respondents and 63% of elderly passengers waited during bus and tram service disruptions. The same study also confirmed that frequent public transport passengers are more likely to wait at the stop (45%). People with more experience in public transport networks were found more likely to wait on their return journeys (Adelé et al., 2019). The authors of this paper did not expect to find that these travellers were less proactive to search alternative travel options. They were even willing to wait longer than people without time constraints. Strong habits increase waiting time on both outbound and return journeys and people who wait longer are more unlikely to search for travel information. The same study found that waiting time at the stop during a disruption increases when people live at the end of the line, probably due to the low number of alternatives at these stations which are stationed in less densely populated areas. The extensive study of Rahimi et al. (2019) also found factors that decrease waiting tolerance during unplanned disruptions: passengers have experience with ride-hailing and bike-sharing services, higher level of education, higher density of pedestrian-oriented roadways, higher frequency of public transport, travelling by bus compared to rail and travelling with others. It is assumed that when the frequency of the public transport service is higher there are more other public transport options available. Bai & Kattan (2014) found an influence of gender on waiting tolerance; males are less likely to wait for the service to resume than females for both commuter and non-commuter trips. Waiting tolerance is also influenced by weather since a typical winter day leads to a lower waiting tolerance. A summary of all the factors that influence the decision to wait for the disruption to be over can be found in Figure 3.5.

Figure 3.5: Trip characteristics and personal characteristics that influence the decision to wait for disrupted services to resume.

Change the route

There is also the possibility to use the disrupted mode of transport but change the route in the network. People are encouraged to change their route when they have a favourable opinion towards traffic information and if they found out about the disruptions en-route (Adelé et al., 2019). This is contradictory to the findings of Currie & Muir (2017) which state that routes are more often changed when the disruption is learned about in advance. About the influence of frequency of using the disrupted mode of transport is also no agreement. Lin (2017) states that frequent users of subway systems are more likely to change to alternative routes because of their assumed familiarity with the system. The study by Drabicki et al. (2021) on the other hand states that frequent travellers are less likely to change their route due to strong habits. Two studies also show an effect of provided information on route change. When information is provided people have a tendency to change their train choice during disruptions (Fukasawa et al., 2012). When travel times on all options are provided 39% of respondents participating in a stated preference study would use other routes to get to their destination (Lin et al., 2018). There is agreement that passengers are more likely to choose the routes with less travel time and smaller detours (Li et al., 2020, Teng & Liu, 2015). Sometimes it is not possible to choose an alternative route especially when living in remote suburbs. These people are more likely to shift to another mode of transport because of the low transport supply (Adelé et al., 2019). Since there is not much consensus on how the different factors influence route change, a summary figure is not provided for this travel option.

Wait for replacement shuttle service

When the disruption is quite severe, public transport operators can decide to deploy replacement shuttles to bridge the disrupted section of the network. Striking is that experience with bus replacement services reduces the overall satisfaction more than disruptions where there was no replacement service (Currie & Muir, 2017). However, about two-thirds of rail passengers waited for the replacement bus service even though it takes around ninety minutes to set up this service. The reason for this phenomenon being that often the buses are already deployed when passengers arrive at the disruption site and do not have to wait at all. This is more in line with the study by Lin et al. (2018) where 10% of passengers reported waiting for the shuttle service and 42% of passengers chose the shuttle bus when they were already available. Auld et al. (2020) found that 49% of respondents would wait for the service to resume or wait for the shuttle that replaces the service. The number of alternative options also influences how long people are willing to wait for the replacement shuttle service (Rahimi et al., 2020). Millennials, people with a higher level of education and people travelling with others are less likely to wait for the shuttle service while a lower density of pedestrian-oriented roadways increases tendency to wait for the shuttle bus. Finally, Teng & Liu (2015) found that there is more interest in using the shuttle service if the average speed of the shuttle is high and vehicles are not crowded. Figure 3.6 shows all the factors that influence the decision to wait for a replacement shuttle.

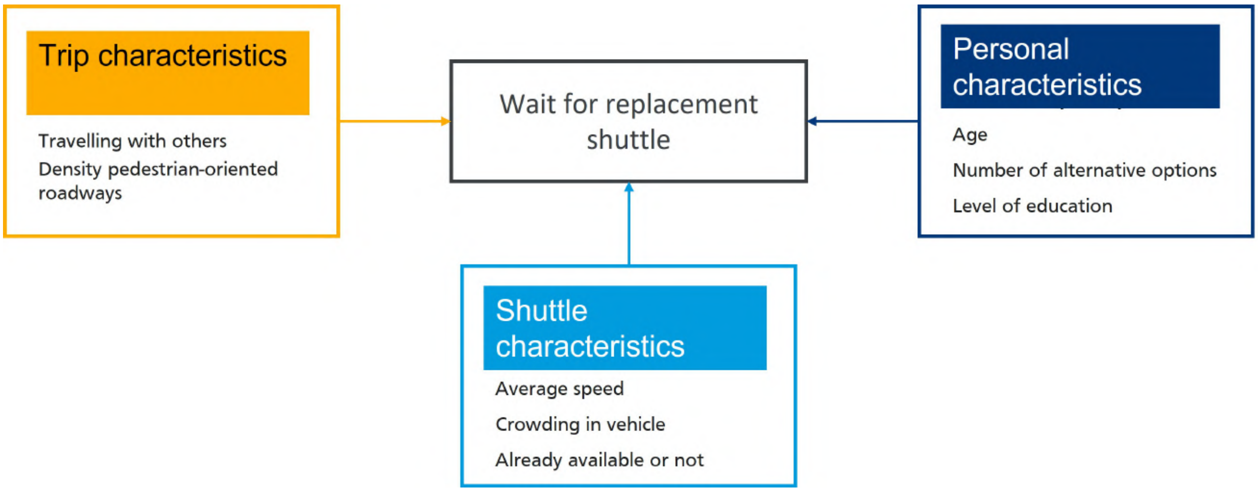

Figure 3.6: Trip characteristics, personal characteristics and shuttle characteristics that influence the decision to wait for a replacement shuttle.

Change destination and departure time

Experiencing disruptions regularly also has an effect on changing the destination of the journey. During a disruption Adelé et al. (2019) found that 62% of respondents altered the departure time and/or departure station. The study by Drabicki et al. (2021) found that of people who regularly experience disruptions 43% changes the alighting stop, 52% sometimes changes the departure time and 30% does so on a regular basis. When finding out about a disruption en-route, about 24% of respondents either cancelled the outbound trip or changed the destination (Adelé et al., 2019). During a hypothetical disruption on people's regular routes, about 15% of travellers would cancel the trip or change destination (Auld et al., 2020). People are less likely to change destination when they have experience with ride-sharing options (Rahimi et al., 2020).

Shift to other modes of transport

When the usual mode of transport is disrupted but people still want to travel to their destination, switching mode of transport can be a feasible option. Several papers have investigated factors that lead to a mode shift during unplanned disruptions. These factors will first be described after which factors that lead to a shift towards specific modes of transport such as car, taxi and bicycles will be described.

The chance to shift to other modes of transport is first of all dependent on alternative routes with the disrupted mode of transport that can be used to avoid the disrupted area. The longer the detour of the alternative route the more likely it is that a passenger will shift to another mode of transport (Teng & Liu, 2015). Similar results were found by the stated preference survey by Li et al. (2020) when all alternative routes in the metro system were disrupted as well. The duration of the disruption is also significant where longer disruptions lead to a higher chance to switch to another mode of transport. The chance to switch to another mode is higher during peak hours since the travellers are often commuters who are very time sensitive. Replacement shuttles can also be a solution to travel to the original destination. The longer the waiting time for these shuttles, the higher the chance to switch to another mode of transport (Rahimi et al., 2020). Personal characteristics such as access to a car on outbound trips and a subscription to the public transport operator's notification service encourage mode shift (Adelé et al., 2019). Students and the youngest respondents have less access to private cars and are therefore less able to switch transport modes. The same study found that during disruptions 19.5% of passengers switched modes on outbound journeys and 13.5% on return journeys. On the return journeys there was often assistance from third parties. The effects of gender on mode shift are contradictory. The study by Li et al. (2020) states that female passengers are more likely to shift while the study by Teng & Liu (2015) found that men are more likely to shift to other travel modes. The study by Li et al. (2020) provided no possible explanation. Teng & Liu (2015) provided as reason that women are more conservative than men and prefer to travel using the same mode of transport. According to this study people who carry big pieces of luggage are more likely to switch modes to avoid crowding in the disrupted mode of transport. Rahimi et al. (2020) found that there is less flexibility to switch to other modes when the passenger has a disability. Their usual mode of transport is adapted to their needs and the other available modes of transport might not be. Travelling with other people is however seen as an incentive to switch to other modes since costs can be split among the travellers. Finally, Li et al. (2020) found that a higher income leads to a higher probability to switch to other modes since these passengers' value of time is high and they will quickly find alternative ways to travel.

In a revealed preference study by Drabicki et al. (2021) 27% of respondents indicated that they walked to their destination during the last disruption they encountered. This modal shift towards walking is especially the case for students (32%) and people in the age between 18 and 35 (31%). In a similar study by Lin et al. (2018) 11% of respondents walked to their destination. When the walking distance to the destination was less than 5 km 24% of respondents choose to walk. This dependence on travel distance to switch to walking and cycling was also found by Nguyen-Phuoc et al. (2018) where the average distance of trips made by bike was 5.6 km and trips on foot 3.7 km. The study concluded that when the trips are short in distance it is likely that there is a switch to non-motorized modes of transport. This conclusion is supported by the study conducted by Rahimi et al. (2019). The authors of this study also noted that millennials are more open to switch to active modes such as cycling and walking. Trips that are made for educational purposes are more likely to be replaced by trips in the car as passenger and non-motorized modes (Nguyen-Phuoc et al., 2018). Students often do not have access to a car and are therefore forced to switch to other modes of transport. External factors such as bad weather conditions have a negative utility on using modes such as cycling and walking (Lin, 2017). Out of 556 respondents in the study by Lin et al. (2018) 6 respondents had a bicycle that they could access but none of them cycled to their destination during the last disruption they had encountered.

Three papers have also investigated the influence of public transport service disruptions on bike-sharing and ride-hailing options. Especially the survey by Rahimi et al. (2020) investigated factors that increase the likelihood of switching to ride-sharing services. They were found to be: have a bachelor or graduate degree, having experience with ride-sharing services, having access to a smartphone and being a millennial. The study by Rahimi et al. (2019) found the same results about millennials being more likely to use ride-sharing services and contributes that to the fact that millennials are more tech-savvy. Bike-sharing and ride-sharing services also have a higher chance to be chosen for shorter trip distances. The likelihood of choosing bike and car sharing also depend on whether passengers have a car available to them or not (Auld et al., 2020). In the stated preference survey 19% indicated they would use bike or car sharing when no car is available compared to 13% when there is a car available.

In the case of a light rail transit (LRT) disruption Bai & Kattan (2014) found that people who had a high familiarity with LRT and no access to a car had a high probability of switching to other transit options. However, quite contradictory to that, frequent LRT users preferred to continue their trip by LRT and not switch to other public transport modes. Another factor that increased the chance of switching to other transit options is when passengers are familiar with advanced passenger information systems (APIS). During train disruptions the revealed preference study by Currie & Muir (2017) stated that 11% of respondents used other local public transport options such as buses and trams. This number is significantly lower than the 39% of respondents switching to trams and buses found by Drabicki et al. (2021). In this study however, the investigated disruptions were either in bus or tram systems which generally result in shorter trips than train trips. During suburban train disruptions Adelé et al. (2019) found an increase in all alternative public transport modes; tram (+567%), metro (+31%) and bus (+19%). There were no explanations provided for this phenomenon.

When looking at the use of the private car during public transport service disruptions Adelé et al. (2019) found that car usage saw an 86% increase during suburban train disruptions and was particularly encouraged when people discovered the disruption before starting the trip. A revealed preference survey from Melbourne found that 51.7% of respondents would switch to being the car driver in case of major public transport service withdrawal (Nguyen-Phuoc et al., 2018). Factors found to be leading to a higher probability of switching to the car were: longer distance trips, higher income, access to a car, having a driver's license, higher number of cars in household, trip purpose was commuting instead of educational and the car was the mode of transport used to access the station. Rahimi et al. (2020) confirmed the influence of trip purpose and trip length. A revealed preference study by Drabicki et al. (2021) found that 4% of all respondents would switch to private car while 7% of employed people and 9% of people with ages between 26 and 45 would switch to the private car. Time flexibility is also a factor that influences car usage. Once flexibility decreases, the likelihood of switching to private car increases (Auld et al., 2020). The stated preference study by Bai & Kattan (2014) investigated the use of a taxi and private car as one aggregated option and found the following factors to increase the likelihood of this option: commuting passengers are not familiar with advanced passenger information, people aged 25-54 during non-commuter trips, people with one car in household, commuting males and having a driver's license. Factors that decreased the chance of switching to taxi or private car were found to be: people use public transport or walking/cycling as their main mode of transportation, no access to a car near LRT station, people use public transport frequently, people aged 25-54 during commuting trips, no car possession and when it is a typical summer day. The fact that people aged 25-54 were less likely to use the car during commuting trips was attributed to possible traffic congestion in the peak hours. The study by Rahimi et al. (2020) also analyzed the option of switching to a taxi and found having a low income, being a senior and longer waiting times for the taxi to decrease the likelihood of switching to a taxi during service withdrawal. Having a full-time job positively influenced the likelihood of switching to a taxi. A summary of all the factors influencing a shift to another mode of transport is shown in Figure 3.7.

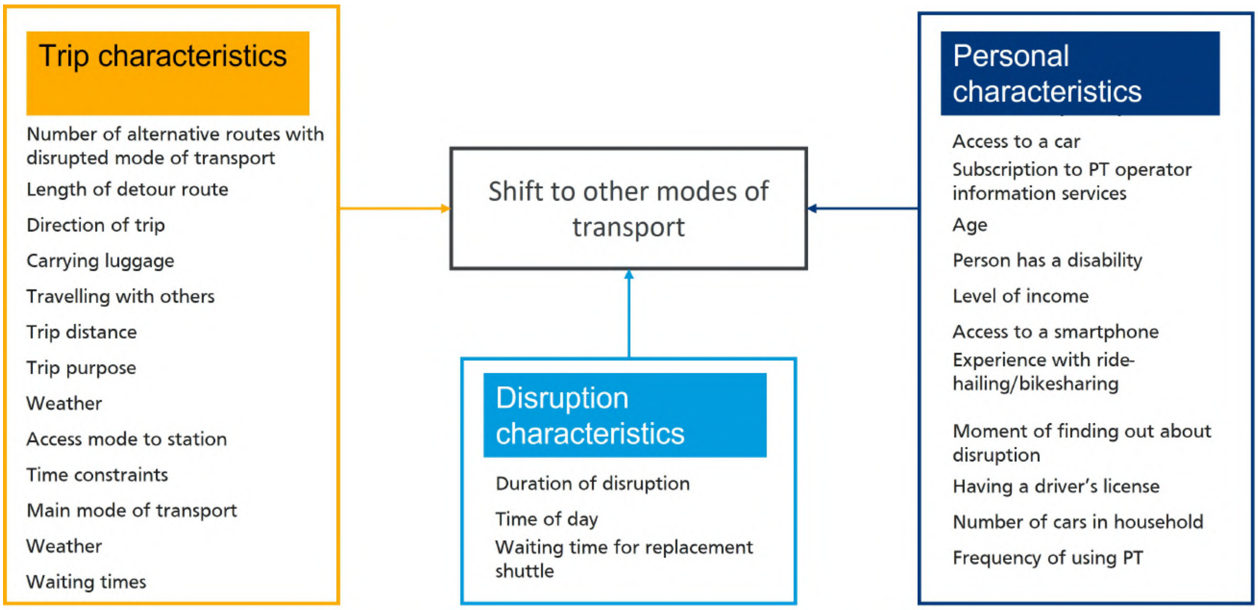

Figure 3.7: Trip characteristics, personal characteristics and disruption characteristics that influence the decision to shift to another mode of transport.

Cancel the trip

Travellers can also consider to cancel their entire trip. Nguyen-Phuoc et al. (2018) found in a revealed preference study that about 13% of trips with an average distance of 17 km were cancelled. The longer the trip, the higher the chance that the trip is cancelled during unplanned service disruptions. For the urban area of Krakow City, Poland about 2% of travellers cancelled their trip. However, trip lengths of the actual trips were unknown. The study by Currie & Muir (2017) found a similar number of 3% of all trips that were cancelled. More trip cancellations were made when travellers learned about the disruption in advance which was confirmed by the revealed preference study by Adelé et al. (2019). Auld et al. (2020) and Adelé et al. (2019) found that 15% and 24% of passengers respectively would cancel the trip or change the destination. Trip cancellation is also encouraged when people live at the end of the public transport line due to the lower number of alternatives as mentioned before (Adelé et al., 2019). Personal characteristics also have an influence on trip cancellation. When people do not have a driver's license they are more likely to cancel the public transport trip and also a higher age is associated with a higher chance to cancel the trip (Nguyen-Phuoc et al., 2018). Rahimi et al. (2020) confirms that seniors have a higher chance to cancel their trip. More flexibility in travelling and performing activities due to retirement is named as the reason. Public transport users who own a car are less likely to cancel their trip since they have another mode of transport to fall back on (Nguyen-Phuoc et al., 2018). Trips to central business districts (CBD) were more often cancelled than trips with other destinations (15.5% compared to 9.4%) probably because the CBD is associated with traffic congestion and high parking costs. The study by Lin (2017) found that bad weather conditions also lead to more trip cancellations. Figure 3.8 shows all the factors that influence the decision to cancel the trip entirely.

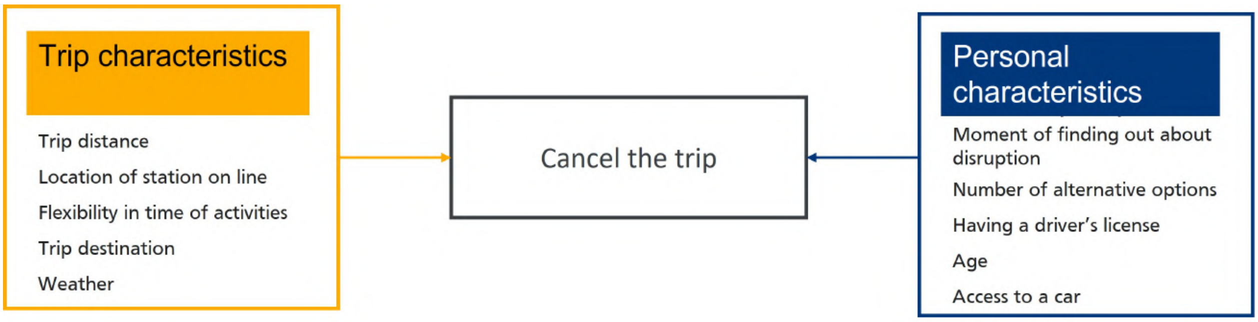

Figure 3.8: Trip characteristics and personal characteristics that influence the decision to cancel the trip.

3.2.4. Important information passenger perspective

Several papers have also looked at information that is given or not given to passengers during the disruption. Passengers require accurate and prompt information during disruptions in order to make informed decisions about their travel plans which reduces stress and anxiety (Pender et al., 2014). Based on the responses from surveys, passengers have indicated which information is valuable during unplanned disruptions. The study by Fukasawa et al. (2012) found that there are two different groups of people regarding types of information they want to receive. Passengers who travel by train to work or school want to receive detailed information on all trains in order to make their own choice. Other passengers just want to know which train they should take based on their objectives (fastest route, avoid congestion etc.). The most important pieces of information required by passengers during unplanned disruptions are: length of delay (Currie & Muir (2017), Lin (2017)), information on alternative routes (Guiver (2013), Lin (2017)) and if and when replacement shuttles will be deployed (Currie & Muir, 2017). The cause of the delay was found to be insignificant by Lin (2017) as long as the length of the delay is communicated to passengers. Social networks were found to be especially of importance when the normal resources for information provision were overloaded (Guiver, 2013). Providing information is also seen as a way to reduce passengers flows and overcrowding in stations (Hua & Ong (2018), Lin (2017)). This however requires a certain penetration rate of information and a higher information spreading speed (Hua & Ong, 2018). It is clear that passengers want to receive information but during unplanned disruptions the information can be received differently by groups of people depending on the amount of trust they have in the public transport operator (Rahimi et al., 2019). Improvements in information provision can be made by public transport operators by better publicly announcing the information in vehicles or platforms and deploying staff to assist in stations (Currie & Muir, 2017).

3.2.5. Conclusion and discussion

Travel behaviour during unplanned public transport disruptions is a recently new topic in literature and has started to gain more attention since 2017. Research is particularly focused on cities in the US, Canada and Australia. Revealed preference, stated preference or a combination of both are most often used to gather data on travel behaviour and the choices people have made or would make. For the data analysis multinomial logit models are often used with additions such as a nested structure and including panel effects with a mixed logit model.

Unplanned disruptions force travellers to adapt their travel plans and require information to make the best informed decisions. The most important pieces of information are the length of the delay or disruption, information on alternative routes and if and when shuttle services will be deployed. Literature has investigated several options as means to change the travel plans namely: wait for disrupted service to resume, change the route but continue with same mode of transport, wait for replacement shuttle service, change destination and/or departure time, shift to other modes of transport or cancel the entire trip. The feasible travel options depend on the network structure of the disrupted mode of transport. Making a certain choice is influenced by individual characteristics such as age, level of education, having a driver's license, access to a car and experience with ride-sharing options. The length or communicated length of the disruption has a large impact on how long people are willing to wait for the services to resume. On top of that, journey specific characteristics such as trip length, location of the station in the network, time flexibility and trip purpose affect the choices people make in disrupted situations.

The reviewed literature is mainly focused on the US, Canada and Australia which are car-centred countries compared to the Netherlands. Dutch infrastructure is much more accommodated to suit cyclists and pedestrians than in the countries mentioned before. Therefore when disruptions occur, the Dutch travellers might make different choices regarding their mode of transport than the respondents in the reviewed studies. The Dutch rail network is also robust due to a large amount of loops in the network structure. This accommodates rerouting in the network when a disruption has occurred and this has not received much emphasis in previous studies. In the reviewed papers heterogeneity is taken into account by using a mixed logit model but a method such as latent class choice models has not been used yet. Finally, crowding in vehicles of the disrupted mode of transport when looking at mode choice has not been considered yet.

3.3. Travel behaviour change during and after the COVID-19 pandemic

This second part of the literature review looks into the change in travel behaviour due to the COVID-19 pandemic. The aim is to answer the second research question which factors related to travel behaviour became more relevant during the COVID-19 pandemic. These factors are taken into account when constructing the stated choice experiment. When entering the search queries "travel behaviour" AND COVID-19 in search engines Scopus and Google scholar, 399 papers were found. Because of the large number of papers it is decided to only focus on studies performed in the Netherlands. Seventeen papers remain and after reading the abstracts six of them are removed. Additional material, including conference papers, is also found via the Delft University of Technology repository and LinkedIn. In total this resulted in 18 papers which are reviewed in the next sections of this chapter. The papers are separated based on whether the data is gathered at one moment in time or longitudinal. The papers with data captured at one moment in time are treated chronologically to investigate changes over time. Figure 3.9 shows an overview of the papers with cross-sectional data and important COVID-related events in the Netherlands on a timeline with the COVID-19 related hospitalizations. The studies that collected longitudinal data are also shown and the length of the arrows indicate over which period the data was collected.

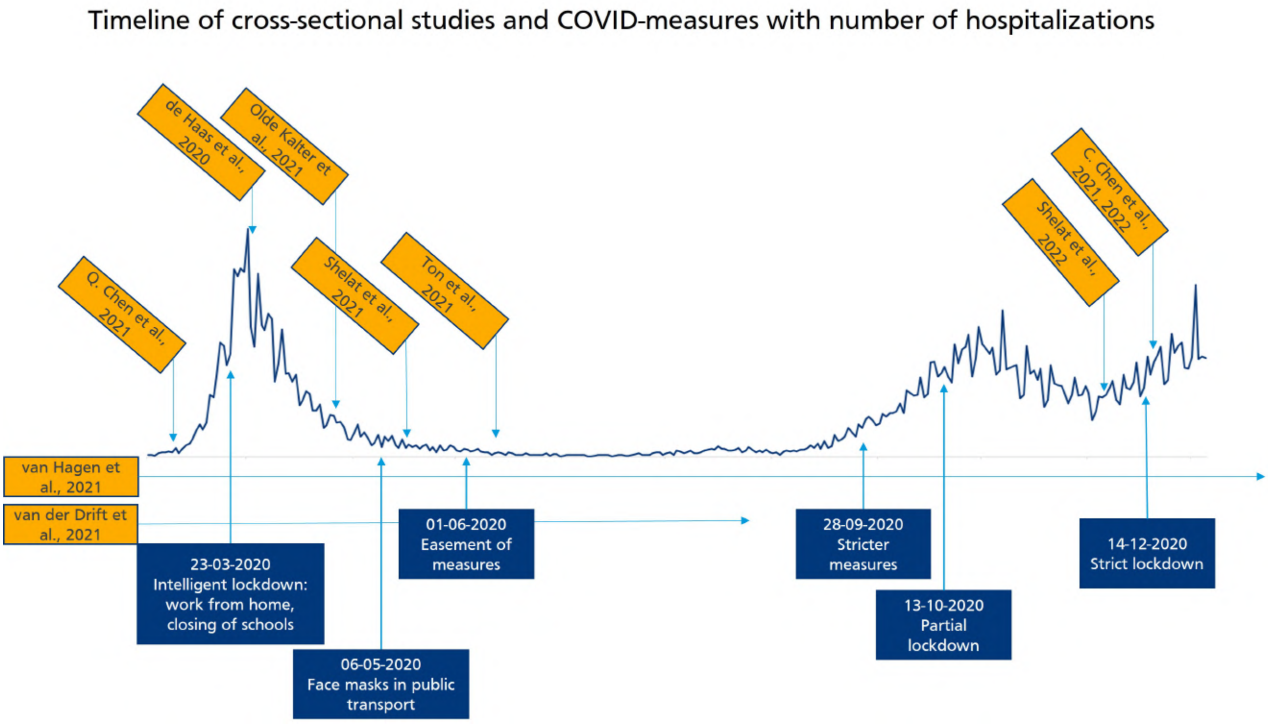

Figure 3.9: Timeline with events related to COVID-19 in the Netherlands, the hospitalization rates and at what points in time the different studies gathered data.

3.3.1. Cross-sectional studies

In late February 2020 the COVID-19 virus was introduced in the Netherlands and the spread was aggravated by the carnival event in the southern region of the Netherlands (Q. Chen et al., 2020). In March 2020 the first measures were taken by the government among which the closing of schools, advice to work from home and the introduction of the 1.5m distance requirement (Rijksoverheid, 2021). One of the first studies investigating travel behaviour under the intelligent lockdown set up by the government is the study by de Haas et al. (2020). In this study panel members of the Netherlands Mobility Panel kept a travel diary between March 27th and April 4th 2020 for three consecutive days. In a separate questionnaire they were also asked about what they expected their behaviour to be like after the pandemic. Already this early on in the pandemic respondents expected that the crisis would have a long-term impact on society. The travel diaries were compared with diaries before the pandemic to see how COVID-19 changed travel behaviour. The study found that young people are affected more by the COVID-19 pandemic because they are usually more active than elderly. Elderly people are however more afraid to become infected with the virus. In April 2020 39% of respondents worked mostly or completely from home compared to 6% in 2019. Respondents seemed to have a positive attitude towards working from home and did not find it difficult to adapt. Out of all the respondents who worked from home in the studied period, about 27% expected to also work from home after the pandemic is over. Scholars were forced to follow education online but did not value it positively. Only 10% of scholars expected to receive more home education after the pandemic is over. The number of trips made by respondents decreased by 55% and the trip distance by 68%. When looking at mode choice especially public transport was affected with a 90% decrease of trips. Public transport use decreased especially because in the vehicles it is difficult or impossible to keep 1.5m distance and also because of the urgent advice from the government to avoid public transport. The 1.5m distance measure also resulted in a smaller capacity for public transport vehicles. The decrease in public transport trips can also be explained by the fact that public transport was often used by students and people with a high level of education and these people worked and followed education from home. The car was more positively looked at than before the pandemic because about 88% of people prefer private modes of transport compared to public transport. Active modes such as walking and cycling became more popular and the number of trips using these modes increased during the pandemic. With people staying home more, round-trips for recreational purposes using active modes also became more popular. After the pandemic 20% of respondents expect to walk and cycle more and travel less by airplane.

Teleworking means that people work from a distance or have the flexibility to sporadically go to the office (Mouratidis et al., 2021). Teleworking has the potential to reduce the distance travelled for commuting but can also induce non-work related travel. The pandemic has given a large boost to teleworking because of the government's urgent advice to stay home. In April 2020 GPS data was collected from members of the Dutch Travel Panel and the respondents were also asked to fill in an online survey to study changes in teleworking (Olde Kalter et al., 2021). Job characteristics and the initial working situation were the main factors that affected teleworking during the lockdown. Office workers and teachers were the most likely to change their commuting behaviour. Office workers were urgently advised to work from home and schools were closed so teachers also started teleworking. Teleworking was associated with an increase in productivity and more pleasure and office workers, especially those that have a high income and education level, expect to increase the number of days they work from home compared to before the pandemic. People who travelled large distances to work before the pandemic are especially positive. Respondents also expect to use their car less after the pandemic because of this increase in teleworking. Olde Kalter et al. (2021) also states that in the short term commuting trips are reduced due to teleworking but that there might be induced travel for other purposes, agreeing with the studies by Mouratidis et al. (2021), Shortall et al. (2021) and van Wee & Witlox (2021).

The study by Ton et al. (2021) focused on teleworking behaviour among train travellers during and after the pandemic in order to support public transport operators and authorities in policy making. The NS panel with 80.000 members was used to spread the survey in April and June 2020. In April 2020 the lockdown measures were still in place while in June 2020 the intelligent lockdown was lifted although some measures remained in place. It was still advised to work from home as much as possible. A latent class cluster analysis was used to analyse the data and led to six different types of teleworkers. The difference between the groups was mainly found in the frequency of teleworking, intentions to continue teleworking in the future, sociodemographics and also employer attitude. About 71% of respondents indicated that they had a high willingness to work from home, 16% a low willingness and 12% were self employed and were the least impacted. The respondents with a high willingness to telework are also expected to change their mobility pattern in the future. Of the distinguished group with a large percentage of full-timers who had experience with working from home before the pandemic 92% intends to work more from home than before the pandemic. This group consists of 32% of the teleworking population which is the largest of the six groups. This group of respondents consists of people who often travel by public transport which can therefore lead to a reduction of public transport trips since these people expect to work from home more often. People with a negative attitude towards teleworking expect to work less from home after the pandemic and return to their workplace as soon as they are allowed.

The study by Shelat et al. (2021) studied behaviour related to crowding, exposure duration and prevalent infection rate among Dutch train travellers. The data was collected using a stated preference experiment distributed among Dutch train traveller between 20 and 25 May 2020. In this period there was a large decline of COVID-19 cases in the Netherlands and the advice to not travel by public transport was less strict. In the survey people were asked to choose between two trains which varied in crowdedness in the vehicle which was graphically presented to respondents and waiting time. After analyzing the data using latent class choice models two classes were found of nearly equal size. The respondents in the first group were called the 'COVID Conscious' and have the strong desire to sit in a train with nobody near them. They were also found to be sensitive to changes in the infection rates. The other class was called the 'Infection Indifferent' class. Their value of crowding was slightly higher than before the pandemic but the difference was small. Respondents who frequently use the train are more likely to be Infection Indifferent while females and older people are more likely to be COVID Conscious. The COVID Conscious class were willing to wait 8.75 minutes to reduce one person on board.

Just before a strict lockdown in December 2020 Shelat et al. (2022) conducted a study on risk perception in public transport. The study contained a stated preference experiment with two stages which was distributed in the first week of December 2020. In the first stage respondents were asked how risky a certain situation felt to them. In the second stage respondents had to make decisions between different travel options and the risk was an attribute of the travel options. The factors that were found most important for risk perception by respondents were the on-board crowding and infection rates. Travellers are more likely to choose routes which have a lower COVID risk. People who usually make longer trips by train value risk four times as much as the respondents who make shorter trips. The study also investigated the value of time and willingness to pay for risk reduction. The value of time has not changed significantly compared to a previously executed extensive study in the Netherlands. Travellers who make long trips are willing to pay 4.54 euros to reduce their risk rating by one point (out of five). They would also pay 0.53 euros for a ten percent point reduction in seat occupation, 0.65 euros for increased sanitization and 0.98 euros for on-board mask mandates.

The next two studies were conducted in December 2020 as well but during a strict lockdown. People were only allowed to have two visitors per day, all recreational buildings were closed, all schools were closed and public transport was only available for essential trips (Rijksoverheid, 2021). Both studies use the same stated choice experiment and dataset. The study published in 2021 focused on how policies and latent attitudes regarding COVID-19 influence travel decisions (C. Chen et al., 2021). The study from 2022 on the other hand investigated the effect of COVID-19 related countermeasures on the use of public transport (C. Chen et al., 2022). In the experiment respondents were asked to choose between car, bus, bike, shared e-bike, walking and not travel at all. The context included the COVID-19 restrictions policies which were varied, the distance of the trip (2.5 or 5 km) and the travel purpose. The different modes included attributes which relate to COVID-19 such as face mask obligation, disinfection frequency, if the 1.5m rule applies and if disinfectants are provided. The study by C. Chen et al. (2021) aims to give insights in barriers and drivers of a successful restriction policy. The authors found that traditional attributes such as travel time and travel cost became less significant when making decisions. Latent factors such as social responsibility, perceived risk, travel anxiety and fear of infection significantly relate to travel preferences. Respondents who are more socially responsible tended to travel less during the pandemic. When the lockdown policy became more strict, more respondents answered they would cancel their trips. Stricter lockdown also resulted in a higher popularity for the bicycle and car and decreasing usage of the bus. This decrease in popularity of the bus also correlates with the crowding in the bus and highly valuing perceived risk. Factors that positively influence the choice for the bus are a higher disinfection frequency and a face mask requirement. A general result is that during the pandemic private modes have become the preferred modes of transport compared to public and shared transport. In the study by C. Chen et al. (2022) the obtained dataset was used to estimate a latent class choice model which resulted in two classes. The first class primarily consists of respondents with a lower education level and the

COVID related travel policies have a negative effect on their public transport usage. The second class is more sensitive to the severity of the lockdown compared to the other class, more sensitive to attributes related to time and more sensitive to the number of people on board while travel costs are not significant. The second class mainly consists of respondents with a high level of education and older people or married couples with children are also more likely to be in the this class. Both classes are sensitive to the lockdown levels but class two has a larger negative parameter than class one. Based on the classes the study found that elderly and highly educated people (likely to belong to class two) are more susceptible to enforcement measures while young and single Dutch people (likely to belong to class one) are more susceptible to non-compulsory measures.

3.3.2. Longitudinal studies

Studies investigating travel behaviour during longer periods of time have the ability to show changes in behaviour over time. The study by van der Drift et al. (2021) collected data from the Dutch Mobility Panel using a smartphone app which automatically tracked respondents' mobility behaviour. The data was collected from February 2020 until August 2020. The research shows that one week after the start of the intelligent lockdown on March 12th, the largest decrease in travel was detected. Public transport usage decreased by 90% and car usage by almost 50%. The percentage decrease for public transport was also found in the study by de Haas et al. (2020). Most of the typical public transport users were able to work from home during the lockdown or did not have the need to travel. If they did travel, 50% of them used a different mode of transport. Not only did the demand for public transport decrease, the demand was also more spread out over the day removing morning and evening peaks. As demand started to increase slowly over time and with easing measures, demand peaks started to slowly appear again. Also in accordance with the previously mentioned study, travel times for active modes (walking and cycling) increased. Especially an increase in short walking round trips increased. When looking at trip purposes, offices, schools and medical facilities were less often visited than before the lockdown which correlates with the measures of closing the schools and strictly advising people to work from home. Travelling to destinations in nature gained popularity during the lockdown. During the lockdown travel behaviour became more homogeneous and therefore independent of age and income which normally would lead to different travel behaviour. Over time, independent of the measures that were taken, mobility gradually increased. Especially the opening of the schools in May resulted in a boost of car usage.

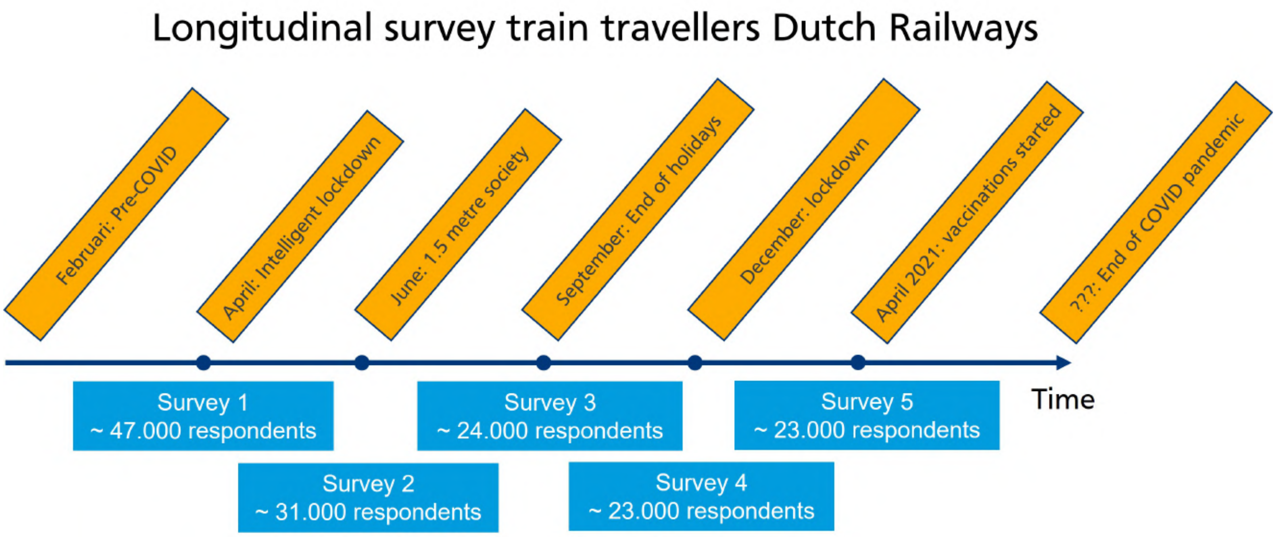

Figure 3.10: Timeline of important COVID-related events and the distribution of surveys to NS panel. Adapted from (van Hagen, de Bruyn, et al., 2021a).

The longitudinal study by van der Drift et al. (2021) gives an insight into the changes in travel behaviour but not the factors that influence them since the data collection was executed via GPS data. NS also performed longitudinal research together with the Delft University of Technology by distributing a survey via the NS panel. In the surveys, questions about travel behaviour, working from home and attitudes towards train travel were asked. At the moment of writing this literature review, six surveys have been sent out to train travellers in

April, June, September and December 2020 and April and September 2021. The data from the surveys have been used for studies in scientific papers but also in Master Theses of students from the Delft University of Technology. Since the studies were performed at different times during the pandemic, not all studies have taken all distributed surveys into account. The cooperation between NS and Delft University of Technology resulted in three scientific papers (van Hagen, de Bruyn, et al., 2021a,b, van Hagen, van Oort, & Ton, 2021). The first paper focused on the surveys distributed between April and December 2020 (van Hagen, de Bruyn, et al., 2021b). The other two papers investigated the results of the surveys distributed between April 2020 and April 2021 (van Hagen, de Bruyn, et al., 2021a, van Hagen, van Oort, & Ton, 2021). Thesis work by Dirkzwager (2021) and Hafsteinsdóttir (2021) used the survey data to investigate relations between travel behaviour, attitudes and risk perception. First the scientific papers are reviewed for general information extracted from the surveys after which the thesis work is explored where relationships are investigated based on the data. Figure 3.10 shows the timeline of the most important COVID-related events and when the surveys were distributed among the NS panel including the number of respondents of each survey.

The study by van Hagen, de Bruyn, et al. (2021a) explored the data from the first five surveys distributed via the NS panel between April 2020 and April 2021. The study looks into change of attitudes and travel behaviour of train travellers. The first survey was distributed in April 2020 which was the start of the intelligent lockdown imposed by the Dutch government. Only people working in vital professions were allowed to travel by train at this moment. The second survey was distributed in June which was after the end of the lockdown but multiple measures were still in place. In September people were allowed to work more in the office which was when the third survey was distributed. The fourth survey was distributed around the time when there was news of a vaccine, December 2020. The last survey from April 2021 was sent out during a time when easements were announced. In each survey additional questions were asked on different topics such as teleworking which was used in the study by Ton et al. (2021) but also attitudes and intentions of travellers. Before the pandemic about 37% of all respondents travelled by train once per week or more. In April 2020 93% of participants indicated that they did not all travel by train. When the lockdown eased in June and September the percentage decreased to 81% and 71% respectively. When measures became more strict again, train travel decreased again. Attitudes related to train travel also correlated with strictness of measures imposed by the government. Attitudes became more negative with increasing measures during the first wave. However, during the second wave attitudes did not become as negative as during the first wave. Over the course of a year, the percentage of respondents with a positive attitude towards the train increased from 20% to 42%.

The Netherlands Institute for Transport Policy Analysis (KiM) performed a study on working from home during the pandemic which the study by van Hagen, de Bruyn, et al. (2021a) compared their results to. The study found that during the pandemic approximately 45-56% of the working population started working from home while this percentage was only 6% before the pandemic (Hamersma et al., 2020). The study based on data from the NS panel found that 62% of the respondents worked from home full-time indicating that a large part of those who teleworked used to travel by public transport. The number of people working from home also correlated with the strictness of the measures imposed by the government and shows the same trend as the travel weeks per day. In April the percentage of teleworkers is the highest and slowly decreases until in December 2020 strict measures were again imposed which caused an increase in the percentage of people teleworking. Attitudes regarding teleworking and intentions regarding teleworking after the end of the pandemic were also investigated. Even though over time a smaller percentage of respondents were less positive about teleworking, the percentage of respondents with the intentions of teleworking more after the pandemic increased over time. The study by van Hagen, de Bruyn, et al. (2021a) also cites the study on different types of teleworkers by Ton et al. (2021) and states that teleworkers with a negative attitude towards teleworking will return to travelling by public transport whenever they are allowed. On which days of the week people intend to travel to work was also investigated. The most popular days of the week seem to be Tuesday and Thursday with 67% and 66% of working respondents respectively. The least popular days are Wednesday and Friday with 50% and 40% respectively. Therefore, there is a risk of imbalance in demand over the week which is a negative development for NS. However, a positive development is that 30% of respondents stated that they will continue to travel outside of rush hours which creates a more homogeneous demand over the course of a day.

In addition to a change in commuting behaviour a shift was observed in access and egress modes as well. Travelling by foot, or as a car passenger showed an increase and especially local public transport experienced a decline. The decrease of using local public transport was also observed for egress modes. Especially the bicycle and the car as a passenger were more often used to get from the station to the destination. The study also shows that about 1.5% of respondents bought a new vehicle (mostly cars and (e-)bikes) to replace train journeys (van Hagen, van Oort, & Ton, 2021).

In this study emotions were investigated and it was found that they were mainly influenced by the strictness of the government measures (van Hagen, van Oort, & Ton, 2021). In September 2020 the emotions were mainly positive because the measures were eased and infections low. However, in December 2020 infections had increased and measures became more strict and during this time emotions were predominantly negative. Whether emotions are positive or negative seems to have a large influence on the intention to resume previous travel behaviour. Negative emotions due to strict measures and high infection rates increase the expectation to return to respondents' previous travel behaviour. The change in intentions to return to travel behaviour from before the pandemic is the smallest for school and work related trips and largest for leisure and social trips. The emotions measured before also influence the attitude towards the train. When looking at data from the strict lockdown in December 2020 and April 2021, a period with less strict measures, reasons for not liking travelling by train differ. In December 2020 the main reason was that travelling by train was discouraged by the government and that respondents do not have to make necessary journeys. In April 2021 this shifted to respondents not wanting to stand close to other passengers and lack of faith that their fellow travellers follow the rules regarding wearing face masks. Respondents also stated reasons for them to able to freely travel by train again. The main arguments that were mentioned in April 2021 were when many people are vaccinated including the respondents themselves, the face mask not being obligated anymore and the removal of the 1.5m distance measure. The arguments have changed over time since in the first surveys the vaccine was not ready to be distributed yet.

The study by Dirkzwager (2021) investigated the relationships between attitude, perception of risk and travel behaviour by car and train and used data from the surveys distributed among the NS panel from April, June, September and December 2020. The study shows that autoregressive effects are the largest meaning that if a respondent has a negative attitude towards train travel in June, they are likely to also have a negative attitude in September. Bidirectional relationships were also found between travel behaviour and attitudes. However, it was expected that behaviour would have a larger effect on attitude than the other way around but this was not confirmed in this study. Another bidirectional relationship for train travel shows that a higher perception of risk leads to less train travel but also that more train travel leads to a lower perception of risk. Risk perception plays a larger role for travelling by train than for travelling by car. As discussed before, car travel has increased during the pandemic to higher levels than before the pandemic indicating a mode shift to car.

Hafsteinsdóttir (2021) investigated factors that influence anxiety levels among train travellers. Data from all six distributed surveys from April 2020 up to September 2021 among the NS panel was used. People were labelled as anxious if they answered that they did not feel free to travel by train. It was implied by the author that if respondents answered that they did not feel free to travel they felt unsafe and therefore anxious. When looking in time, the number of anxious people has decreased between April 2020 and September 2021 from 72% to 20%. The number of anxious people increases when the infection rates are higher and government measures stricter. The profile of an anxious person is that they are likely older than 25 years old, female and not vaccinated. Therefore anxiety levels are affected by gender, age and vaccination status. People who are anxious have a more negative attitude towards the train than people who are not anxious. They also travelled less by train and expect to travel less by train after the pandemic than before the pandemic. A reason for this phenomenon could be that anxious people are more afraid to be infected with the COVID-19 virus.

3.3.3. Conclusion

Since the start of the COVID-19 pandemic in the Netherlands in February 2020 travel behaviour has changed. The initial change in travel behaviour was caused by government measures urging citizens to stay home and work from home as well. Car usage decreased but especially public transport trips decreased drastically in this initial period of the pandemic because people who travel by train often had the option to work from home and the train was only available for essential trips. Of all the people working from home during the pandemic a large part had a positive attitude towards teleworking and expect to continue teleworking even after the end of the pandemic. This phenomenon also changes the demand of public transport over the week since the Tuesday and Thursday are more likely to become office days than the Wednesday and Friday. People with a negative attitude towards teleworking are more likely to return to the office full-time if the company allows it.

Not only the attitude towards teleworking alters travel behaviour, the attitude towards travelling by train during the pandemic influences behaviour as well. Some people tend to avoid crowds because of fear of being infected with the virus. A negative attitude towards the train leads to people expecting to travel less by train after the end of the pandemic. For the people who are very conscious of COVID-19, traditional attributes such as travel time and travel cost have become less important while perceived risk, fear of infection and social responsibility have become more leading in their choices. There is however an additional group of people who are indifferent to crowding in vehicles, do not value perceived risk highly and do not feel unsafe while travelling by train. It is expected that people who are very conscious of COVID-19 might make different travel options based on crowding in the vehicle while for the COVID-19 indifferent people this will not be a leading factor. The ability to telework might also have an impact on the decision commuters make during disruptions since they might more easily return home and work there instead of continuing their journey to the office.

3.4. Conceptual framework

The variables that influence travel behaviour during unplanned disruptions in the aftermath of the COVID-19 pandemic are summarized in a conceptual framework. This conceptual framework is based on the literature review performed in this chapter and expert information from NS. The factors presented in the framework are based on the alternatives that are chosen to be included in the study. Therefore the framework does not give a full overview of all factors influencing the choices people make but only the factors that might influence the choice for one of the three specified alternatives. The following section will explain which alternatives are focussed on and why.

3.4.1. Alternatives

The literature review performed in this chapter led to the discovery of seven identified travel options when faced with an unplanned disruption; wait for disrupted service to resume, change the route within the same network, wait for replacement shuttle service, change destination and departure time, shift to other modes of transport and cancel the trip. The focus of the study is based on research gaps found while performing the literature review and is described in Section 1.2. Since the study aims to help train operators make better predictions of traveller flows during unplanned disruptions the alternatives 'wait for disrupted services to resume' and 'change the route within the network' are included in the framework.

NS only deploys replacement shuttles when there are no viable rerouting options within the train network so that option is not considered in this study since it is assumed that rerouting is possible.

The number of passengers that would make a mode shift is valuable information for a train operator but to which modes of transport they shift is interesting to a lesser extent since they exit their network and enter another public transport operator's network. Data from train trips from NS also shows that the average trip by train is approximately 35 minutes which translates to a distance of roughly 50 kilometres depending on the number of stops in between. Trips of such a distance or longer are difficult to cover by other modes of public transport in the Netherlands when the train is excluded. On top of that, the potentially applied control strategies are most beneficial for travellers that only have the train as an option while travellers who travel short distance trips have other alternatives and do not have to stay within the train network to reach their destination. Therefore the mode shift alternative will not be taken into account and the focus lies on trips that are of roughly average length or longer.

The option of departure time change is not considered in this study since the travellers postpone their trip until the disruption is over and do not enter the train network during the disruption. Therefore they do not contribute to the passenger flows and do not have to be considered while making the predictions. Changing the destination when a disruption occurs has not been extensively studied previously and factors that influence this decision are unknown. Studying it would require a different focus than has been chosen during this study and therefore it will not be considered.

The option to cancel the trip is included in the framework since it is expected that due to the increase in teleworking since the start of the COVID-19 pandemic this option will be chosen more often in the case of disruptions than was found in previously conducted studies. The option is renamed to 'returning to origin station' to also entail that passengers do not only cancel the trip but travel back to their origin as well which can possibly include travelling back by train.

Another possible travel option not yet found in literature is that stranded travellers can connect with each other and share a taxi. Although this is an interesting option, the share of travellers choosing this alternative is expected to be small and is therefore not considered in this study.

3.4.2. Attributes

The papers reviewed in Section 3.2 which use a stated preference experiment as a part of their data collection method are scanned to extract the attributes that are included. Common attributes can be found in this way and added to the stated choice experiment when deemed important for this current study. The results can be found in Table 3.3.

Table 3.3: Attributes in reviewed papers with stated preference experiments.

References	Travel time	Travel cost	Number of transfers	Departure time	Arrival time	Crowding	Relative speed	Waiting time
Fukasawa et al. (2012)	✓		✓	✓	✓	✓		✓
Teng & Liu (2015)						✓	✓	
Lin (2017)	✓	✓						
Lin et al. (2018)	✓	✓						
Auld et al. (2020)	✓	✓			✓			✓
Li et al. (2020)	✓	✓	✓					
Rahimi et al. (2020)	✓	✓			✓			✓

The paper by Bai & Kattan (2014) provided respondents with two scenarios and for each scenarios there were four questions where trip purpose and weather conditions were varied. Respondents were asked what travel option they would choose but to the best knowledge of the author, there were no attributes such as travel time and costs involved. Therefore this study has been removed from the table above. For similar reasons, the studies by Nguyen-Phuoc et al. (2018) and Drabicki et al. (2021) were also removed from this analysis. Respondents were asked which mode of transport they would choose in case of public transport service disruption but information on travel time and other characteristics of these modes of transport were not given.

The attributes travel time and travel cost appear in almost all of the reviewed papers with a stated preference experiment. The other attributes are more specifically related to the goal of the papers for example departure time change, waiting time and crowding. The attributes that are expected to influence the choice for a certain alternative are included in the framework. Travel costs are not included in this study since the price of a trip only depends on the check-in and check-out station and not on the route travelled between the two stations. General terms such as waiting time and travel time are renamed to better fit each specific alternative. For example the waiting time in the 'waiting for the disruption to be over' option is actually the disruption length.

3.4.3. Sociodemographics / background variables

The sociodemopgrahics and background variables that are expected to influence the utility and therefore people's choices are found based on the performed literature review and also retrieved from discussions with NS colleagues. COVID-19 risk perception has not been found in literature yet but is added because it might influence how travellers perceive crowding. Since crowding is a common phenomenon during disruptions it might give valuable information on the importance of avoiding crowds during disruptions. Ability to telework is included due to the expected increase of people returning home during a disruption when they are able to telework. It is expected that previous experience with disruptions and attitude towards travel information create a certain behaviour pattern when a disruption occurs and might be the basis for a travel preference.

3.4.4. Trip and disruption characteristics

Characteristics of the disruption such as the expected length of the disruption, time of day when it occurs and the information provision during the disruption are factors found in literature to influence people's choices. The trip characteristics of individuals also determine what alternatives are feasible. If the direction of the journey is homebound for example it is much less likely that a traveller would choose to return to the origin of their trip. Behaviour is also expected to differ based on the trip purpose since commute trips can be very time constrained while leisure activities might no be.

The full conceptual framework can be found in Figure 3.11. At the top of the figure the dashed boxes contain the factors that are expected to influence the choices that are made. The three rectangular boxes on the right and left of the utility are the three possible alternatives. The boxes within the alternatives are the attributes of the alternatives. Rectangular boxes are variables that are directly observable while information within oval boxes is not directly observable. The black lines that run from the alternatives to the utility indicate the main effect of the variables on the utility. The yellow line depicts that the variables are expected to interact with the utility of the alternatives. The blue lines indicate that variables have a direct effect on the utility of the alternatives.

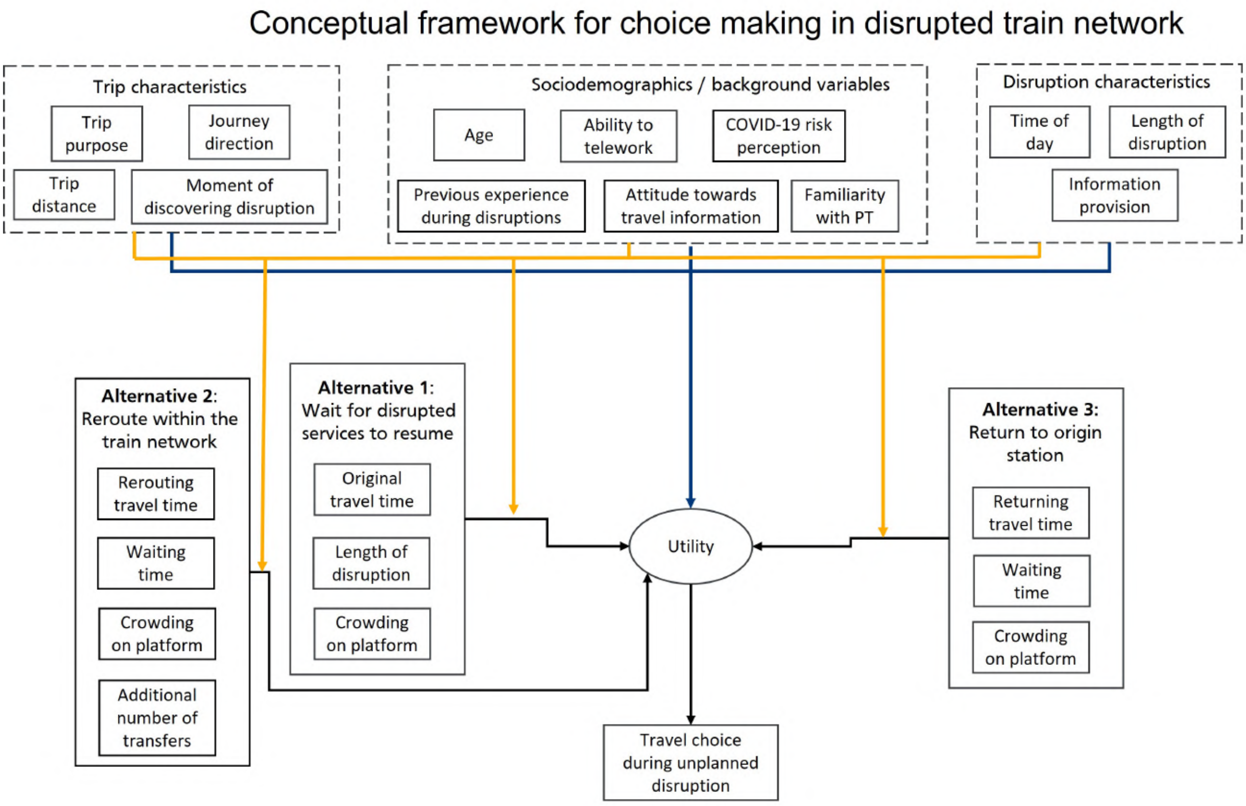

Figure 3.11: Conceptual framework for the stated choice experiment. Rectangular boxes show observable variables, oval boxes show unobservable variables. The black lines are the main effects of the variables on the utility. Yellow lines indicate interactions between variables and utility of alternatives. Blue lines indicate variables that have an effect on utility. The solid black boxes are the alternatives while dashed boxes contain context variables and sociodemographic variables.

3.5. Conclusion

Summary

- Literature has not yet discussed the effects of COVID-19 on travel behaviour during train disruptions.
- Due to the robustness of the Dutch train network rerouting in the network is studied.
- COVID-19 has caused a rise in teleworking which most people have a positive attitude towards.
- People who are conscious of COVID-19 are expected to avoid crowds and possibly avoid the train altogether.
- The studied travel alternatives are; wait for the disrupted services to resume, reroute within the train network and returning to origin station.
- In the stated choice experiment disruption length, travel times, waiting times, crowding and the additional number of transfers are varied.

In this chapter an extensive literature review is executed which results in a conceptual framework for decision making during a train disruption. The literature review is executed to find factors that influence travel behaviour during disruptions before the COVID-19 pandemic and how the pandemic has changed general travel behaviour. The biggest changes due to the pandemic are that people were urged to work from home by the government. This turned out to be a positive experience for many teleworkers to the extent that they will continue working from home after the end of the pandemic. Due to this change in working behaviour it is expected that returning home will become a viable alternative during train disruptions. The pandemic has also made some people very conscious of avoiding crowds and therefore people's risk perception due to COVID-19 is also expected to have an influence on travel behaviour during disruptions since crowding is common. Attitude towards information and previous experiences during disruptions are expected to affect the choices people make during disruptions since their previous experiences and attitudes might lead to a preferred travel alternative.

4 Stated choice experiment design

In order to collect data to answer the main research question, a stated choice experiment is designed. The design of the stated choice experiment is explained in this chapter. A three-step approach to design the experiment is followed which focusses on the model specification, experimental design and creating the questionnaire (ChoiceMetrics, 2021). Based on the conceptual framework defined in 3.4 the experiment is designed. This conceptual framework described all factors and attributes that might have an effect on choosing between the three specified travel alternatives. First, the context of the stated choice experiment is described in Section 4.1. Which factors will be varied and which are set for all choice sets is explained in this section. The following sections describe how the stated choice experiment choice tasks are designed and how the questionnaire is distributed.

4.1. Context

During the stated choice experiment respondents are asked to imagine they are making a train trip and at a certain point in their journey a disruption occurs. Specifying the context sets the scene for respondents in which they answer the choice tasks.

Trip purpose: Travel behaviour during disruptions is expected to vary depending on the purpose of the trip. Since this study is the first piece of the puzzle it is decided to focus on situations in which disruptions have the greatest impact. During peak hours most travellers are affected by a disruption. Since commuters are the most common travellers during peak hours they are chosen as a focus group. The trip purpose for the imaginary trip is therefore set to commute.

Time of day and journey direction: As discussed before, disruptions impact most passengers during peak hours. One of the changes after the COVID-19 pandemic is that people are expected to remain working more from home. Upon discovering a train disruption it is possible for people to return home given that they have the option to work from home. If the disruption would happen during the trip from work to home, this option is not feasible. Therefore, in this study the choice is made to focus on the morning peak hours when people travel towards their work.

COVID-19 measures: In this study it is assumed that there are no COVID-19 measures in place. This complies with the research goal to look at behaviour during the aftermath of the COVID-19 pandemic. At the moment of distributing the survey there were no COVID-19 measures in place in the Netherlands (Rijksinstituut voor Volksgezondheid en Milieu, 2022).

Figure 4.1: Context in normal situation.

Figure 4.1 shows what a normal trip would look like in the stated choice experiment. Respondents first travel from their home to the train station using their normal access mode of transport. From the train station they take the train to their workplace and then use their normal egress mode to travel to the workplace.

Moment of discovering disruption: The goal of the study is to better predict passenger flows based on available data. If travellers find out about the disruption before leaving their home they do not enter the train system if they decide to stay at home. Data on these travellers is not available since they never entered the NS system and therefore cannot contribute to predicting passenger flows. Two disruption scenarios are created which capture two different moments of finding out about the disruption. In the first scenario the disruption occurs when travellers arrive at the train station and have not yet travelled by train, see Figure 4.2.

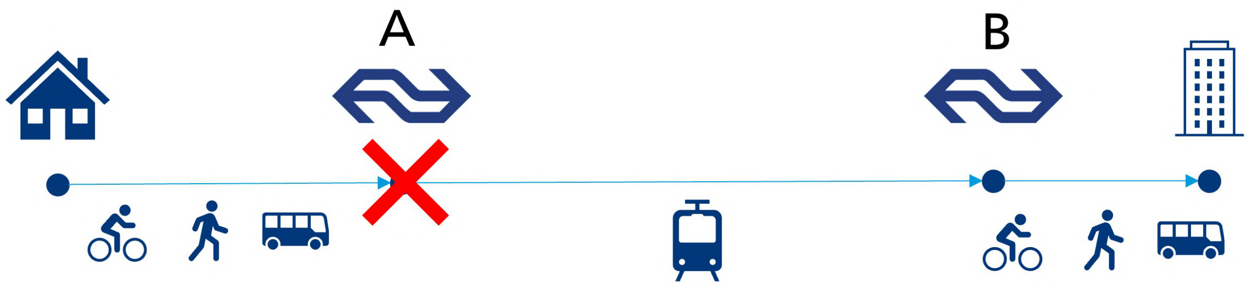

Figure 4.2: Disruption scenario where disruption occurs at origin train station.

The second disruption scenario differs in the sense that travellers find out about the disruption while they already covered part of their train trip. The disruption can either occur at a transfer station or that their current train is discontinued. It is assumed that passengers strand at a station and are not inside the train anymore. This scenario is shown in Figure 4.3.

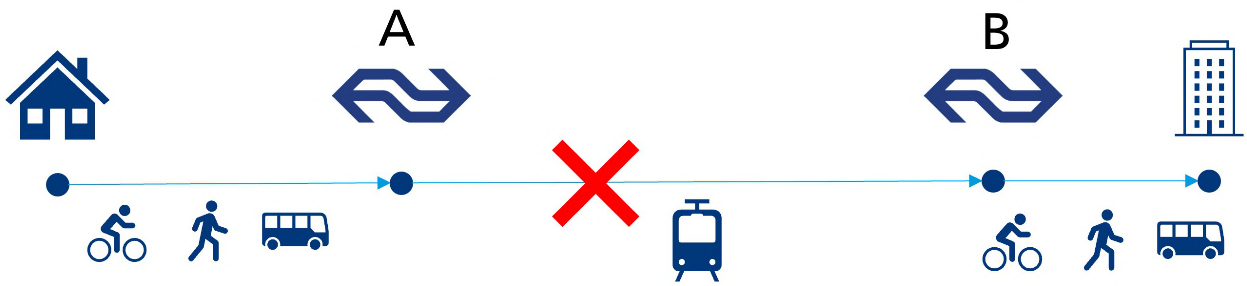

Figure 4.3: Disruption scenario where disruption occurs while already travelling by train.

Information provision: When disruptions occur NS provides a prognosis of the disruption length within three minutes on average. Therefore the assumption is made that there is always a prognosis of the disruption length available. In the context description it is stated that the disruption length is equal to the prognosis provided by NS and is an indication and not precise. It is assumed that travellers have the option to reroute within the train network and that this option is known to them. During some disruptions NS communicates rerouting to travellers with station announcements or in the travel-planning apps. Travel-planning apps such as 9292 incorporate disruptions in their travel advice.

4.2. Model specification

In this first step of designing the stated choice experiment the model that will be estimated is specified (ChoiceMetrics, 2021). The performed literature review provides the basis for hypotheses of which factors will have an influence on travel behaviour during unplanned disruptions. Alternatives and attributes are selected based on the literature review and the main goals of the study. For an extensive explanation on the selection of the alternatives and attributes the reader is referred to Section 3.4 where a conceptual framework is created that summarizes the travel alternatives, attributes and factors that are expected to influence travel behaviour during disruptions.

4.2.1. Alternatives

An increasing number of alternatives can increase the information retrieved from a small sample size. However, it can also complicate the choice task for the respondents (Weng et al., 2021). The survey in this study will be distributed to members of the NS panel and obtaining a large sample size is possible (NS, n.d.). Therefore it is chosen to limit the number of alternatives to three per choice task to simplify the experiment. The three alternatives that are included in the choice experiment are: waiting for the disruption to be over, reroute in the train network and returning home. These alternatives are selected based on the travel options that are most relevant to investigate to fill the research gap identified in Chapter 3. Alternatives are also chosen based on what are the most relevant travel options in the NS train network. For a more detailed description of why these alternatives are chosen the reader is referred to Section 3.4.1.

All respondents will be offered the same alternatives regardless of whether they have the option to work from home or not. Respondents might also consider first travelling back home and then using a different mode of transport to travel to their workplace. Therefore the returning home option might be feasible for every respondent.

4.2.2. Attributes

Each alternative contains attributes which are varied among choice tasks. It is important to include the most relevant attributes in the choice experiment to prevent respondents from making assumptions about the attributes that are not included (Kløjgaard et al., 2012). The conceptual framework constructed in Section 3.4 shows the attributes for the different alternatives that might be of relevance. These attributes are found based on literature. The attributes differ between the two disruption context scenarios and are included based on the literature review and also the research goal of this project.

It is decided to not include the travel costs as an attribute in this study. The price of a trip in the NS network depends on the stations where a traveller has tapped in and out with their smartcard. The price does not depend on what route is taken between the two stations. Therefore the price for continuing on the same route and rerouting within the train network is the same. The only exception to this rule is when travellers travel via the high speed line between Rotterdam Central and Schiphol Airport. For this itinerary an additional fee has to be paid. If travellers would decide to travel home they tap in and out at the same station which will make their trip free of costs. In short, the returning home option would lead to no train costs and there might be a small difference in costs between the waiting for the disruption to be over option and the rerouting option. It is however assumed that costs will not play a big role in this study since in the scenarios travellers have already started their trip and therefore already accepted the resulting costs of their journey.

Table 4.1 shows which attributes are varied for each alternative. The different disruption scenarios lead to different attributes for the returning home option. This is indicated with a star sign. In the first scenario the traveller only has to travel back from the origin station to their home. In the second scenario the returning home option includes another train trip. This train trip also requires a waiting, travel time and crowding component.

Table 4.1: Overview of attributes for each of the alternatives. The star sign * indicates that the attributes are only considered in the scenario where the disruption occurs during the train trip.

Attributes / alternatives	Wait for disruption to be over	Reroute within train network	Return home
Disruption length	x		
Waiting time		x	x*
Original travel time	x		
Rerouting travel time		x	
Returning travel time			x*
Travel time between station and home			x
Crowding on platform	x	x	x*
Additional number of transfers		x	

4.3. Experimental design

In the second phase of creating the stated choice experiment the choice tasks for the respondents are designed (ChoiceMetrics, 2021). Each choice task contains the alternatives and attributes with a certain level. In this phase the levels for the attributes are assigned to the different choice tasks. Multiple decisions have to be taken which will be explained below.

4.3.1. Labelled or unlabelled alternatives

Alternatives have to be given a name. This name can be generic such as: 'option 1', 'option 2', 'option 3' etc. In that case the alternatives do not represent a characteristic (ChoiceMetrics, 2021). When a label is added, the name of the label already provides a meaning to the respondent (Rose & Bliemer, 2004). The name of the option gives extra information to the respondents on top of the attributes (Louviere et al., 2000). In this stated choice experiment the names of the options (waiting for disruption to be over, reroute within the train network and return home) already give the respondents extensive information about what the travel option entails. Therefore the alternatives in this study are labelled which give the option to estimate alternative specific constants. These constants capture the preference for a certain alternative when all alternatives would have the same utility due to taste parameters.

4.3.2. Attribute levels

For the different attributes three choices have to be made. First whether or not the attribute levels are balanced meaning that each attribute level occurs the same number of times for each attribute (ChoiceMetrics, 2021). Maintaining this attribute level balance is desirable because it ensures the parameters can be well estimated over the entire range. The range of the attributes is the second choice that has to be made. The range should not be too narrow since a wider range will lead to estimated parameters with a smaller standard error (ChoiceMetrics, 2021). A range that is too narrow might also lead to alternatives that are hardly a trade-off for the respondent. When the range of the attribute levels is too wide it might lead to dominant alternatives. Caution should also be taken that the values are realistic for the respondents (Green & Srinivasan, 1978). Therefore the range of the attribute levels requires a trade-off between practical considerations to limit the range and statistical considerations for a wider range. The last choice to make on attribute levels is the number of attribute levels for each attribute. This choice depends on what kind of effects are expected for a certain attribute. If a non-linear effect is expected more than two levels should be chosen otherwise the non-linear effects cannot be estimated (ChoiceMetrics, 2021). The number of levels also influences the minimum number of choice tasks required in the experiment. The levels should be evenly spaced to make it easier to interpret the estimated effects (Lancsar & Louviere, 2006).

Values for the disruption length are based on data from previous disruptions (Rijden de Treinen, 2022). When looking at the course of a day there are several smaller disruptions however the average time of disruptions is quickly increased by a small number of very large disruptions. After testing the experiment on a small set of colleagues and family, disruption lengths of over 90 minutes led to the waiting alternative hardly being chosen at all. Therefore it is decided to focus on shorter disruptions during this study to avoid dominant alternatives.

Original travel times are based on the scope of the research which is longer distance trips to rule out the possibility of making the trip using other modes of transport. Data from NS on the length of commuter trips is used to determine the upper range of the original trip time.

The rerouting travel time is defined as an addition to the original travel time. The values are determined using popular apps such as 9292 (9292, 2022) and Google Maps (Google, 2022) by creating a train itinerary and imagining it is disrupted. The travel apps are used to determine an alternative itinerary and analyzed to determine the extra travel time. This way the range for the additional travel time for rerouting is constructed. The additional travel time is a flat addition meaning that the rerouting option is defined as being a certain number of minutes longer than the normal travel time in the train.

The waiting time for the train is based on the frequency of trains in the NS network. On most parts of the network trains run every fifteen minutes. The same values are used for waiting times in the returning home option.

For the travel time between the respondent's home and the station actual input is used from respondents. This is done to make the experiment more realistic for the respondent. It is difficult to imagine a situation where the access time is much larger than it is in reality for the respondent. This approach is unfortunately not possible for the travel times since the survey tool is not suited for this. Also, the rerouting travel time is an additional travel time and cannot be added to the original travel time in the survey.

Usually crowding is shown to respondents as crowding or seat occupation in the train, as is the case in research by Shelat et al. (2021). This seat occupation is only known to travellers at the moment that they step into the train. Therefore a new approach is chosen where the crowding is shown as crowding on the platform where the train will be departing. For crowding on the platforms the Fruin levels of service are used (Fruin, 1970). Visualizations are used in the experiment instead of density values to make it more realistic and comprehensible for respondents. Another advantage of using crowding on the platforms is that NS Stations has camera footage of platforms and can estimate the crowding level which makes the used values tangible.

Table 4.2: The level of service for flow rates and densities by Fruin (1971).

Level of service	Flow rate (pedestrian/minute/meter)	Density (pedestrian per squared meter)
A	≤ 7	≤ 0.08
B	7 - 23	0.08 - 0.27
C	23 - 33	0.27 - 0.45
D	33 - 49	0.45 - 0.69
E	49 - 82	0.69 - 1.66
F	≥ 82	≥ 1.66

Table 4.3 shows all the attribute levels for each alternative. For the return home option the values with a star sign indicate that those only occur in the disruption scenario where the traveller has already covered a part of the train journey when the disruption occurs. All attributes have three levels to be able to test for non-linearity. All attribute levels are chosen to be equidistant.

Table 4.3: Attribute levels for each alternative in the stated choice experiment. The star sign * indicates that the attributes are only considered in the scenario where the disruption occurs during the train trip.

Attributes / alternatives	Wait for disruption to be over	Reroute within train network	Return home
Disruption length (min)	30, 45, 60	-	-
Waiting time (min)	-	5, 10, 15	5, 10, 15*
Original travel time (min)	25, 40, 55	-	-
Returning travel time (min)	-	-	10, 15, 20*
Rerouting travel time (additional min)	-	20, 30, 40	-
Travel time between station and home (min)	-	-	Input from respondent
Additional number of transfers	-	0, 1, 2	-
Crowding on platform	Fruin level B, D, F	Fruin level B, D, F	Fruin level B, D, F*

4.3.3. Design type

After specifying the attributes and attribute levels the different choice tasks are created. For this purpose several experimental design types exist among which the one best fitting for the study is chosen. For this study two experimental designs are created because the two disruption scenarios contain different attributes. The most commonly used design types are full factorial, fractional factorial, orthogonal and efficient designs (Rose & Bliemer, 2009). Full factorial designs construct all the possible choice situations to estimate all possible effects including interaction effects. For typical studies containing multiple attributes and alternatives this often leads to too many choice situations for the respondent. Fractional factorial designs contain a subset of the choice tasks from the full factorial design. The orthogonal design is a fractional factorial design which has a goal to minimize the correlations between attribute levels in the selected choice tasks. Lastly, efficient designs aim to maximize the information that is obtained from each choice task. The efficiency of this design does however depend on the accuracy of prior parameters which can sometimes be deducted from earlier studies (ChoiceMetrics, 2021). Since there is limited research available on this specific topic of travel behaviour during disruptions, prior parameters are difficult to obtain. It is therefore chosen to use an orthogonal design. A full fractional design is not feasible due to the relatively large number of attributes. When comparing fractional factorial and orthogonal designs, the latter is preferred since it aims to minimize the variances of parameter estimates (Rose & Bliemer, 2009). Since the experiment is labelled, the choice tasks are constructed simultaneously instead of sequentially. This ensures there are no correlations within and between the alternatives. However, it does lead to a larger number of choice sets.

4.3.4. Choice tasks

The number of choice tasks is determined based on maintaining attribute level balance and limiting the number of choice tasks per respondent. Since all attributes have three levels it is chosen create a number of choice tasks that is divisible by three to maintain attribute level balance. The choice tasks are created using the software Ngene (ChoiceMetrics, 2021). For the scenario where the disruption occurs at the origin station the smallest experimental design results in twelve choice tasks. However, the other disruption scenario which contains more attributes requires 36 choice tasks. Respondents are subjected to both disruption scenarios which would lead to 48 choice tasks per respondent. This is not deemed feasible due to possible fatigue and also the time limit of ten minutes that NS poses on their surveys. It is decided to use blocking to reduce the number of choice tasks for each respondent. Blocking can increase the required number of choice tasks which is the case for the first disruption scenarios. For both experiments 36 choice tasks are created which are divided over six blocks of six choice tasks each. Each respondent is randomly assigned to one block from each scenario, leading to a total of 12 choice tasks per respondent. The syntax to create the experimental designs for both disruption scenarios can be found in Section B.1 and Section B.2. The final choice tasks including which blocks the tasks are assigned to can be found in Section B.3 and Section B.4.

4.4. Questionnaire design

In order to reach potential respondents an online questionnaire is created in which the stated choice experiment is incorporated. Questions about respondents' work, normal travel behaviour, attitude towards COVID-19 and information during disruptions are asked to find possible correlations between personal characteristics and the choices people make in the experiment. Figure 4.4 shows the structure of the online questionnaire. Rectangle blocks with the same colour indicate questions with a similar topic. The questionnaire is designed in such a way to incorporate variety in questions in order to increase the respondents' attention span. This section explains each block in the survey in the order of the flowchart.

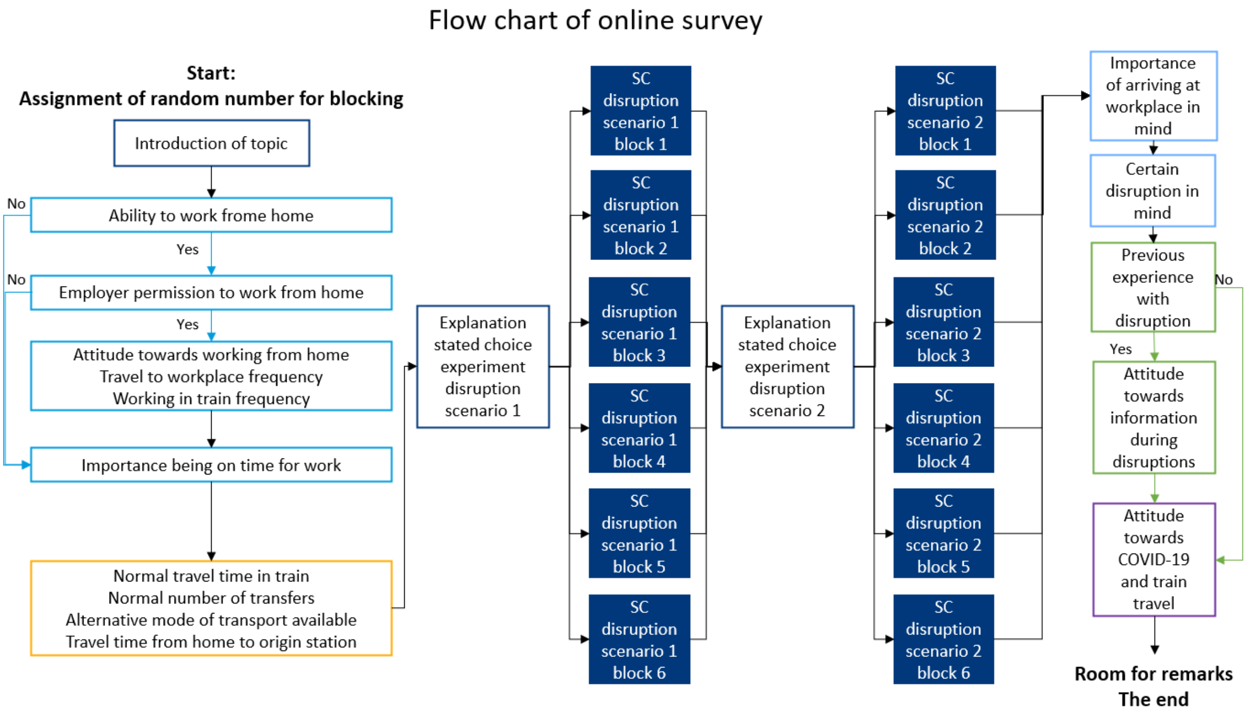

Figure 4.4: Flow chart of online survey distributed to members of the NS panel. Blocks with the same colour lining contain questions on the same topic.

4.4.1. Working characteristics

Upon entering the online questionnaire via the invitation email, the topic is briefly introduced to respondents after which questions are asked about their working situation. A random number between 1 and 6 is also given to the respondents which assigns them to a block of questions. Respondents do not see to which block they are assigned. Table 4.4 displays the information that is asked from respondents about their working situation including the available answer options. Multiple questions are asked about respondents' ability to telework and attitude towards teleworking to incorporate the possible long-term effects of the COVID-19 pandemic on people's working situation which is defined as a research gap. The ability to telework is expected to have an influence on travel behaviour during train disruptions since it enables the option to travel back home and telework. After the stated choice experiment respondents are asked if they had in mind that it was essential to arrive at their workplace to investigate whether this affected the choices they make.

Table 4.4: Information about respondents' working situation that are investigated in the online questionnaire.

Working characteristics	Answer options
Ability to telework	Yes No I am currently unemployed
Employer permission to telework	Yes No I don't know / I don't want to say
Teleworking attitude	Very negative Negative Not negative / not positive Positive Very positive
Travelling to workplace frequency	Each workday 3-4 days per week 1-2 days per week 1-2 days per month Less than 1-2 days per month
Telework during train ride to work	Always Often Regularly Sometimes Never
Importance of getting to work on time	Very unimportant Unimportant Neutral Important Very important
Necessary to arrive at workplace in mind during experiment	Yes No

4.4.2. Commuter trip characteristics

After the questions about teleworking and necessity to arrive at the workplace in time questions are asked on respondents normal commuter trips. Normal commuting behaviour might influence the choices that people would make during disruptions. People who have to transfer during their normal commuting trip might feel less resistance to transfers in rerouting trips during a disruption. The information that is asked from respondents is shown in Table 4.5. Other information such as respondents' normal access mode of transportation towards the train station is known from NS panel data and does not have to be asked in this questionnaire.

4.4.3. Stated choice experiment visuals

The stated choice experiment designed in Section 4.3 has to be converted to a format which allows the respondents to see the available travel options with the attributes and make a decision which one they would choose in a certain disruption context. Research shows that the presentation format of the stated choice design has an impact on the choices that people make (Murwirapachena & Dikgang, 2021). It is chosen to incorporate text and visuals into the presentation of the choice task. Visuals are used in the description of the

Table 4.5: Information about respondents' normal commuter trip that are investigated in the online questionnaire.

Commuter trips characteristics	Answer options
Travel time in train to work	Less than 15 minutes Between 15 and 30 minutes Between 30 and 60 minutes More than 60 minutes
Number of transfers train to work	I do not have to transfer, it is a direct connection 1 transfer 2 transfers More than 2 transfers
Availability other travel modes to travel to work (multiple answers possible)	No Yes, a car Yes, a(n) (e-)bike Yes, a scooter Yes, a motorbike Yes, a different travel mode
Travel time from home to origin station in minutes	Open question

alternatives and also for the crowding attribute. Crowding on the platform is easier to comprehend visually than written down as the number of waiting passengers per square meter. On the other hand, disruption lengths, waiting times and travel times are hard to display using pictures. Since the waiting time and travel time attributes have a different meaning between alternatives it is chosen to display those in text to avoid generalization of the concepts. Figure 4.5 shows final design of the stated choice experiment questions. The picture on the left shows the disruption scenario where the disruption occurs at the origin station. On the right the visual for the context where the disruption occurs during the train trip is shown.

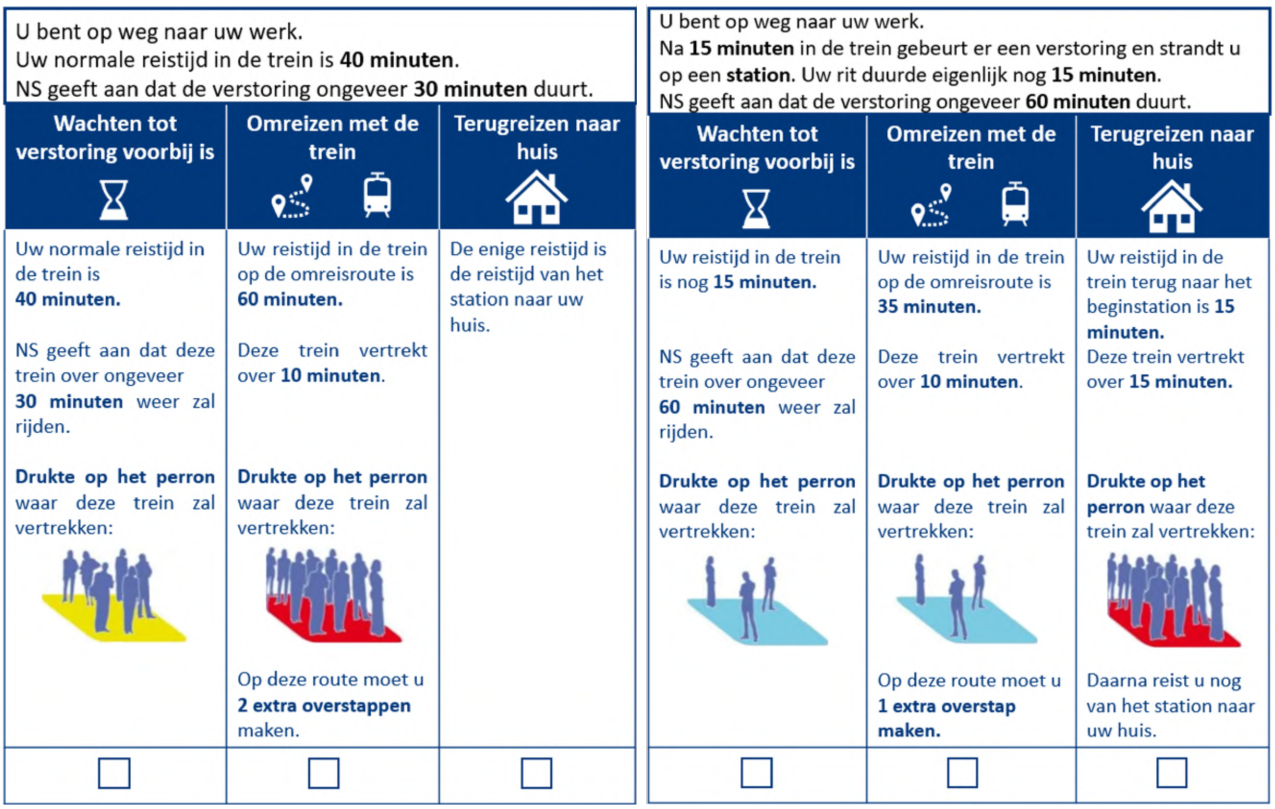

Figure 4.5: Visuals of stated choice experiment. Left: questions for context where disruption occurs at origin station. Right: questions for context where disruption occurs during the train trip.

Each respondent is given a random number between one and six when starting the online questionnaire. This number determines which block of questions the respondent answers. An explanation of the context, alternatives and attributes is provided for the first disruption scenario before answering the questions. First the respondent answer six questions for the first disruption scenario and then an explanation is provided on how the second disruption scenario differs from the first. Respondents then answer six more questions for the second disruption scenario. Respondents can make their choice by clicking the box underneath the preferred alternative in the picture.

4.4.4. Disruption and information provision

After the stated choice experiment a final set of questions is given to respondents. The first part of this final section contains questions about what kind of disruptions people had in mind and if they imagined it was necessary to arrive at their workplace while answering the questions in the stated choice experiment. Afterwards respondents are asked if they ever had experienced a disruption during a train trip and what their attitude is towards information provided by NS and travel planner apps during disruptions. The questions are presented in the form of statements that respondents can agree or disagree with and are shown in Table 4.6. It is expected that people who have a negative association with travel information provided by NS during disruptions have a lower tendency to wait for the disruption to be over.

Table 4.6: Information about respondents' attitude towards information during disruptions that are investigated in the online questionnaire.

Disruption related questions	Answer options
Certain disruption in mind during experiment	No Yes, a signal failure Yes, train material failure Yes, a collision Yes, rail switch failure Yes, a different disruption type
Experienced a disruption during train trip	Yes No
'During a disruption I trust the information about the expected disruption length from NS.'	Strongly disagree Disagree Neutral Agree Strongly agree
'During a disruption I follow the travel advice provided by NS.'	Strongly disagree Disagree Neutral Agree Strongly agree
'During a disruption I trust the information in the travel planner app.'	Strongly disagree Disagree Neutral Agree Strongly agree
'During a disruption I let previous experiences with disruptions guide me.'	Strongly disagree Disagree Neutral Agree Strongly agree
'During a disruption I rely more on previous experiences with disruptions than the travel information from NS.'	Strongly disagree Disagree Neutral Agree Strongly agree

4.4.5. COVID-19 attitude

Since a research gap this research aims to fill is what travel options people choose during disruptions in the aftermath of the COVID-19 pandemic, pandemic-related questions are included as well. The questions are presented in the form of statements. The statements are equal to the statements used in the COVID-19 research that has been performed by the TU Delft and NS. This is done to ensure consistency and increase the usability of the results by NS. It is expected that people who are cautious of COVID-19 and crowds might be less likely to choose travel options in which the platforms are very crowded. Table 4.7 shows the statements and answer options.

Table 4.7: Information about respondents' attitude towards the COVID-19 virus in relation with train travel that are investigated in the online questionnaire.

COVID-19 related questions	Answer options
'I am afraid to get infected with the COVID-19 virus.'	Strongly disagree Disagree Neutral Agree Strongly agree
'I avoid crowded places.'	Strongly disagree Disagree Neutral Agree Strongly agree
'I like to travel by train.'	Strongly disagree Disagree Neutral Agree Strongly agree
'I will continue to wear a face mask in the train for a while.'	Strongly disagree Disagree Neutral Agree Strongly agree
'I do not feel free to travel by train because of the crowding.'	Strongly disagree Disagree Neutral Agree Strongly agree

The survey is programmed using software from market research agency MWM2 (MWM2, 2021). The full survey in the final format can be found in Figure B.1 - B.13.

4.4.6. Pilot

A small pilot is executed among family and friends to test the programming of the survey, understandability of the questions and average completion time. Most people who filled in the survey are not part of the target group since they never travel by train and therefore results from the stated choice experiment are not analyzed. The average completion time was approximately 10 minutes which is the target for the survey since this is the time limit for surveys distributed via the NS panel. Based on comments from the pilot the formulations of some questions are altered and the context of the stated choice experiment questions is repeated above the pictures. The experimental design is not changed based on the pilot.

4.5. Survey distribution

NS has a panel of approximately 80,000 members who voluntarily sign up to participate in questionnaires on different topics to help NS improve services and products (NS, n.d.). Participants are informed that when they participate the results of the questionnaire can be published or shared but the information can never be traced back to individual respondents. The panel members are managed by market research agency MWM2. This agency offers an online tool to create surveys which is used in this study. The aim is to approach one hundred participants for each block of questions. Since it is desired to also have a sufficient number of respondents that are not able to telework the approached number of respondents is slightly increased. Based on the average response rate of approximately 25% for surveys sent out to the NS panel 4018 respondents are approached to fill in the online questionnaire. Respondents are filtered on the requirement that they currently have a job and commute to work by train. The age distribution of NS train travellers is used as a basis to approach a representative sample of the train commuter population. The survey is distributed on the 7th of June 2022 after approval of the ethical committee of the TU Delft. Results were collected on the 13th of June 2022 at 12:00.

4.6. Conclusion

Summary

- The stated choice experiment context is defined as commuting to work by train, there are no COVID-19 measures in place, information on the expected disruption length is provided by NS and the disruption is discovered either when arriving at the origin train station or during the train trip.
- The alternatives in the choice tasks are; waiting for the disruption to be over, reroute in the train network or return back home.
- Each respondent answers 6 questions for each disruption scenario leading to 12 in total.
- Questions on working characteristics, normal travel behaviour, previous experience with disruptions, attitude towards information provision and risk perception of COVID-19 are included as well.

In this chapter the process of designing the questionnaire is explained. The choice tasks are set in a certain context which is explained first. The trip purpose is commuting to work and a disruption then occurs either at the origin station or during the train trip. There are no COVID-19 measures in place and information on the expected disruption length is provided by NS.

In each choice task respondents can choose one of the three specified alternatives; wait for the disruption to be over, reroute in the train network or return back home. The attribute levels are chosen based on literature and expert information from NS. All attributes have three levels allowing to test for non-linear relationships and are equidistant. Since prior values for the parameters are difficult to obtain for this experiment, an orthogonal design is chosen for the stated choice experiment. To limit the number of choice tasks for each respondent, blocking is applied. Six blocks of six questions are constructed for each disruption scenario. Respondents therefore answer six questions for each disruption scenario resulting in a total of twelve questions.

In the questionnaire additional questions on working characteristics, normal travel behaviour, previous experience with disruptions, attitude towards information provision and risk perception of COVID-19 are included. These questions aim to provide characteristics which can be included in the discrete choice models.

A pilot was executed among a small group of friends and family after which the wording of some questions and the explanation of the stated choice experiment were adapted. The survey was distributed on the 7th of June 2022 among approximately 4.000 members of the NS panel.

5 Descriptive statistics

In this chapter the data resulting from the online survey is investigated and described in terms of sample distribution. The online survey was sent out on the 7th of June 2022 and respondents could access the survey until the 13th of June 2022. At the time of sending out the survey there were no COVID-19 measures in place in the Netherlands. Before analyzing the data it must be filtered. This data filtering procedure is described in Section 5.1. A description of the sample is given in Section 5.2 and a comparison is made with the train traveller population. In Section 5.3 and Section 5.4 the outcomes of the questionnaire are described in detail.

5.1. Data filtering and repairing

The online survey was sent by MWM2 to 4018 people who are part of the NS panel. In total 1128 people opened the online survey via the invitation email of which 888 people completed the survey. Most respondents who did not finish the survey stopped participating at the explanation of the stated choice experiment. Only the completed survey results are added to the dataset. The first data filtering step is removing the respondents who answered that they are currently unemployed. This group of respondents is not a part of the target group since the influence of their working situation on the choices they make during train disruptions cannot be investigated. This results in removing 19 respondents from the dataset. All respondents with completion times lower than five minutes are removed from the survey since there are twelve stated choice questions and multiple other questions which require some time to think through. During this filtering step 52 respondents are removed from the dataset. A final check to filter the data focusses on looking at the statement questions related to information during disruptions and COVID-19 to see if there are respondents who always choose the same option. This is the case for two respondents and they are removed from the dataset. Respondents who always choose the same travel option in the stated choice experiment are not removed from the dataset since it can also show a very strong preference for one alternative over the others. After filtering the data the results of 815 respondents (92% of respondents who finished the survey) are used for the descriptive statistics and discrete choice modelling. The data filtering process is summarized in Figure 5.1.

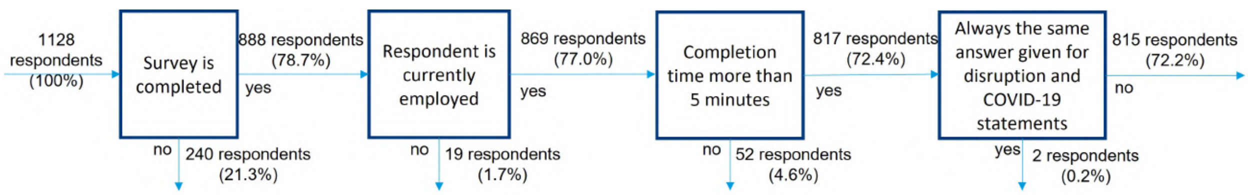

Figure 5.1: The data filtering process.

While inspecting the data it was noticed that some respondents reported very large access times from their house to the train station from which they travel to work. It seems that some respondents misinterpreted the question and reported their full trip time which was checked using travel apps. Since the reported access time is used to estimate the choice models it is decided to repair the data using respondents' postal code, reported origin station and preferred mode of transportation for access trips. Using Google Maps (Google, 2022) access times are checked and repaired if necessary for all respondents that reported an access time over thirty minutes. For random other respondents the access times were checked in the same manner and the estimations made by Google Maps are quite accurate. The access time data obtained from 84 respondents is repaired and these respondents are flagged in the final dataset.

5.2. Sample description

In this section the sociodemographic characteristics of the respondents are investigated and compared to sociodemographic characteristics of the train commuter population. Data on the commuter population is provided by NS. This data is confidential and therefore only the sample sociodemographic distributions are shown in this section. Confidential Appendix C shows the distributions across the train commuter population as well. In this section a comparison between sample and population will be made without mentioning the specific percentage values. The results from the sociodemographic characteristics in the sample can be found in Table 5.1.

5.2.1. Sociodemographic characteristics

The online survey is only sent out to people whose main travel goal is travelling to work or for business. The gender distribution closely resembles the distribution in the train commuter population with males being slightly over-represented.

Table 5.1: Sample description based on sociodemographic characteristics.

Characteristic	Categories	Sample (N=815)
Gender	Female	44.7%
	Male	54.0%
	Prefer not to say	0.7%
	Other	0.6%
Age	Under 18 years old	-
	18 to 24 years old	1.7%
	25 to 34 years old	15.3%
	35 to 44 years old	24.5%
	45 to 54 years old	26.4%
	55 to 64 years old	32.0%
	Over 65 years old	-
Household	Living with partner	38.8%
	Living with partner and children	32.9%
	Living alone	20.6%
	Living with parents/carers and/or brothers and sisters	4.1%
	Living with children without partner	2.9%
	Living with multiple adults	0.7%
	Other	-
Education level	Doctorate degree	16.6%
	Master degree	33.5%
	Bachelor degree	30.9%
	MBO	9.7%
	VWO/HAVO/MAVO/VMBO	7.9%
	Other	1.4%
Employment status	Working for employer	67.0%
	Working for the government	24.4%
	Freelancer	3.9%
	Entrepreneur	2.6%
	Student	0.8%
	Retired	0.4%
	Other	0.9%
Travel frequency by train in 2019	4 days per week or more	51.4%
	1-3 days per week	27.6%
	1-3 days per month	12.4%
	6-11 days per year	5.6%
	3-5 days per year	1.8%
	1-2 days per year	0.9%
	Less than one day per year	0.2%
Train subscription	Has a subscription	39.8%
	No subscription	60.2%

The age distribution is similar for the group of 45 to 64-year-old respondents. However in NS data there is also a percentage of people above 65 years old who make work related trips while in the sample there is not one person with an age above 65 years old. This may be caused by the market research agency not sending out the online survey to respondents over 65 years old since it is assumed that they do not make work related trips. In the sample the 25 to 44-year-old age group are therefore over-represented. The sample has a similar distribution of household composition as the train commuter population. When looking at education level the sample is highly educated with over 50% of the respondents having a master's or doctorate degree. While the train commuter population is also highly educated people with a master's degree are over-represented while respondents with an MBO or VWO/HAVO/MAVO/VMBO education are under-represented. In terms of working situation people who work for an employer of the government are over-represented in the sample while freelancers, entrepreneurs and retired people are under-represented. The sample contains a large percentage of experienced travellers since over 50% of respondents travelled 4 days per week or more by train in 2019 (before the COVID-19 pandemic). This groups is over-represented in the sample while the less experienced travellers are under-represented. The train subscription distribution across the sample is almost flipped compared to the train commuter population. A possible reason could be that the train commuter population data stems from 2019 which is before the COVID-19 pandemic. The data from respondents in the NS panel is updated each six months. It could be the case that respondents stopped their train subscription during the COVID-19 pandemic resulting in less train subscriptions.

The sample of respondents represents the entire commuter train population quite well. The slight overrepresentation of males in the sample is not expected to have an influence on the results since it not expected that gender has an effect on travel behaviour. The overrepresentation of 25 to 44-year-old people might have an effect on the results since it is expected that younger train travellers might be more adventurous and used to following travel advice and therefore being more inclined to reroute or return home than the train travellers with an age over 45 years old. The sample is highly educated but this is not expected to have an influence on travel behaviour and therefore on the results. The respondents are also very experienced with travelling by train which might lead to an overestimation of people rerouting since they know the train network well and might rely on their own knowledge to find their way. In the sample there are less people with a train subscription however the data from NS on the subscriptions stems from 2019 (before the COVID-19 pandemic) so a meaningful comparison cannot be made.

5.2.2. Working characteristics

A large part of this research consists of looking into travel behaviour during train disruptions in a time where many people can work from home. Questions about teleworking and attitudes towards teleworking are asked to respondents and the results are shown in Table 5.2. Of all respondents 18.8% responded that they cannot execute their work from home. This is a larger percentage than expected based on previous research during the COVID-19 pandemic by NS and the TU Delft (van Hagen, de Bruyn, et al. (2021a);Ton et al. (2021)). Questions about teleworking attitude and teleworking during the train ride are not asked to this group of respondents which results in a lower number of respondents for those questions as shown in the table. Approximately 70% of the people who can work from home have a positive attitude towards working from home. This is similar to previous measurements of teleworking attitude (van Hagen, de Bruyn, et al. (2021a);Ton et al. (2021)). After the COVID-19 restrictions and working from home obligations people start travelling to their workplace again. It seems there is a new balance where most people go to the office once or twice a week instead of each working day which was more common before the pandemic. The largest part of people who can work from home usually do not use their travel time in the train to work. The importance of arriving at work on time is distributed such that for a part of the respondents it is important and for an approximately equal amount of respondents it is unimportant. During the experiment about 60% of respondents had in mind that it was necessary to arrive at their workplace. This mindset can have a large impact on what choices people make during a disruption and the influence is tested when estimating the discrete choice models.

Table 5.2: Sample response to working related questions.

Working characteristics	Answer options	Number of respondents	% chosen
Ability to telework (N=815)	Yes	662	81.2%
	No	153	18.8%
Employer permission to telework (N=662)	Yes	658	99.4%
	No	4	0.6%
Teleworking attitude (N=658)	Very positive	260	39.5%
	Positive	266	40.4%
	Not negative / not positive	85	12.9%
	Negative	36	5.5%
	Very negative	7	1.1%
	I never work from home	4	0.6%
Travelling to workplace frequency (N=658)	Each workday	5	0.8%
	3-4 days per week	110	16.7%
	1-2 days per week	428	65.0%
	1-2 days per month	68	10.3%
	Less than 1-2 days per month	47	7.1%
Telework during train ride to work (N=658)	Always	88	13.4%
	Often	92	14.0%
	Regularly	79	12.0%
	Sometimes	181	27.5%
	Never	218	33.1%
Importance of getting to work on time (N=815)	Very unimportant	57	7.0%
	Unimportant	215	26.4%
	Neutral	267	32.8%
	Important	212	26.0%
	Very important	64	7.9%
Necessary to arrive at workplace in mind during experiment (N=815)	Yes	478	58.7%
	No	337	41.3%

5.2.3. Commuter trip characteristics

In the online survey respondents were asked questions about their normal commuter trip before COVID-19. Of all respondents 25.9% indicated that their train trip takes more than 60 minutes which is higher than expected based on data from NS on the average commuter trip length. The 42.7% of respondents who have to transfer during their train journey is also higher than expected. In the NS network approximately 80% of travellers do not have to transfer during their train journey. This higher percentage of people in the sample having to make a transfer might correlate with the higher percentage of trips taking over 60 minutes. 67.1% of all respondents have a different mode of transport available to travel to work with the car being the most popular one available to 56% of all respondents. The respondents who answered that their is a different mode of transport available to them mostly reported different forms of public transport such as the bus, metro and ferry.

Table 5.3: Sample response to commuter trip related questions.

Commuter trips characteristics	Answer options	Number of respondents	% chosen
Travel time in train to work (N=815)	Less than 15 minutes	81	9.9%
	Between 15 and 30 minutes	187	23.0%
	Between 30 and 60 minutes	328	40.2%
	More than 60 minutes	219	26.9%
Number of transfers train to work (N=815)	I do not have to transfer, it is a direct connection	467	57.3%
	1 transfer	289	35.4%
	2 transfers	52	6.4%
	More than 2 transfers	7	0.9%
Availability other travel modes to travel to work (N=815)	No	268	32.9%
	Yes, a car	456	56.0%
	Yes, a(n) (e-)bike	122	15.0%
	Yes, a scooter	2	0.2%
	Yes, a motorbike	18	2.2%
	Yes, a different mode of transport	45	5.5%

Figure 5.2 shows the distribution of access modes of transport in the sample. Most respondents use their bicycle to travel to the station. The car is used as an access mode in approximately 7% of the cases but might become a relevant alternative to potentially replace the train trip. Walking and cycling together make up for 80% of the access modes in the sample which is also reflected in the short access times to the station shown in Figure 5.3. The very large access times above an hour mostly come from respondents who live on the island of Texel and Goeree-Overflakkee. Approximately 75% of respondents can travel to the train station from their home in under 15 minutes. It is expected that for this group of people the option of returning to home might be more attractive than for people with longer travel times towards the station.

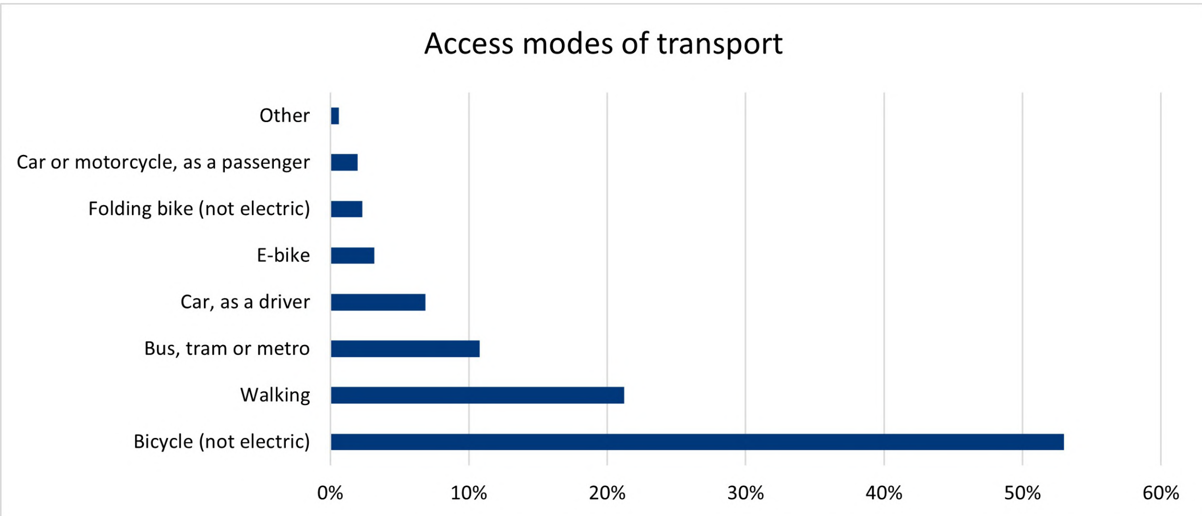

Figure 5.2: Access modes of transport distribution in sample.

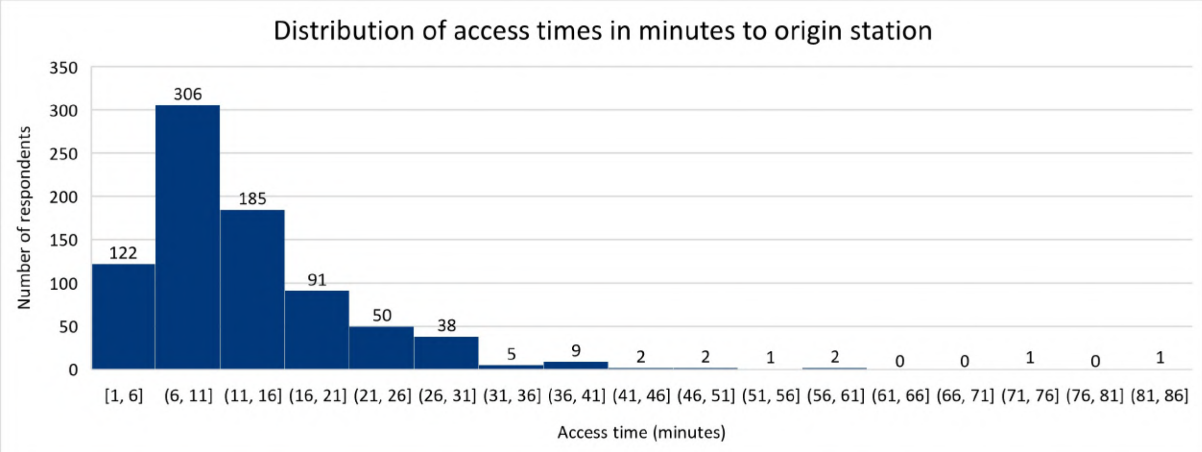

Figure 5.3: Access times distribution in sample.

5.2.4. Disruption characteristics

On top of the stated choice experiment in which respondents choose the travel option they would follow when faced with a certain disruption scenario, questions are also asked about the disruption that respondents had in mind during the stated choice experiment. 69.3% of respondents did not have a specific disruption in mind. Of the people who had a specific disruption in mind a rolling stock failure was imagined by 11.5% of the respondents. This is also the disruption that occurs most often on the train network in the Netherlands (Rijden de Treinen, 2022). The second and third most often occurring disruptions are signal and rail switch failures while the second most thought of disruption among respondents is a collision. Collisions occur less often but often have a big impact and this might be the reason that respondents keep this specific disruption in mind during the experiment. The respondents that had a different disruption in mind often reported that they had all the reported disruptions in mind. Of all respondents participating in the study 97.4% has experienced a disruption during a train trip at least once. This high percentage can be either caused by the fact that disruptions are common and almost all train travellers experience one at some point or that the people who have experienced disruptions in the past are interested in the topic of the study and therefore participated in the online survey.

Table 5.4: Sample response to disruption related questions.

Disruption related characteristics	Answer options	Number of respondents	% chosen
Certain disruption in mind during experiment (N=815)	No	565	69.3%
	Yes, a signal failure	44	5.4%
	Yes, rolling stock failure	94	11.5%
	Yes, a collision	51	6.3%
	Yes, a rail switch failure	26	3.2%
	Yes, a different disruption type	35	4.3%
Experienced a disruption during train trip (N=815)	Yes	794	97.4%
	No	21	2.6%

The respondents who answered that they have experienced a disruption in their train journey are presented with five statements on information during disruptions. The results can be found in Figure 5.4. Approximately 45% of respondents do not trust the information that NS distributes about the disruption length. Whether respondents follow the travel advice given by NS is less clear since 46% of respondents reported that they do not agree nor disagree. In the remarks at the end of the online survey multiple respondents indicated that NS often does not provide travel advice during disruptions which might be the reason that almost half of the respondents chose this option. While 50% of respondents have trust in the information in travel planner apps 75% of respondents indicate that they are guided by their previous experiences during a disruption. Half of the respondents rely more on their previous experience during disruptions than the travel information provided by NS when making travel decisions. According to these statements information provision on disruption length should be improved as well as providing travel advice during disruptions since it is often not announced.

Previous experiences also seem to stick with respondents and therefore improving the information provision could help create positive experiences.

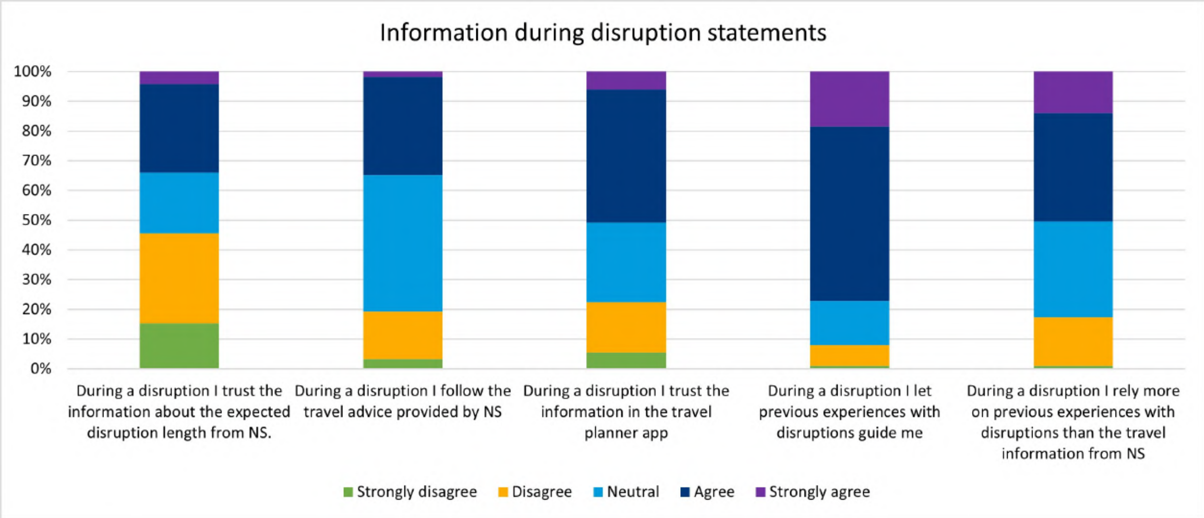

Figure 5.4: Statements on information during disruptions (N = 794).

5.2.5. COVID-19 attitude

The last COVID-19 measures in the Netherlands were dropped in March 2022. Since the online survey was distributed in June of 2022 it is interesting to investigate how respondents look at COVID-19 three months after the COVID-19 measures are dropped. The statements presented to respondents in the survey are in line with the statements presented in the research by NS and the TU Delft in order to make a comparison (van Hagen, de Bruyn, et al., 2021b). It should however be noted that in the studies conducted by NS and TU Delft the full NS panel was asked to participate in the study while in this current study only a part of all the train commuters in the panel are invited to participate in the study. Figure 5.5 shows the response to the COVID-19 statements presented in the online survey. Figure 5.6 shows three out of five statements in the online survey compared with the results of the seven studies on COVID-19 among train travellers by NS and TU Delft. The question regarding wearing the face mask even though it is not obliged anymore was only asked in the seventh study and this current study. In the study in March 2022 17.6% agreed with the statement compared to 4.6% in the current study. The percentage of people strongly disagreeing increased from 26.6% to 43.4%.

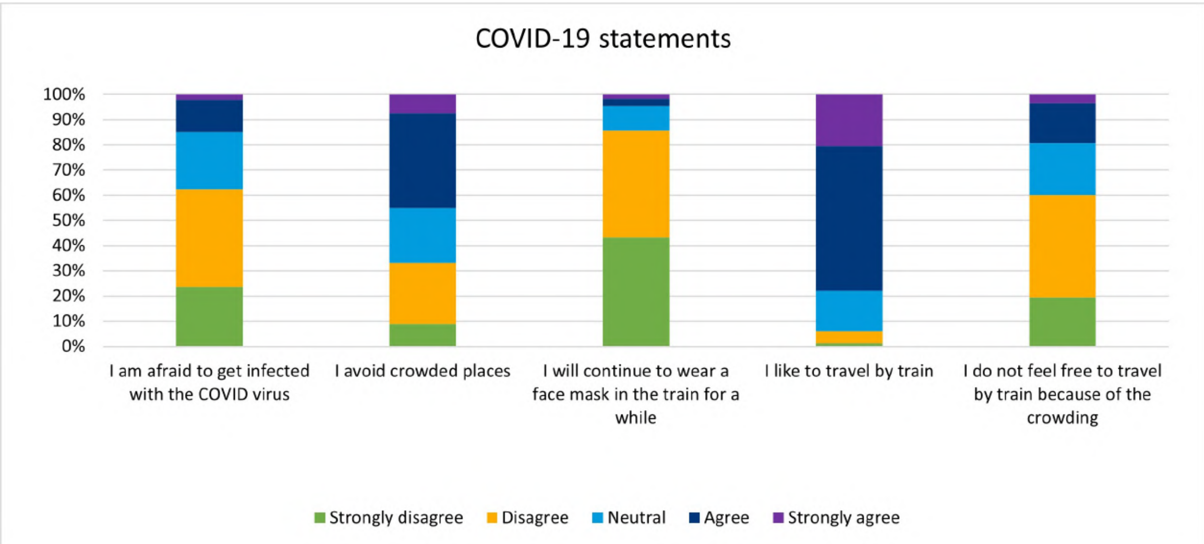

Figure 5.5: Statements on attitude towards COVID-19.

In June 2022 respondents seemed to be less afraid to get infected with the COVID-19 virus. At the time of the distribution of the online survey there were no COVID-19 measures in place in the Netherlands (Rijksinstituut voor Volksgezondheid en Milieu, 2022). In the beginning of 2022 the Omicron variant of the COVID-19 virus became dominant which among the population is associated with a lower chance of becoming ill compared to previous variants of the virus (Rijksoverheid, 2022b). In March of 2022 there was a peak of positive COVID tests but people still seem less afraid to get infected (Rijksoverheid, 2022a). This trend seems to continue in time looking at the measurement in June 2022.

In the beginning of the COVID-19 pandemic in April 2020 the amount of people who liked to travel by train was 34.4% which is the lowest value in all studies. This number steadily increases to a value of up to 78.1% in this study.

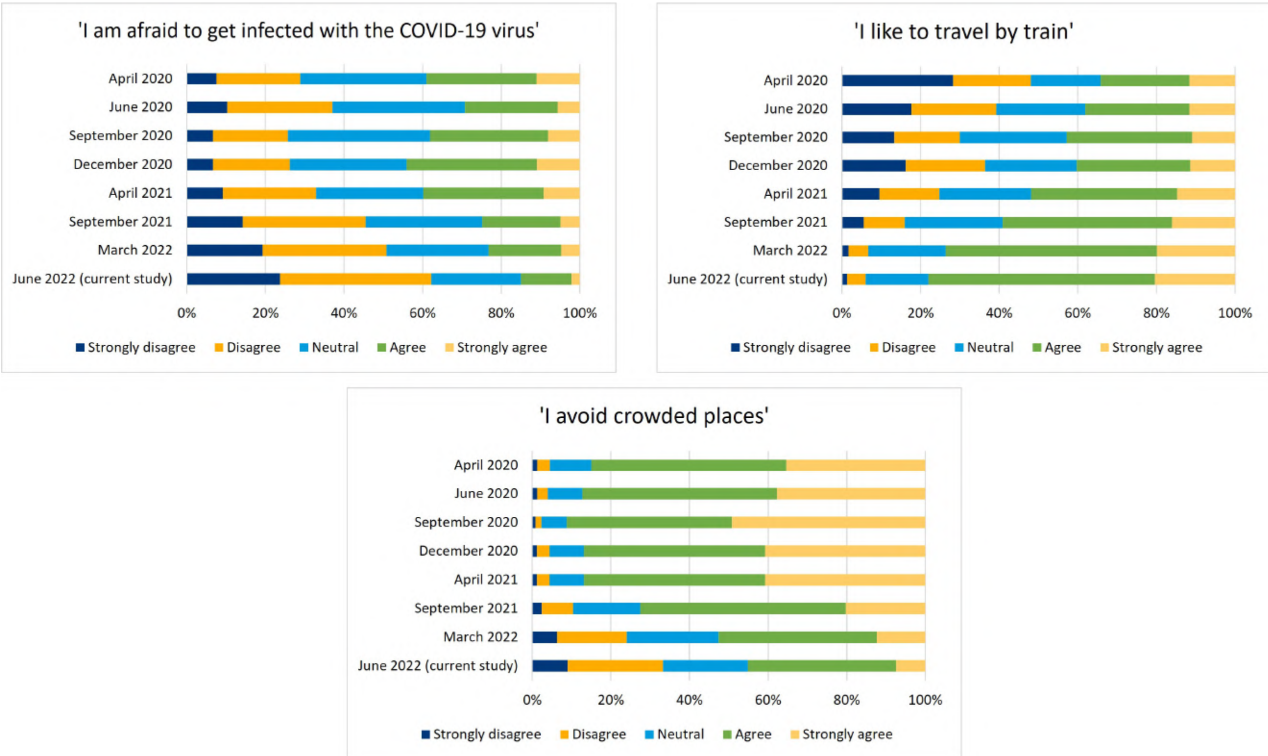

Figure 5.6: COVID-19 statements in the seven conducted COVID-19 studies by NS and TU Delft including the results of this current study.

During the first phase of the pandemic the share of people avoiding crowded places is relatively constant at about 85% of participants in the studies. From September 2021 onwards this percentage decreases rapidly to 45.2% in June 2022. This is however still a large share of participants who would rather avoid crowded places. This is expected to have an influence on the choices they make during the stated choice experiment where crowding on the platform varies. This is investigated during the discrete choice modelling part of this study.

5.3. Travel choices

In this part of the chapter the travel options that respondents chose during the stated choice experiment are investigated. Some patterns might already be recognized when comparing travel choices between different groups of respondents. It should however be noted that this investigation only looks at the choices that people made and not the trade-off between the alternatives and their different attribute levels.

Figure 5.7 shows the choices for the travel options in the two different disruption scenarios made by all respondents. For the choice tasks where the disruption occurs at the origin station 46% of all choices consists of returning home. The share of returning home drops to 30% when the disruption occurs during the train trip.

This is according to the expectation since returning home in the second disruption scenario also includes an extra travel time and waiting time increasing the total travel time compared to only the access time in the first disruption scenario. The share of both rerouting and waiting for the disruption to be over increase when the disruption occurs during the train trip.

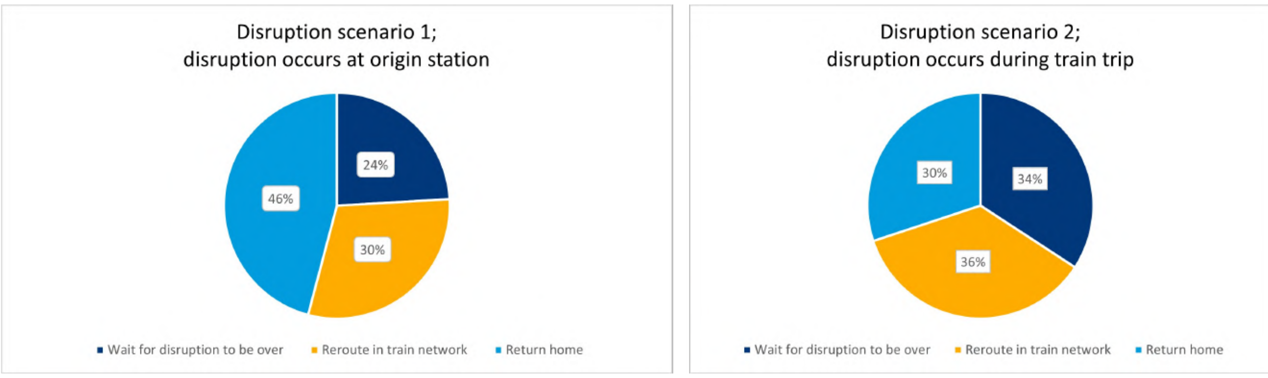

Figure 5.7: Choice overview of all respondents.

Whether respondents can or cannot work from home is expected to make a difference in the travel options people choose. If people can work from home returning home might become more attractive. The respondents are split based on whether they can work from home or not and the choices made during the stated choice experiment are shown in Figure 5.8.

Figure 5.8: Left: choice overview of all respondents who **cannot** work from home. Right: choice overview of all respondents who **can** work from home.

When looking at the share of the 'returning home' option it indeed increases when people have to option to work from home. For the scenario where the disruption occurs at the origin station 28% and 50% of choice tasks are answered with 'return home' respectively. Of the respondents who cannot work from home 55.5% has chosen the option to return home at least once during the stated choice experiment. Out of 85 respondents in this group 70 respondents have an alternative travel mode available to them of which the car is the most popular one available to 60 respondents. The other 15 respondents have at least once chosen to travel home but have no alternative transportation option available. An explanation on how this group would arrive at their destination is not found from the data.

In the dataset there are 57 respondents who chose the same travel option during each choice task they were presented with. Of which 6 respondents always chose to wait for the disruption to be over, 11 respondents chose to reroute and the remaining 40 respondents always chose the return home. Of the last group 32 respondents have the option to work from home. The remaining eight respondents cannot work from home but seven of them have an alternative mode of transport available and the last respondent stated that arriving at work on time is not important. A characteristic of the group who always chose to reroute is that 10 out of 11 respondents had in mind that it was necessary to arrive at their workplace while participating in the stated choice experiment. They also seem to be critical on the travel information provided by NS. On the other hand the group of respondents who always chose to wait until the disruption is over seems to have more trust in the information NS provides during disruptions. Of this group the majority does not have an alternative travel mode available to them.

264 respondents chose two different travel options in the stated choice experiment. Of this group 128 respondents either chose the option to wait for the disruption to be over or to reroute. 61.7% of these respondents do not have an alternative mode available, 88.3% had in mind that it was necessary to arrive at the workplace and only 48.4% of respondents are able to work from home. 72 respondents always chose to either return home or wait for the disruption to be over and the remaining 64 respondents always chose to either reroute or return home. Of the two latter groups 94.4% and 87.5% respectively are able to work from home. The remaining 494 respondents have chosen all travel options at least once during the stated choice experiment. These findings are summarized in Figure 5.9.

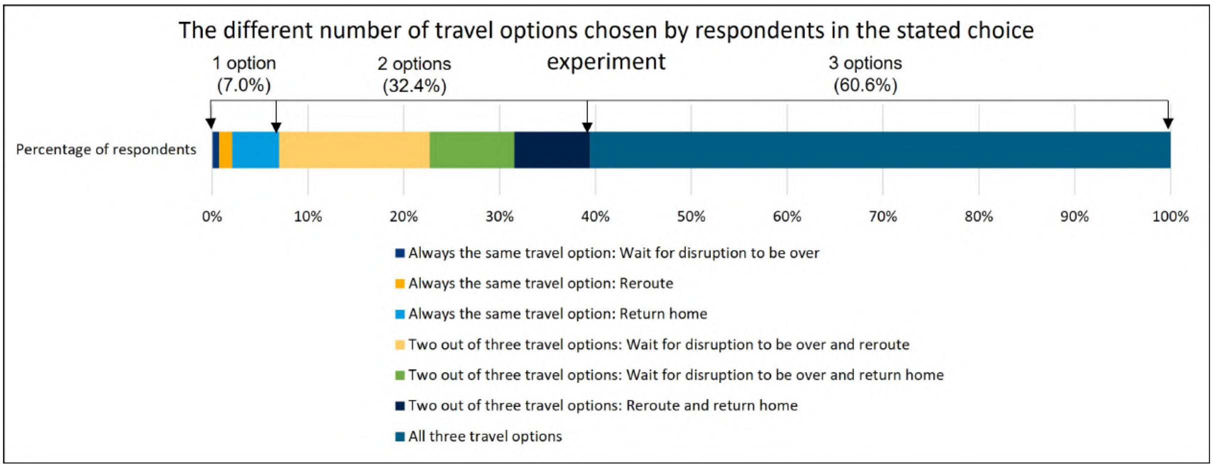

Figure 5.9: Different number of travel options chosen by respondents (N=815).

The choice tasks' disruption length varied between 30 and 60 minutes. The travel choices made during the experiment for each disruption length are shown in Figure 5.10. When the disruption length is 30 minutes approximately 50% of the choices involved waiting for the disruption to be over. It should again be noted that the other attribute levels are not taken into account here, just the choices that respondents made during the experiment. When the disruption occurs during the train trip this percentage increases to 63%. For a disruption length of 45 minutes these values decrease to 16 and 31% respectively. This decrease in share is larger than when looking at a disruption length of 60 minutes where the shares are 9.5 and 6.5% respectively. The utility contribution of the disruption length is expected to be non-linear and will be tested during the discrete choice modelling.

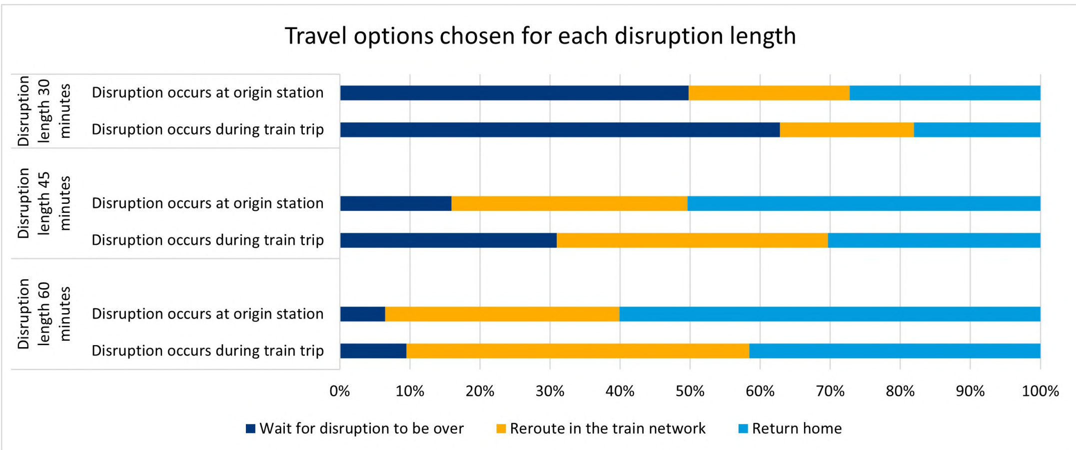

Figure 5.10: Choice overview for the different disruption lengths and disruption scenarios.

5.4. General remarks

At the end of the online surveys respondents had the option to leave a remark. Out of 815 respondents 143 respondents left a remark. The remarks can be categorized in roughly four groups; explanations of choice behaviour, comments on NS information provision during disruptions, constructive criticism on survey and general frustration. The group of respondents explaining their choice behaviour mostly describe on what criteria they base their decision and their decision rules. The general comments on the NS information provision mostly entail that respondents do not trust communicated disruption lengths and that alternative travel options are often not communicated to travellers. Respondents also miss NS employees in the trains or at the stations to guide them during disruptions. The constructive criticism remarks mostly discuss factors that respondents missed in the online survey. For example some respondents state that the type of station where they would have to wait would influence their decisions and other factors which were not mentioned in the survey. A group of respondents also mentions that it was hard to project themselves in the disruption scenarios because they do not have a rerouting option or because their train journey is short. Respondents also would have liked to answer questions about a disruption occurring on their trip from work to home since they expect that their behaviour would be very different. A small group of respondents feel frustrated about disruptions and feel like they are on their own but also general comments like crowding in trains and non-constructive remarks about the survey are given.

5.5. Conclusion

Summary

- After filtering the data 815 valid responses were collected of train commuters in the NS panel.
- The sample is representative of the commuter train traveller population except for a overrepresentation of people aged between 25 and 44 and more experienced travellers.
- About 80% of respondents is able to work from home and of these respondents 70% has a positive attitude towards teleworking.
- Approximately 45% of respondents does not trust the information that NS provides on the expected disruption length.
- Respondents are less afraid of the COVID-19 virus than during previously executed studies on COVID-19.
- For disruptions of 30 minutes waiting for the disruption to be over is the dominant option. This percentage quickly drops for longer disruption lengths. It is expected that there is a non-linear relationship for the disruption length.
- Respondents who can work from home chose the return home option more often than respondents who cannot work from home.

Data gathered from the online questionnaire distributed among commuting train travellers of the NS panel is analyzed in this chapter. 815 valid responses are analyzed after filtering the data. The sample is in general representative of the commuting train traveller population. People aged between 25 and 44 are however overrepresented in the sample. It is expected that this age group is more adventurous and knows how to use advice from travel planner apps and might therefore be more likely to reroute or return home than the slightly older age groups. The sample also consists of more experienced travellers who might have a lot of knowledge of the train network and therefore opt to reroute instead of wait for the disruption to be over.

Among respondents the trust in provided information seems to be low with 45% of respondents not trusting the provided information by NS on the expected disruption length and 50% of respondents who rely more on previous experienced with disruptions than on the information provided by NS.

For disruption scenarios with a disruption length of 30 minutes waiting for the disruption to be over was chosen in more than 50% of the choice tasks. This number quickly drops for longer disruption lengths. When the disruption occurs during the train trip the option to return home was chosen less often than when the disruption occurs at the origin station.

6 Discrete choice modelling

In this chapter the estimated discrete choice models are presented. The goal of this chapter is to analyze the decisions travellers would make during train disruptions and analyze what factors influence their decisions. First, the multinomial logit model is presented in Section 6.1. The latent class choice models presented in Section 6.3 aim to capture heterogeneity by estimating an MNL model for each uncovered class. This gives an insight in taste heterogeneity and factors that influence the behaviour of the different classes.

6.1. Multinomial logit model

First, the multinomial logit model is estimated as a benchmark. The results can easily be interpreted and later on used to see if the uncovered latent classes differ from the base MNL model. When estimating the base MNL model it is assumed that all respondents have the same taste parameters and panel effects are not accounted for yet. Both disruption scenarios are combined into one model by including interaction effects for the alternative specific constants. At first the model is estimated with all parameters specified for each alternative. Model fit is improved by turning some parameters into generic parameters which have the same value across alternatives. Quadratic components are also added to the model and tested to see if certain attributes are possibly weighed non-linearly. The equations below show the systematic utilities of the base MNL model. The two disruption scenarios each have a separate utility for the option return home since there are different attributes involved for the two scenarios. The disruption scenarios are coupled to the waiting for disruption to be over and rerouting option by adding an interaction term to the ASCs. The explanation of all the terms can be found in Table 6.1.

$$\begin{aligned} V_{wait} =& ASC_{wait} + SCE * ASC_{waitSCE} + \\ & \beta_{DisruptionLength} * disruption\_length + \beta_{DisruptionLength\_Q} * disruption\_length^2 + \\ & \beta_{Original\_tt} * tt_{wait} + \\ & \beta_{Crowding\_D} * crowding_{D\_wait} + \beta_{Crowding\_F} * crowding_{F\_wait} \end{aligned} \tag{6.1}$$

$$\begin{aligned} V_{reroute} =& ASC_{reroute} + SCE * ASC_{rerouteSCE} + \\ & \beta_{wait} * wt\_reroute + \\ & \beta_{Additional\_tt} * tt_{reroute} + \\ & \beta_{Crowding\_D} * crowding_{D\_reroute} + \beta_{Crowding\_F} * crowding_{F\_reroute} + \\ & \beta_{Transfer\_1} * transfer_1 + \beta_{Transfer\_2} * transfer_2 \end{aligned} \tag{6.2}$$

$$\begin{aligned} V_{return\_SCE1} =& ASC_{return\_SCE1} + \\ & \beta_{Access} * access\_time + \beta_{Access_Q} * access\_time^2 \end{aligned} \tag{6.3}$$

$$\begin{aligned} V_{return\_SCE2} =& ASC_{return\_SCE2} + \\ & \beta_{Access} * access\_time + \beta_{Access_Q} * access\_time^2 \\ & \beta_{wait} * wt\_return + \\ & \beta_{Return\_tt} * tt_{return} + \\ & \beta_{Crowding\_D} * crowding_{D\_return} + \beta_{Crowding\_F} * crowding_{F\_return} \end{aligned} \tag{6.4}$$

Table 6.1: Meaning of all terms in utility functions.

Term in utility function	Description
V_{wait}	Systematic utility for 'waiting for disruption to be over' option
$V_{reroute}$	Systematic utility for rerouting option
V_{return_SCE1}	Systematic utility for 'returning home' option, disruption scenario 1; disruption occurs at origin station
V_{return_SCE2}	Systematic utility for 'returning home' option, disruption scenario 2; disruption occurs during train trip
ASC_i	Alternative specific constant for alternative i for disruption scenario 1; disruption occurs at origin station
ASC_{i_SCE}	Addition to ASC_i to form ASC for disruption scenario 2; disruption occurs during train trip
SCE	Dummy coded disruption scenario; 0 = disruption occurs at origin station 1 = disruption occurs during train trip
$\beta_{DisruptionLength}$	Parameter for disruption length waiting time
$\beta_{DisruptionLength\_Q}$	Parameter for quadratic component for disruption length waiting time
β_{wait}	Parameter for waiting time for train departure in rerouting and returning home option
$\beta_{Original\_tt}$	Parameter for original travel time in train
$\beta_{Additional\_tt}$	Parameter for additional travel time on top of original travel time while rerouting
β_{Return_tt}	Parameter for travel time in train when returning home in disruption scenario 2
β_{Access}	Parameter for access time (time between origin station and home)
β_{Access_Q}	Parameter for quadratic component for access time
$\beta_{Crowding\_D}$	Parameter for Fruin crowding level D (reference is Fruin level B)
$\beta_{Crowding\_F}$	Parameter for Fruin crowding level F (reference is Fruin level B)
$\beta_{Transfer\_1}$	Parameter for one additional transfer during rerouting (reference is no additional transfers)
$\beta_{Transfer\_2}$	Parameter for two additional transfers during rerouting (reference is no additional transfers)

The disruption scenario is dummy coded so that the ASCs for the wait and reroute option receive an addition when the disruption scenario changes from scenario 1 to 2. Scenario 1 is the reference level in this case and is defined as the scenario where the disruption occurs at the origin station. This way both disruption scenarios are captured in one utility function for both wait and reroute option. Since the utility functions for the return home option differ between disruption scenarios in terms of attributes it is chosen to keep them separate. The dummy coding scheme can be found in Table 6.2. The additional number of transfers and crowding are dummy coded as well since the relationship is found to be non-linear. An extra parameter can be added for a quadratic component however, dummy coding leads to the same number of parameters and is therefore preferred.

Table 6.2: Dummy coding scheme for disruption scenario, transfers and crowding.

Disruption scenario	**SCE**	
Scenario 1; disruption occurs at origin station	0	
Scenario 2; disruption occurs during train trip	1	
Transfers	**transfer1**	**transfer2**
1 additional transfer	1	0
2 additional transfers	0	1
no additional transfers	0	0
Crowding	**crowding_D**	**crowding_F**
Fruin crowding level D	1	0
Fruin crowding level F	0	1
Fruin crowding level B	0	0

The Biogeme code syntax for estimating the base MNL model can be found in Section D.1. The estimated base model has a ρ^2 of 0.184, a final log-likelihood of -8767.99 and a BIC value of 17692.17.

Table 6.3 shows the results of the base MNL model estimation. In the model estimation the ASC of waiting for the disruption to be over is fixed to zero. Therefore the ASCs for rerouting and returning home are relative to the waiting option. The ASC for the rerouting option is equal to -2.7 for disruption scenario 1 and becomes -2.7+1.2 = -1.5 for disruption scenario 2. Although the ASC for the waiting option is fixed to zero for disruption scenario 1 an additional parameter is estimated for the ASC for disruption scenario 2. Since all alternatives have different attributes the ASCs cannot be compared directly. Only the signs of the ASCs can be compared. It can be seen that the ASCs for waiting and rerouting increase when the disruption occurs during the train trip compared to when the disruption occurs at the origin station. This is according to expectation since returning home involves another trip by train and takes longer than when the disruption occurs at the origin station.

The table also shows that two parameters are not significant and the model fit would improve if those parameters are removed. However, since a latent class choice model is estimated later on in the study it is decided to keep the insignificant parameters since they might become significant in one or more classes. The original travel time in the train does not seem to influence the choice in the context of a disruption since the parameter is insignificant. It was expected to have an influence but the reason it might not be is that it is assumed to be the normal travel time in train that the commuters experience each time they commute to work. The other parameter that is insignificant is the linear parameter for access time. Only the quadratic component of access time is significant. This shows that the relationship for the access time is quadratic. Therefore the disutility increases faster when access times are higher. All other parameters are significant.

Before performing this study it was expected that all parameters would have a negative sign since increasing attribute values were expected to only contribute disutility. The parameters that are significant are all negative except for one quadratic component for the disruption length. However, over the entire range of tested disruption lengths the total contribution of the disruption length when adding linear and quadratic component together is still negative. Therefore all significant parameters have the expected signs.

Table 6.3: Parameter value estimates for the base MNL model. LL = -8767.99, BIC = 17692.17, ρ^2 = 0.184. *** parameters are significant at 99% confidence interval. Other parameters are not significant.

Name	Unit	Value	Robust t-test
ASC_{wait}	-	0	-
$ASC_{reroute}$	utils	-2.7	-5.72***
$ASC_{reroute\_SCE}$	utils	1.2	7.27***
ASC_{return_SCE1}	utils	-4.99	-10.6***
ASC_{return_SCE2}	utils	-2.7	-8.5***
ASC_{wait_SCE}	utils	1.5	9.41***
β_{Access}	utils/minute	-0.0105	-1.43
β_{Access_Q}	utils/minute^2	-0.000461	-2.82***
$\beta_{Additional\_tt}$	utils/additional minute	-0.0597	-20.5***
$\beta_{Crowding\_D}$	utils	-0.192	-5.04***
$\beta_{Crowding\_F}$	utils	-0.849	-22.2***
$\beta_{DisruptionLength}$	utils/minute	-0.174	-7.9***
$\beta_{DisruptionLength\_Q}$	utils/minute^2	0.000886	3.5***
$\beta_{Original\_tt}$	utils/minute	0.00115	0.465
$\beta_{Transfer\_1}$	utils	-0.184	-3.3***
$\beta_{Transfer\_2}$	utils	-0.721	-12.3***
β_{Return_tt}	utils/minute	-0.0531	-6.13***
β_{wait}	utils/minute	-0.0637	-13.6***

When looking at the crowding, Fruin level B is the reference alternative and the utility decreases by 0.192 when crowding increases to level D and decreases by 0.849 for level F. This means that the utility decreases by 0.657 when crowding on the platform increases from level D to level F which is much larger than the difference between level B and D. This confirms the non-linear relationship for the crowding. A similar effect is found for the additional number of transfers present in the rerouting option. One additional transfer contributes -0.184 to the utility while a second additional transfer further decreases the utility by 0.537. This indicates that people value a second additional transfer more negatively than the first. Currently NS uses a constant penalty for a transfer but these results indicate that it might be more realistic to use different values for a first and second transfer.

The model results also show that waiting time is perceived more negatively than in-vehicle-times such as the additional travel time and return travel time in train. This is line with literature and expectations since waiting causes stress, frustration and is less comfortable than being seated in the train (Wardman, 2004).

It is difficult to directly compare the time parameters since different ranges were tested in the stated choice experiment. The maximum and minimum contribution to utility are depicted in Table 6.4. It shows how the contribution of disutility of the disruption length is moderated by the quadratic term. It however still has the largest negative contribution to the utility. The access time can also have a large contribution to the utility since they are squared. When someone lives far from the station it indeed makes sense that returning home has a lower utility than for someone who lives very close to the station. The waiting time for the rerouting train and returning home train in the second disruption scenario do not contribute much to the utility.

Table 6.4: Time related attributes' contribution to utility.

Parameter	Value	Attribute range [min]	Min. utility contribution	Max. utility contribution	Difference
β_{Access_Q}	-0.000461	1 - 85	-0.000461	-3.331	-3.3305
$\beta_{Additional\_tt}$	-0.0597	20 - 40	-1.194	-2.388	-1.194
$\beta_{DisruptionLength}$	-0.174	30 - 60	-5.22	-10.44	-5.22
$\beta_{DisruptionLength\_Q}$	0.000886	30 - 60	0.7974	3.1896	2.3922
$\beta_{DisruptionLength}$ + $\beta_{DisruptionLength\_Q}$	-	30 - 60	-4.4226	-7.25	-2.8274
β_{Return_tt}	-0.0531	10 - 20	-0.531	-1.062	-0.531
β_{wait}	-0.0637	5 - 15	-0.3185	-0.9555	-0.637

6.2. MNL model with interactions

It is expected that people's perception of attributes and therefore also the choices people make is influenced by individual characteristics such as sociodemopgrahics. The relevant interactions are also expected to give an indication which characteristics are important to include in the class membership when estimating the latent class choice models. Interactions are tested in the base MNL model to capture taste variation. Each characteristic is estimated separately as an interaction in the model to isolate the effect of each characteristic. For each characteristic two models are estimated. First, the interaction is added to the ASCs and secondly to the taste parameters. The utility function below is modified to include age as an interaction and this is repeated for all alternatives.

$$\begin{aligned} V_{wait} = & ASC_{wait} + SCE * ASC_{waitSCE} + ASC_{wait\_Age} * Age + SCE * ASC_{waitSCE\_Age} * Age \\ & (\beta_{DisruptionLength} + \beta_{DisruptionLength\_Age} * Age) * disruption\_length + \\ & (\beta_{DisruptionLength\_Q} + \beta_{DisruptionLength\_Q\_Age} * Age) * disruption\_length^2 + \\ & (\beta_{Original\_tt} + \beta_{Original\_tt\_Age} * Age) * tt_{wait} + \\ & (\beta_{Crowding\_D} + \beta_{Crowding\_D\_Age} * Age) * crowding_{D\_wait} + \\ & (\beta_{Crowding\_F} + \beta_{Crowding\_F\_Age} * Age) * crowding_{F\_wait} \end{aligned} \tag{6.5}$$

Some of the characteristics are dummy coded since they are categorical. An example is the possibility for a respondent to work from home. If they can work from home this is coded as a 1 and if they cannot it is coded as a 0. The latter is the base category and therefore also the reference level to which the interactions can be compared. For example if a parameter $\beta_{Crowding\_F\_Teleworking}$ is significant it shows how people who can work from home are more or less sensitive to crowding level F than people who cannot work from home. Some characteristics such as age are not dummy coded since it is an ordinal variable and dummy coding all these characteristics would lead to a large number of parameters. A downside of this approach is that it is assumed that the ordinal variables are linear which might not be the case. Some categories are aggregated to ensure that each category contains a sufficient number of respondents. The full coding scheme can be found in Table D.1. The models including the interactions are again estimated using the Biogeme package and the code can be found in Section D.3. In this section of the report only the insights that are most relevant for this study are discussed. For the full table of all interaction effects and an explanation of how to interpret them, the reader is referred to Section D.4.

Teleworkers and having to arrive at the workplace: When looking at people who can telework they are less likely to wait or reroute compared to people who cannot telework and are more likely to return home. A contrary effect is found for people who have to arrive at their workplace since they are less sensitive to the additional travel time than people who do not have to arrive at their workplace. A longer rerouting time for people who can telework and do not have to arrive at their workplace might lead to them returning home. People with a negative attitude towards teleworking are more inclined to reroute or wait then people with a positive attitude towards teleworking. All these results are as expected.
When looking at the taste parameters the interaction effects are less present. People who can telework are more sensitive to additional travel time but less sensitive towards access times and moderate crowding levels than people who cannot telework. When people have a positive attitude towards teleworking they are more sensitive to the disruption length. The characteristic of having to arrive at the workplace or not however does have a large effect on the taste parameters. If someone has to arrive at their workplace they are more sensitive to access time and moderate crowding. They are however less sensitive to: additional travel time (29%), extreme crowding (15%), disruption length (14%), a second transfer (34%) and waiting time (36%) compared to people who do not have to arrive at the workplace.

COVID-19 attitude: When starting this study it was expected that the attitude towards COVID-19 would impact the perception of crowding and possibly even travelling by train in general. Respondents that indicated they avoid crowded places and do not feel free to travel by train because of the crowding indeed are more sensitive to extreme crowding (Fruin level F) but there is hardly any effect for moderate crowding (Fruin level D). Being afraid to get infected with the virus does not have any effect on perception of crowding and hardly any effect on the ASCs of the alternatives. The general trend seems to be that people who are more aware or afraid of COVID-19 are more likely to return home than the people who are indifferent to the effects of COVID-19. The effects are however not as large as expected.

Attitude towards information during disruptions: The attitude towards travel information during disruptions seems to have a bigger effect on the ASCs of the different alternatives than on the taste parameters. People who trust the information on prognoses are less sensitive towards the disruption length than people who do not trust the information. People who trust information from the travel apps and state that they follow the travel advice provided by NS are more likely to wait for the disruption to be over than the people who do not trust the travel apps or follow travel advice. In general it seems that people who distrust the information brought out by NS or the travel apps are more likely to return home or reroute and less likely to wait for the disruption to be over. This makes sense since they do not trust the prognoses and might expect the disruption to take longer than NS states and therefore are more inclined to reroute or return home.

Subscription and station type: When passengers check in with their smartcard certain characteristics are known to the train company. In the case of NS it is known what the origin station of the passenger is which can be coupled to a station type as defined by van Hagen & de Bruyn (2002) and whether or not the passenger has a train subscription (off-peak discount, unlimited travel off-peak, unlimited travel on trajectory etc.). People who start their usual train trip from smaller stations with less facilities are more sensitive towards waiting time for the train to depart. People with subscriptions are more sensitive to additional travel times, crowding, disruption length and much more sensitive to waiting time than people who do not have a subscription. A possible explanation could be that these are frequent travellers and usually travel without complications but when a disruption occurs they are more disturbed by this than the people who do not travel as frequently.

6.3. Latent class choice models

After testing different interactions it is evident that characteristics such as attitude towards information and teleworking have an effect on the choices that people make and how they perceive certain attributes. In this section of the report another way to capture heterogeneity is tested by estimating latent class choice models. The aim is to find classes that are homogeneous within but the classes themselves differ as much as possible. Different MNL models are estimated corresponding to the number of latent classes. Respondents are probabilistically assigned to a class. Another addition on top of the basic MNL model is that the data is formatted into panel data meaning that the model takes into account that one respondent makes a series of choices.

6.3.1. Number of classes

The latent class choice models are estimated using Biogeme and the utility functions previously mentioned are unaltered. The first step in estimating latent class choice models is determining how many latent classes there are based on the data. Therefore the model is estimated using different numbers of classes with a static class membership function. The model with one class is the base MNL model estimated previously. The results are shown in Table 6.5. For the different models the rho-squared, final log-likelihood and BIC values are reported to compare the models and look for the best fit. It should be noted that each model is estimated ten times with randomly generated starting values since latent class choice models are prone to getting stuck in local optima.

Table 6.5: Different number of classes model estimation. Initial log-likelihood is -10744.43.

# of classes	ρ^s	Final log-likelihood (LL)	# of parameters (k)	BIC
1 (base MNL)	0.184	-8767.99	17	17692.17
2	0.291	-7614.82	35	15464.24
3	0.319	-7313.98	53	14983.23
4	0.342	-7070.55	71	14617.03
5	0.351	-6970.745	89	14538.07
6	0.358	-6895.548	107	14508.34
7	0.365	-6821.759	125	14481.42
8	0.373	-6734.058	143	14426.67
9	0.377	-6696.677	161	14472.57

The number of latent classes is chosen based on a number of criteria. First, it is checked whether the classes contribute to the interpretation of the model. As a second criterion the sizes of the classes are investigated whether they are not too large (>50%) or too small (<10%). The number of latent classes to be used is also investigated by looking at the BIC value which penalizes increasing model complexity (Louviere et al., 2000). When estimating the latent class choice models for an increasing number of classes the BIC value at first drops quickly when estimating models with two, three and four classes. After this point adding more classes does continue to lead to decreasing BIC values but the differences become smaller as can be seen in Figure 6.1. The models are investigated to see if the different classes are still distinct enough in behaviour. When investigating the four-class model it was found that the classes are distinct in terms of trade-offs however the five-class model contained two classes with nearly similar trade-offs. Based on this finding it is decided to estimate a model with four classes even though it does not have the lowest BIC value.

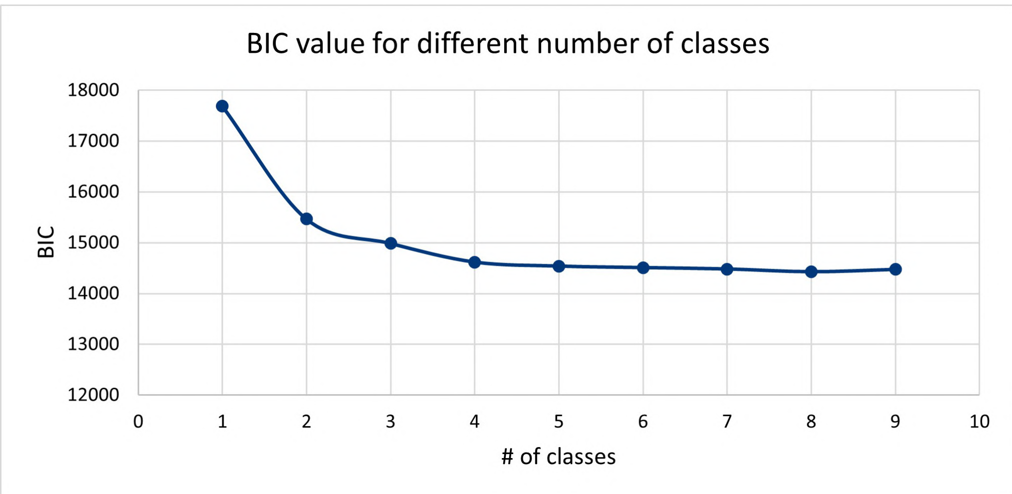

Figure 6.1: The BIC value for estimated models with different numbers of classes.

6.3.2. Estimation results

To make the comparison between trade-offs of the different classes more insightful it is decided to fix one taste parameter across classes. Since the waiting parameter is almost constant between classes it is chosen to fix this parameter. The parameter for the original train trip length is not significant in any of the four classes and therefore removed from the model. After these two steps all characteristics collected in the study are simultaneously added to the class membership function. After each iteration a maximum of three characteristics which have a p-value over 0.2 for all classes are removed. When there are no more characteristics in the class membership with a p-value over 0.2 the insignificant characteristics (p-value <0.1) are removed one by one until only characteristics remain that are significant in at least one of the classes. The final model and the resulting parameter estimates for the four classes is shown in Table 6.6. Model heterogeneity is indeed captured with the latent class choice model since the parameters differ significantly from the base MNL parameters in Table 6.3. The final model contains 97 parameters, has a final log-likelihood of -6900.983, a rho-squared of 0.358 and a BIC value of 14452.17.

Table 6.6: Class specific models including class membership function parameters. Estimated parameters in bold and italic are significant at the 95% level. Estimated parameters in only italic are significant at the 90% level. 97 parameters, final log-likelihood = -6900.983, rho-squared = 0.358 and BIC value = 14452.17.

Attributes	Class 1 (39.0%)		Class 2 (19.8%)		Class 3 (18.2%)		Class 4 (23.0%)	
	Est.	Robust t-test	Est.	Robust t-test	Est.	Robust t-test	Est.	Robust t-test
Constants								
Reroute; disruption origin station	***-4.58***	***-4.51***	*13.2*	*1.94*	*-2.36*	*-1.7*	-0.397	-0.215
Reroute addition; disruption during train trip	***2.13***	***5.95***	***-4.69***	***-2.03***	***2.64***	***4.41***	***1.4***	***2.28***
Return home; disruption origin station	***-7.51***	***-6.9***	*13.4*	*1.92*	***-9.05***	***-5.89***	***-4.86***	***-2.46***
Return home; disruption during train trip	***-4.28***	***-5.92***	***9.9***	***2.15***	***-4.81***	***-3.91***	-0.79	-0.633
Wait; disruption during train trip	***2.53***	***6.63***	***-4.69***	***-2.04***	***2.82***	***4.41***	***1.71***	***2.67***
Taste parameters								
Access time	-0.0258	-0.947	0.0399	0.977	*0.193*	*1.78*	-0.0871	-1.12
Access time quadratic	-0.00022	-0.481	***-0.00193***	***-2.27***	*-0.00702*	*-1.92*	0.000847	0.578
Additional TT	***-0.1***	***-10.7***	***-0.0517***	***-2.49***	***-0.0799***	***-8.18***	***-0.0655***	***-7.16***
Crowding level D	***-0.279***	***-3.53***	0.0264	0.169	***-0.424***	***-3.91***	***-0.307***	***-2.74***
Crowding level F	***-1.25***	***-10.3***	***-0.763***	***-4.48***	***-1.37***	***-6.18***	***-1.09***	***-5.94***
Disruption length wait	***-0.28***	***-5.4***	***0.77***	***2.06***	***-0.152***	***-2.38***	-0.111	-1.22
Disruption length wait quadratic	***0.00158***	***2.69***	***-0.0123***	***-2.48***	0.000607	0.94	-0.00032	-0.28
1 transfer	***-0.298***	***-2.02***	-0.0296	-0.106	*-0.358*	*-1.84*	-0.171	-0.851
2 transfers	***-1.03***	***-5.57***	*-0.509*	*-1.7*	***-1.3***	***-6.5***	***-0.729***	***-3***
Return TT in train	***-0.0859***	***-4.58***	***-0.0651***	***-2.52***	-0.0676	-1.33	***-0.0938***	***-3.07***
Wait (fixed across classes)	***-0.0929***	***-15.3***	***-0.0929***	***-15.3***	***-0.0929***	***-15.3***	***-0.0929***	***-15.3***
Class membership								
Constant	Base class		0.0587	0.104	-0.22	-0.366	***-2.08***	***-3.26***
Age - continuous			***0.609***	***4.52***	0.0147	0.0944	-0.188	-1.28
Alternative transport - dummy			-0.222	-0.815	***-0.596***	***-2.08***	-0.198	-0.751
Avoid crowd - continuous			-0.0941	-0.695	*-0.254*	*-1.7*	-0.0844	-0.534
Wear facemask - continuous			***0.403***	***2.9***	0.0971	0.48	-0.0514	-0.311
Like to travel by train - continuous			*-0.278*	*-1.91*	0.0985	0.52	***0.407***	***2.7***
Necessary to arrive at workplace - dummy			***-0.981***	***-3.8***	***1.57***	***4.66***	***1.91***	***5.32***
Telework possibility - dummy			-0.517	-0.973	***-1.48***	***-3.8***	-0.643	-1.39
Telework attitude - continuous			0.235	1.47	*-0.329*	*-1.84*	-0.191	-1.25
Normal travel time in train - continuous			***-0.599***	***-3.18***	0.2	0.942	***0.703***	***4.04***
Trust prognosis			-0.0979	-0.696	*0.229*	*1.7*	***-0.336***	***-2.2***
Trust travel app			-0.0954	-0.673	0.0834	0.504	***0.352***	***2.12***

Regarding the significant parameters all signs are as expected across all classes. The access times are only significant in class two and three while parameters such as the additional travel time and the dummy parameters for extreme crowding and two additional transfers are significant in all classes. The linear and/or quadratic components of the disruption length are significant in three classes. The fourth class is not sensitive to the disruption length at all which is quite remarkable meaning that travel behaviour of people in this class does not depend on the expected length of the disruption. Similar to findings of the base MNL model the second additional transfer is valued more negatively than the first additional transfer. For some classes the parameter for the first additional transfer is not significant while the second additional transfer is significant across all classes. The same can be said about the crowding parameters. Going from moderate (Fruin level D) to extreme crowding (Fruin level F) is valued more negatively than from no crowding (Fruin level B) to moderate crowding.

The characteristics that are significant in the class membership can be found in the same table. Most characteristics are only significant in one class except for whether or not it is necessary to arrive at the workplace and respondents' normal travel time in the train. If age increases the likelihood of the respondent belonging to class 4 decreases since the parameter is significant and negative. The other parameters can be interpreted in a similar way. Characteristics such as being able to work from home, attitude towards teleworking, trust in the provided information and attitude towards crowding and COVID-19 all have an effect on the class membership as expected. Using the significant parameters each class is described in more detail below. An info-graphic including the distinctive factors and behaviour which characterizes each class is shown in Figure 6.2.

Class 1 (39.0%): 'Trade-off teleworkers' The largest class is mainly characterised by having a preference to trade-off all attributes and therefore do not have a clear preference for one travel option over the others. All attributes except for access times are significant for this class and therefore a trade-off between all attributes is made. The attribute levels have a large impact on the travel choices for this class. For shorter disruptions this class is likely to choose to wait but when disruption lengths increase the share of rerouting and returning home rapidly increases while waiting becomes less likely. Waiting time is preferred over additional travel time on the reroute option which is not seen in the other classes. Travellers in this class are conscious of crowding and would wait roughly 10 minutes to go from extreme crowding (Fruin level F) to moderate crowding (Fruin level D). The train travellers in this class are likely to not have to go to their workplace (51.3%) and have the option to telework (44%). Travellers with a positive attitude towards teleworking are more likely to be found in this class. Travellers in the age group of 35-44 years old are more likely to be in this class.

Class 2 (19.8%): 'Sceptic returners' Travellers in this class are mostly characterised by their preference to not wait at all. Even for short disruption lengths they are much more likely to return home than wait for the disruption to be over or reroute. For this class the choice between rerouting and returning home mostly relies on the access travel times since the quadratic component of the access time quickly decreases the utility of returning home. However returning home always has a large share independent of the disruption scenario. This class is sensitive to crowding and would travel 15 additional minutes in the train to avoid crowding. The train travellers in this class are likely to be sceptic towards prognosis information and information in travel apps. Travellers who dislike travelling by train have a probability of 50.8% to end up in this class. The sensitivity towards crowding is also explained by the probability of COVID-conscious travellers to be assigned to this class. Travellers that indicate that they will continue to wear facemasks, are afraid to get infected with the virus and do not feel free to travel by train because of the crowding are more likely to be in this class. Travellers are also likely to be able to work from home and not having to arrive at the workplace and can therefore easily return home when a disruption occurs. Especially travellers with a normal travel time in the train of below thirty minutes and with an age between 55 and 64 years old are more likely to be in this class.

Class 3 (18.2%): 'Trusting workplace travellers' In behaviour this class is similar to class 1 but with the difference that this class has a larger initial preference for rerouting and are less likely to return home than the travellers in class 1. When disruptions are short they are likely to either wait or reroute but not to return home. This class is however the most sensitive towards additional travel time on the rerouting option and is more likely to wait for the disruption to be over when this additional travel time increases. This is the only class that is not sensitive to travel time in the train while returning home. Contrary to the previous classes this class is characterized by travellers who cannot work from home (43.2%) and have to arrive at their workplace (26.2%). The travellers are likely to be less experienced travellers and trust the provided information on prognoses, follow advice from the travel apps and are guided more by the provided information by NS than their previous experiences with disruptions. Travellers without alternative modes of transport available to them are also more likely to be in this class. People with access times over 30 minutes also have a slightly higher probability of being assigned to this class (22.7%).

Class 4 (23.0%): 'Endless waiters' The travellers in this class are not sensitive to the disruption length at all. Even when the disruption length is 60 minutes and the other travel options are made as attractive as possible, 80% of travellers in this group would wait for the disruption to be over. The main characterization of this class therefore is that they are very likely to wait for the disruption to be over regardless of the disruption scenario. Travellers in this class are likely to not be able to work from home (28.9%), have to arrive at the workplace (32.8%), are between 18 and 34 years old (31.5%), like to travel by train (31.9%), come from rural areas (30.6%) and normally have a train travel time of over 60 minutes (34.7%). However, if they can telework they are more likely to have a negative attitude towards teleworking (30.5%). Travellers that do not trust the disruption length prognosis are much more likely to be in this class (31.4%) which is unexpected since the travellers in this class are very likely to choose to wait for the disruption to be over in each disruption scenario. It was expected that these types of travellers would be more likely to reroute or return home. Travellers with an access time over 30 minutes are more likely to belong to this class as well (27.4%) which makes sense since returning home is less attractive when access times are very high so waiting might be more attractive for this group of travellers.

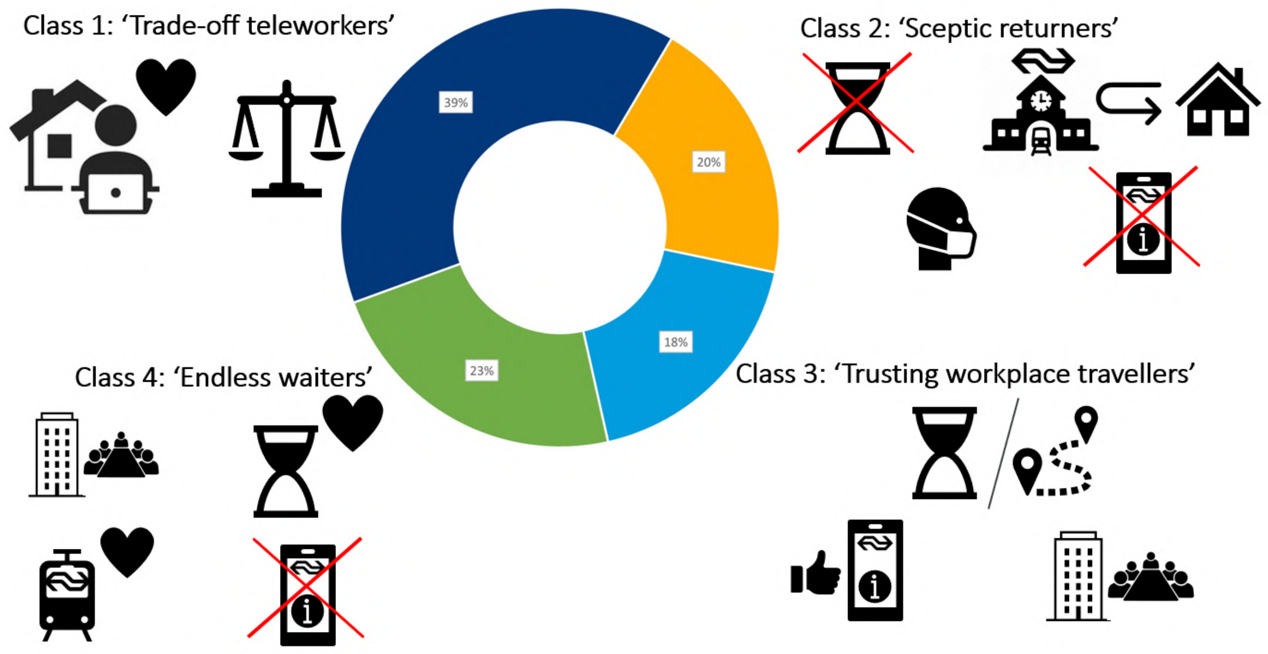

Figure 6.2: The latent classes characterized in terms of class size, preferred travel option and corresponding characteristics.

6.4. Conclusion

Summary

- The disruption length has the largest contribution to the disutility followed by large access times and additional travel time in the train for the rerouting option.
- Teleworkers are more sensitive to additional travel time, extreme crowding, disruption length, two additional transfers and waiting time than people who cannot work from home.
- Train travellers who perceive COVID-19 as dangerous are more sensitive to crowding but the effect is not as large as expected.
- Train travellers who distrust travel information are more likely to return home or reroute.
- Heterogeneity is captured by a latent class choice model with four classes.
- Segments are identified based on travel behaviour and individual characteristics: 'Trade-off teleworkers', 'Sceptic returners', 'Trusting workplace travellers' and 'Endless waiters'.

In this chapter different kinds of discrete choice models are estimated with the goal of investigating which factors influence travel behaviour during disruptions. First, a base MNL model is estimated as a benchmark. All tested attributes such as disruption length and additional travel time have a negative contribution to the utility as expected. The disruption length, access times and additional travel time have the largest contribution to the disutility.

Interactions are added to the base MNL model to investigate attribute perceptions. Sociodemographics related to train travellers' jobs have the largest impact on the taste parameters and initial preference for a travel option. Train travellers who can work from home are less likely to wait for the disruption to be over or reroute than train travellers who cannot work from home. Returning home is much less likely for train travellers who have to arrive at their workplace. These train travellers are less sensitive to additional travel time, extreme crowding, the disruption length, a second transfer and waiting time than people who do not have to arrive at the workplace. People who are conscious or afraid of COVID-19 are approximately 10% more sensitive to extreme crowding than people who have a neutral attitude towards the virus. People who are sceptic towards information provided during the disruption by either NS or travel apps are more likely to return home or reroute.

A latent class choice model is estimated to capture heterogeneity. Four latent classes are uncovered which each exhibit distinct travel behaviour and characteristics. Class membership is mostly influenced by sociodemographics such as age, whether an alternative mode of transport is available or not, normal travel time in train, ability to telework, attitude towards teleworking and whether or not it is necessary to arrive at the workplace. COVID-19 attitude indicators such as wearing a facemask and avoiding crowds also have an influence on class membership. Lastly, the attitude towards information provided during disruptions influences the probability of being in a certain class. With this model approximately 36% of the initial variance is explained.

7 Applications

This chapter investigates the final latent class choice model estimated in Chapter 6 in more depth. First, a sensitivity analysis is performed looking into which factors have the largest effects on the travel option shares for the train traveller population. In the following section two different control strategies are applied and investigated to see what potential effects of the strategies are on the shares of the different travel options.

7.1. Impact of changing attribute values

In the previous chapter different choice models are estimated and in this section of the report the final latent class model is investigated in more depth. An analysis is performed to investigate which factors have the largest effect on the probabilities of choosing a certain travel option in different disruption scenarios. The latent classes are weighed by their predicted size to arrive at probabilities for the commuter train traveller population. The middle level of the attributes from the stated choice experiment is chosen as the reference level. This can also be seen in Table 7.1 since all the middle rows of the attributes have the same choice probabilities indicating that the middle level is the reference level for the attribute. Then the level of a single attribute is changed while fixing all the others to the reference level. This way the effect of changing a specific attribute is isolated. This analysis is performed for both disruption scenarios defined previously.

Table 7.1: Showing the impact of changing attribute values on the probabilities of choosing waiting for the disruption to be over, rerouting or returning home for the train traveller sample.

Attribute	Level	Disruption occurs at origin station			Disruption occurs during train trip		
		Wait (%)	Reroute (%)	Return (%)	Wait (%)	Reroute (%)	Return (%)
Disruption length (minutes)	30	61.0%	9.0%	30.0%	75.6%	9.1%	15.2%
	45	30.3%	19.6%	50.0%	38.8%	26.7%	34.5%
	60	22.8%	23.4%	53.8%	24.9%	33.9%	41.2%
Additional travel time reroute (minutes)	20	26.6%	31.9%	41.5%	32.0%	42.0%	26.0%
	30	30.3%	19.6%	50.0%	38.8%	26.7%	34.5%
	40	33.5%	11.2%	55.3%	44.2%	14.7%	41.2%
Waiting time until reroute train leaves (minutes)	5	28.2%	26.0%	45.9%	35.2%	35.0%	29.8%
	10	30.3%	19.6%	50.0%	38.8%	26.7%	34.5%
	15	32.3%	14.4%	53.3%	41.9%	19.5%	38.6%
Additional number of transfers on reroute	0	29.2%	22.9%	47.9%	36.7%	31.0%	32.3%
	1	30.3%	19.6%	50.0%	38.8%	26.7%	34.5%
	2	33.8%	11.3%	54.9%	44.0%	15.6%	40.5%
Travel time in train to return to origin station (minutes)	10	-	-	-	36.4%	23.7%	39.9%
	15	-	-	-	38.8%	26.7%	34.5%
	20	-	-	-	41.0%	29.7%	29.4%
Waiting time until return train leaves (minutes)	5	-	-	-	35.6%	22.2%	42.1%
	10	-	-	-	38.8%	26.7%	34.5%
	15	-	-	-	41.6%	31.0%	27.4%
Travel time from home to origin station (minutes)	5	30.5%	19.9%	49.7%	38.9%	26.6%	34.5%
	15	30.3%	19.6%	50.0%	38.8%	26.7%	34.5%
	25	31.5%	22.4%	46.2%	40.3%	30.2%	29.5%
Crowding level on platform where disrupted service will continue	Level B	33.3%	17.9%	48.8%	43.1%	24.2%	32.7%
	Level D	30.3%	19.6%	50.0%	38.8%	26.7%	34.5%
	Level F	23.9%	23.2%	52.8%	28.3%	32.4%	39.4%
Crowding level on platform where reroute train leaves	Level B	28.7%	23.4%	47.9%	36.3%	31.4%	32.3%
	Level D	30.3%	19.6%	50.0%	38.8%	26.7%	34.5%
	Level F	34.0%	10.3%	55.7%	44.6%	13.7%	41.7%
Crowding level on platform where return train leaves	Level B	-	-	-	37.0%	24.3%	38.7%
	Level D	-	-	-	38.8%	26.7%	34.5%
	Level F	-	-	-	44.0%	34.5%	21.5%

The first noticeable difference is the shares of travel options for the reference levels between both disruption scenarios. When the disruption occurs at the origin station 50% of train travellers going to their work would return home when assuming the reference levels described above. When the disruption occurs during the train trip this percentage decreases to 34.5%. Rerouting and waiting for the disruption to be over have bigger shares when the disruption occurs during the train trip than when it occurs at the origin station. This is according to expectation since travelling back home when the traveller already performed part of the train trip adds waiting time and train travel time while in the other scenario only access times are relevant.

Upon examining the attributes and the effect they have on the shares of travel options the disruption length has the largest impact. For a disruption length of 30 minutes 61% of travellers would wait for the disruption to be over when it occurs at the origin station and 75.6% when the disruption occurs during the train trip. These shares sharply decrease by roughly 30 and 37 percentage points respectively when the disruption length increases to 45 minutes. When the disruption length further increases to 60 minutes waiting decreases by another 8 and 14 percentage points. Another large effect on waiting for the disruption to be over is when the crowding on the platform increases from Fruin level D to Fruin level F. The share of travellers that would wait then decreases by 6 and 10 percentage points respectively.

The share of travellers choosing to reroute is mostly affected by the length of the disruption, additional travel time, whether or not there is an additional second transfer and the crowding level on the platform where the rerouting train will leave. For a longer disruption length, it is likely that more travellers choose to reroute. The share of travellers choosing to reroute decreases by 12 and 16 percentage points respectively when the additional travel time increases from 20 to 30 minutes. This decrease becomes smaller when the additional travel time increases to 40 minutes. A second transfer results in a decrease of the rerouting share of 8 and 11 percentage points respectively compared to when there is one additional transfer on the rerouting option.

Whether or not train travellers return home is affected by the disruption length, waiting time until the train back to the origin station leaves. Access times seem to have a smaller influence on whether or not to return home. Only for access times over 15 minutes the share of travellers choosing to return decreases.

For a train operator company it is desired that train travellers do not return home but wait or reroute to avoid losing revenue. Increasing the share of people rerouting or waiting for the disruption to be over might therefore be preferred. However, making the rerouting option more attractive also again attracts more travellers on the rerouting option again increasing crowding. Therefore, it might not always be preferable considering that train operators also focus on ensuring that all travellers can safely be transported. Therefore a share of people choosing to return back home is not always a disadvantage for the train operator company since it reduces crowding and keeps the disruption situation more manageable. In a revenue increasing approach, ways to increase the share of people rerouting could be executed by decreasing additional travel time and number of additional transfers on the rerouting option, decrease crowding on the platform where the rerouting train leaves or decrease the waiting time for the reroute train. Decreasing additional travel time and the number of transfers would lead to expensive infrastructure investments which is not feasible on the short-term. Decreasing crowding on the platform can however be realized by extending the rerouting train assuming that this is communicated to passengers and that they distribute more evenly over the platform. The waiting time for the rerouting train could be decreased by increasing the frequency of the rerouting train. Increasing the frequency of the rerouting train also increases the capacity and therefore crowding also reduces with this control strategy. These two control strategies are investigated in the next section of this chapter. It should be noted that increasing the share of rerouting would also result in extra crowded platforms which might again influence travel behaviour but this iterative phenomenon is not taken into account when applying the control strategies.

7.2. Exploring control strategies

In this section two control strategies are explored which could increase the number of train travellers that reroute when a disruption occurs. This involves decreasing the crowding on the platform from which the rerouting train departs and decreasing the waiting time for the rerouting train. This can be achieved by extending trains and increasing the frequency of the trains respectively. For this purpose a trajectory that is part of the NS network where rerouting is possible is investigated. First, a reference level is defined for the attributes based on travel times but also assumptions on crowding levels and access times.

7.2.1. Case study: disruption occurs at origin station

In the first case study the trajectory Amersfoort to Utrecht Centraal is analyzed where rerouting is possible via Hilversum. This trajectory is chosen since it lies in the Randstad, which is a highly urbanized area with large passenger flows, and rerouting is a viable option when the normal itinerary is disrupted. The normal travel time between the two cities is 13 minutes by intercity. The study originally focussed on longer trips but the estimated choice models show that the original travel time in the train is not significant when making decisions. Travelling by other forms of public transport is not feasible on this trajectory. When rerouting via Hilversum the travel time is 37 minutes including an extra transfer which leads to an additional travel time of 24 minutes. In the first example the disruption occurs at the origin station which in this case is Amersfoort Centraal. The two routes including travel times and transfer times are shown in Figure 7.1. For simplicity it is assumed that there are no more direct trains between Amersfoort and Utrecht and that the travellers starting their journey at Amersfoort Centraal discover the disruption upon arrival at that station.

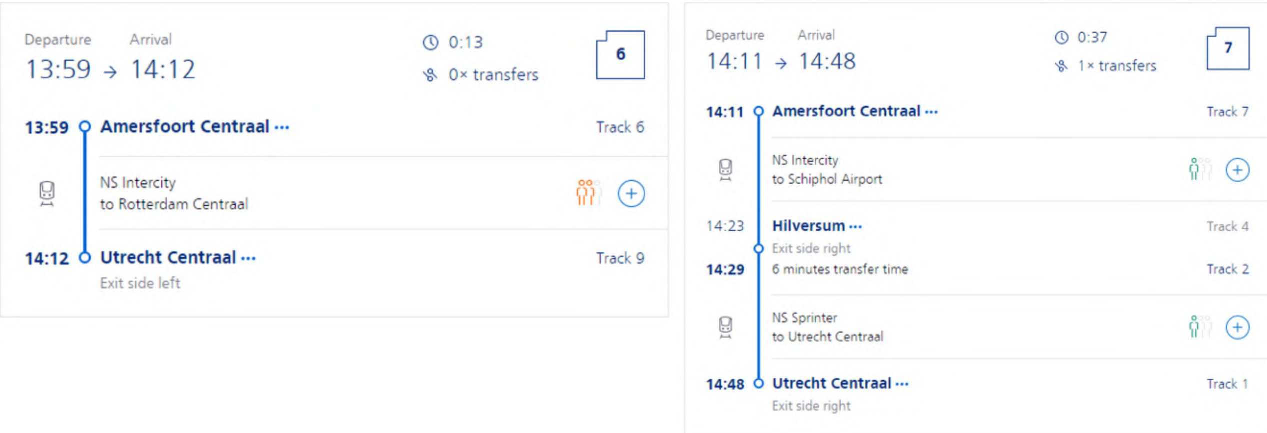

Figure 7.1: Travel planner routes between Amersfoort Centraal and Utrecht Centraal. Left figure: direct route between Amersfoort and Utrecht. Right figure: reroute between Amersfoort and Utrecht via Hilversum. (NS, 2022)

Reference scenario: In the reference scenario the disruption occurs at the origin station which in this case study is Amersfoort Centraal. The disruption occurs during peak hours on a weekday. Only behaviour of people travelling to their work is investigated. It is assumed that travellers have to wait for 15 minutes for the rerouting train to depart. The disruption length is expected to be 45 minutes. The additional travel time is fixed to 24 minutes and there is one additional transfer. The crowding levels on the platforms where the disrupted service will resume and where the rerouting train departs are set to Fruin level F. For the access time it is investigated what the average access time is for people usually travelling from Amersfoort Centraal based on train traveller data from NS. This average access time is fixed and set to 14 minutes.

Control strategy 1; extend the rerouting trains: In this scenario the rerouting trains are extended and it is assumed that this will reduce crowding on the platform where the rerouting train departs from Fruin level F to Fruin level D. It is also assumed that the train extension is communicated to passengers so that they spread more evenly over the platform which then results in the reduction of the crowding.

Control strategy 2; double the frequency of the rerouting trains: The waiting time for the rerouting train is decreased by doubling the frequency of the rerouting trains. The waiting time for the rerouting train decreases from 15 minutes to 7.5 minutes when implementing this measure. Since the capacity also increases when applying this strategy crowding will also decrease. Therefore, the crowding level is decreased from Fruin level F to level D as well.

The results of applying the first and second control strategy are summarized in the Sankey diagrams in Figure 7.2. The Sankey diagram is applied differently than usual since the flows from left to right are split to show the behaviour of the four different classes. First, the reference scenario is applied which leads to a probability for each travel option which is shown on the left of the diagram. For example when looking at the left figure the probability of waiting is 26.9% in the reference disruption scenario, rerouting 13.3% and returning home 59.8%. In the middle of the figure the classes are shown with their respective class sizes in percent. These values stay constant throughout all disruption scenarios since they are the class sizes. On the right of the figure the probabilities for the travel options are shown when the control strategy is applied. So when trains are extended the probability of waiting decreases to 24.0%, rerouting increases to 23.5% and returning home decreases to 52.4%. The classes in the middle are added to show what the preferred travel option of each class is and how their travel behaviour changes when control strategies are applied. For example in the left figure there is a yellow flow line going from the rerouting option to class three which is the widest yellow flow line indicating that most people who choose the reroute are part of class three. When the control strategy is applied the yellow line from class three becomes broader meaning that more people would reroute from class three once the control strategies are applied. The figure also shows that most people who would wait belong to class four. When the control strategies are applied the widths of flows for class four do not change much meaning that the control strategies have a small effect on the travel behaviour of class four. The same phenomenon can be seen for class two. For class one and three the widths of the flows differ quite a bit meaning that the control strategies have an effect on their travel behaviour.

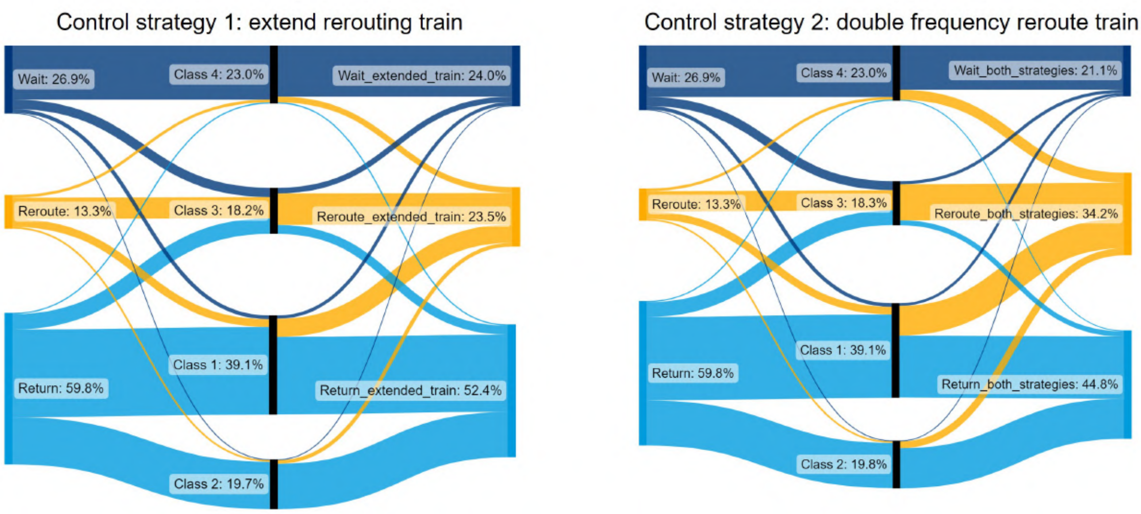

Figure 7.2: Sankey diagrams that show the effect of the control strategies. Left figure: rerouting trains are extended to reduce crowding. Right figure: waiting times and crowding for the rerouting train are decreased by increasing the frequency and therefore increasing the capacity of the rerouting train.

When comparing the two control strategies increasing the capacity by doubling the frequency of the rerouting train has a larger effect on the number of people rerouting than extending the rerouting train. Extending the train is however easier to accomplish since there might be an additional train conductor required, the number of train drivers does not have to be increased. When doubling the frequency the number of staff members required to run the service also doubles. It also might be difficult to add extra trains to an already busy infrastructure network. Based on these factors, doubling the frequency of the rerouting trains is probably not beneficial when comparing the additional number of travellers with the difficulties and costs of setting up this extra train service.

7.2.2. Case study: disruption occurs during train trip

The previous analysis on the impact of changing attribute levels shows that the place where the disruption happens in the journey has an influence on the expected shares of the different travel options. Therefore, a new scenario is created which investigates train travellers going from Apeldoorn to Utrecht Centraal. When travelling to Utrecht travellers first travel from Apeldoorn to Amersfoort and then transfer to another train going to Utrecht. Assuming that the disruption again occurs between Amersfoort and Utrecht Centraal, this scenario becomes an extension of the previously discussed scenario but now travellers have already travelled by train from Apeldoorn to Amersfoort. If they want to continue travelling to Utrecht they have to reroute via Hilversum according to the previously defined scenario. The reference scenario is the same as before but now more attribute levels are defined for the returning home option. The time in train to return back to the origin station is set to 25 minutes, the waiting time until this train leaves is 15 minutes and the crowding level is set to Fruin level F. In this case study the example of the control strategy where the frequency of the rerouting train is doubled is applied. The results can be found in Figure 7.3.

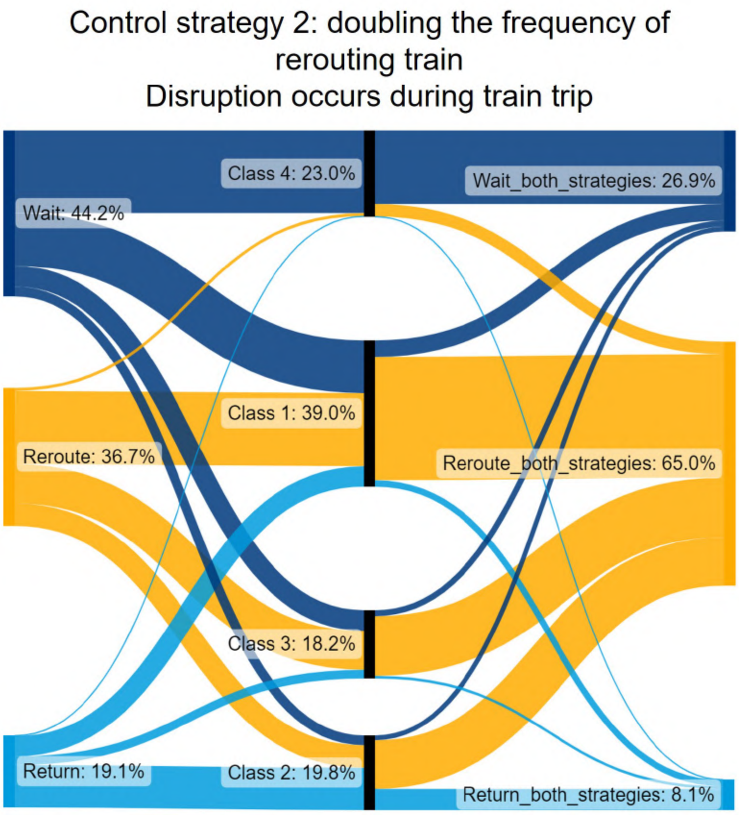

Figure 7.3: Sankey diagram that shows the effect of applying both control strategies when train travellers have already travelled from Apeldoorn to Amersfoort and can reroute via Hilversum to arrive in Utrecht.

The first noticeable change is that the share of rerouting is much larger in the reference scenario when the disruption occurs mid-trip (36.7%) than when it occurs at the origin station (13.3%). This is according to expectations since travelling back home in this scenario includes the access time (14 minutes), travel time back to origin station (25 minutes) and waiting time before this train leaves (15 minutes) compared to only the access time in the previous scenario. By implementing control strategies that decrease both the crowding and waiting time for the rerouting train a large increase can be made in the expected share of travellers choosing to reroute instead of returning home from 37% to 65%. The figure also shows that travellers belonging to class one and three can be influenced by making certain travel options more attractive. This fits the earlier characterizations of the classes since class one is characterized by making trade-offs based on the attributes and class 3 has to arrive at their workplace which makes waiting and rerouting more attractive. Surprising is that in this scenario the 'Sceptic returners' from class 2 also make a large shift from returning home to rerouting when the control strategies are applied. This might be caused by the fact that class two is more sensitive to the travel time in the train when returning compared to the additional travel time when rerouting. For class four the share of rerouting becomes slightly larger but still the majority of this class would wait implying that is difficult to influence the travel behaviour of the travellers belonging to this class.

7.3. Conclusion

Summary

- Disruption length and whether the disruption occurs at origin station or during the train trip have the largest impact on travel behaviour during disruptions.
- Effect of crowding and additional transfers on the shares of the different travel options is not linear.
- Waiting time, travel time in the train when returning home and access times have a small effect on travel behaviour during disruptions.
- Control strategies can be applied to increase the number of train travellers that reroute while decreasing the number of train travellers that would otherwise return home.
- Increasing the frequency of the rerouting trains has a larger effect on increasing the number of train travellers that would reroute than extending rerouting trains. However, the costs of this strategy are larger since double the staff is required which is difficult due to staff shortage. The infrastructure corridors in the Randstad are also very busy making it difficult to add extra trains.
- The behaviour of travellers belonging to the 'Endless waiters' and 'Sceptic returners' is difficult to influence by making the rerouting option more attractive.

The estimated latent class choice model is investigated in more depth in this chapter by performing an analysis of the impact of changing attribute levels on choice probabilities and a case study. The factors that have the largest impact on travel behaviour are the disruption length and in which part of the journey the disruption occurs. Fruin crowding level F can decrease the share of the travel option by 10 percentage points compared to Fruin crowding level D. For short disruptions of 30 minutes the 'waiting for the disruption to be over' travel option has the largest share. The share quickly decreases with increasing disruption length. Travellers are less sensitive to changing waiting time, travel time in train when returning home and access times.

A case study is defined with a reference disruption scenario to which control strategies are applied with the goal to decrease the number of train travellers that return home by making the rerouting option more attractive. This is achieved by extending the rerouting trains to reduce crowding and increase the frequency of the rerouting train to decrease waiting time and increase capacity. Doubling the frequency of the rerouting train has a larger effect on increasing the share of rerouting than extending the rerouting trains. Doubling the frequency of the rerouting trains has the potential to increase the number of train travellers that choose to reroute by 30 percentage points compared to the reference level where no control strategies are applied.

The 'Trade-off teleworkers' and 'Trusting workplace travellers' are most sensitive to changes in attributes and can be influenced to reroute more by making the option more attractive by reducing crowding and waiting time. The 'Sceptic returners' and 'Endless waiters' have strong preferences for either waiting for the disruption to be over or returning home respectively. Their behaviour is difficult to influence and making rerouting more attractive only has a small effect on the behaviour of these classes.

8 Conclusion and discussion

In this final chapter the performed study is concluded and discussed. First, a conclusion answering the research questions is given. Lastly, in the discussion the findings are compared to literature and limitations of the study with resulting recommendations for NS and further research are given.

8.1. Conclusions

The objective of this study was to investigate travel behaviour during unplanned rail disruptions and what factors influence behaviour to make a first step in predicting passenger flows during disruptions. With insight in the passenger flows potential control strategies can be applied to better accommodate passengers during disruptions. In recent studies performed on this topic changed behaviour due to the COVID-19 pandemic has not been taken into account yet. Travel behaviour has changed due to the rise of teleworking and consciousness of crowding which both have an effect on travel behaviour during disruptions as was expected. The main research question following from the goals of the study therefore was defined as:

How do different groups of train travellers travel during unplanned rail disruptions in the Dutch train network in the aftermath of the COVID-19 pandemic and what factors influence their travel behaviour?

To answer this question several sub-research questions were defined. The sub-research questions consecutively lead up to answering the main research question.

SQ 1: Which factors influenced travel behaviour during unplanned disruptions before the COVID-19 pandemic?
A literature study was performed to investigate which factors influenced travel behaviour during disruptions before the COVID-19 pandemic. Dependent on the travel options different categories of characteristics were found to influence travel behaviour. Trip characteristics such as the journey direction, time constraints, the possibility of rerouting, the length of the detour, the moment in time of finding out about the disruption, trip distance and trip purpose were found to influence the choices people make. On top of that disruption characteristics including the expected length of the disruption, the time of day when the disruption occurs and the information provision during the initial phases of the disruptions were expected to impact choice behaviour. Lastly, personal characteristics among which previous experience during disruptions, attitude towards travel information, familiarity with public transport and age were found to influence decision making during disruptions.

SQ 2: Which factors related to travel behaviour became more relevant to train travellers during the COVID-19 pandemic?
During the COVID-19 pandemic general travel behaviour changed rapidly. Working from home was instructed by the Dutch government for people with jobs that did not require being at the workplace physically. A large percentage of teleworkers had a positive attitude towards teleworking and expected to keep working from home after the COVID-19 pandemic ended. When faced with a train disruption the possibility to telework adds a new travel option namely returning back home and continue to work there. In previous studies it was assumed that people who travel for work have to arrive at their workplace but the share of people returning back home was expected to become much larger after the COVID-19 pandemic. The attitude of people towards teleworking was also expected to have an influence since a negative attitude towards teleworking might lead to people still travelling to the workplace during a disruption. The introduction of the COVID-19 virus has also changed the perception of crowding since avoiding crowds became normal during the pandemic. Research on COVID-19 in combination with train travelling by NS and the TU Delft also showed that during the pandemic the attitude towards the train in general became more negative as well. These additional factors were therefore taken into

account in this study as well.

SQ 3: What decisions do train travellers make during unplanned rail disruptions in the aftermath of the COVID-19 pandemic and which factors influence their travel behaviour? and **SQ4: Which factors influence the behaviour of different train traveller groups during unplanned disruptions in the aftermath of the COVID-19 pandemic?**
To answer these research questions a dataset consisting of 815 Dutch train commuters gathered via an online questionnaire sent out in June 2022 was utilized to estimate choice models. In June 2022 there were no more COVID-19 measures active in the Netherlands. Both a multinomial logit with interactions and a latent class choice model were estimated to capture heterogeneity in travel behaviour during unplanned rail disruptions in a Dutch post-pandemic context. This study shows that travel behaviour is mostly influenced by the disruption length, at which moment in the journey the disruption occurs, the additional travel time on the rerouting option, ability to telework, attitude towards information and whether or not someone has to arrive at their workplace. Heterogeneity in travel behaviour was captured by uncovering four latent classes each with their own preferred travel options and sensitivity to attributes. This segmentation provides insight in travel behaviour during disruptions after the COVID-19 pandemic taking into account the rise of teleworking. Based on the segmentation measures can be applied targeting the different classes which contributes to a possible improvement of the level of service during train disruptions.

The four uncovered latent classes were defined as the ’Trade-off teleworkers’, ’Sceptic returners’, ’Trusting workplace travellers’ and ’Endless waiters’. The ’Trade-off teleworkers’ (39% of the sample) are more likely to be able to work from home and have a positive attitude towards teleworking. This class does not have a strong preference for one travel option over the others but makes a decision by trading-off the attributes. This class would wait for ten minutes to avoid extreme crowding and are likely to be between 35 and 44 years old. The ’Sceptic returners’ (20% of the sample) have a sceptic attitude towards travel information, are also more conscious of COVID-19 than the other classes and are likely to be between 55 and 64 years old. This class has the lowest waiting tolerance of the four classes and is 1.8 times as sensitive to waiting compared to additional travel time in the train. This class is very likely to return home as that is the preferred travel option. ’Trusting workplace travellers’ (18% of the sample) are characterized by their higher likelihood of not being able to work from home and trust the provided travel information since they are likely to be less experienced travellers and therefore comply with the travel information. They make trade-offs between attributes but waiting for the disruption to be over or rerouting are preferred since they have to arrive at the workplace. This class is the most sensitive to additional transfers out of all the classes and would wait 14 minutes to avoid any additional transfers. The last class is defined as the ’Endless waiters’ (23% of the sample) since they are the only group who are indifferent to the disruption length and choose to wait in almost any disruption scenario. They are likely to not be able to work from home and have to travel to their workplace. They like to travel by train and are likely to not trust the prognosis on the disruption length provided by NS.

Control strategies such as extending the rerouting trains or increasing the frequency of those trains can be applied to reduce crowding and waiting time. Increasing the frequency of the rerouting trains and therefore increasing the capacity have a larger effect on the number of people that would reroute than extending the rerouting trains. It is however not advised to apply this strategy since the number of extra travellers in the train does not weigh up to the costs and difficulties of implementing another train service due to staff shortage and busy infrastructure corridors. The ’Endless waiters’ and ’Sceptic returners’ do not change their travel choices much when the rerouting option is made more attractive and their behaviour is therefore difficult to influence. The ’Trade-off teleworkers’ and ’Trusting workplace travellers’ however do change their behaviour when the rerouting option is made more attractive since they weigh the attributes more and have a less defined preferred travel option than the other two classes. The ’Sceptic returners’ and ’Endless waiters’ class have set preferences for returning home and waiting for the disruption to be over respectively and their travel behaviour does not notably change when both aforementioned control strategies are applied.

8.2. Discussion

In the discussion a reflection is made on the study including the methodology and assumptions that were made during the study. First, the results are compared to previous studies to find similarities and differences. Second, the limitations of the study are mentioned. Lastly, recommendations are given for further research and also practical recommendations for NS.

8.2.1. Comparison with literature

In this section the results of the study are compared with previous studies. This current study is unique in the way that it takes the COVID-19 pandemic and the resulting rise of teleworking into account by adding a travel option to return home during a disruption when travelling to work. This extra option is often only available for people who have the ability to work from home therefore increasing inequity since this group of travellers is still relying on train services and information provision by NS. To the best of the author's knowledge this extra travel option has not been investigated before. Previous research has however investigated different kinds of factors which influence travel behaviour during disruptions. Literature provided factors and attributes that were incorporated in the stated choice experiment. For the three different travel options offered in this study factors were summarized that would influence the choice for that travel option and the effect of the factors are compared to the results of this study.

The study by Rahimi et al. (2019) found increasing age, increasing trip distance and increasing trust in travel information to increase the tolerance for waiting. The effect of increasing age was also found by (Drabicki et al., 2021). In this study however the youngest age group (18-34 years-old) were found to be most likely to wait. A possible explanation could be that people in this age group enjoy working at their workplace after the isolation in the COVID-19 pandemic since people with a negative attitude towards teleworking are also more likely to wait. The increasing trip distance in this study also had a positive effect on waiting since people with a normal travel time in train of over 60 minutes were more likely to wait which is in agreement with the study by Rahimi et al. (2019). The increasing trust in travel information was not found as a factor to increase the waiting tolerance in this study. People who distrust the information on the expected disruption length were more likely to wait for the disruption to be over in this study. These travellers might expect the disruption to take longer than is communicated by NS. Maybe they are frequent travellers who have the habit of waiting when a disruption occurs. Research by Drabicki et al. (2021) has shown that train travellers who are frequent travellers are more willing to wait showing that habits might play a role in making travel choices during disruptions. The study by Bai & Kattan (2014) found that gender also has an effect on waiting tolerance but this phenomenon was not found in this study.

In literature there was no real consensus on the factors that increased the probability of choosing to rerouting. Some studies stated that people with travel experience would choose to reroute since they know the network and on the other hand studies indicated that people who have travel experience often also have habits and therefore are less likely to reroute. In this study no effect of travel experience was found on the likelihood of rerouting. The study by Adelé et al. (2019) found that travellers who have a positive attitude towards travel information are more likely to reroute. This is in agreement with the current study since people who trust travel information are most likely to belong to the 'Trusting workplace travellers' class which has the highest shares of rerouting across all four classes.

In literature cancelling the trip was mostly found to be done by seniors since they are more flexible with their time (Rahimi et al. (2020); Nguyen-Phuoc et al. (2018)). In behaviour teleworkers could be more similar to seniors than people who cannot telework since teleworkers are more flexible with their time just like seniors. In this study seniors did not participate in the stated choice experiment since commuters were the focus of the study. In the previous studies teleworking was not yet common since they were executed before the COVID-19 pandemic. Nguyen-Phuoc et al. (2018) found that the longer the trip distance the higher the probability that a trip was cancelled with approximately 13% of trips with an average distance of 17 km cancelled. In an urban setting researchers found that roughly 2% of travellers cancelled their trips (Drabicki et al., 2021). In the study by Currie & Muir (2017) approximately 3% of the trips were cancelled. Learning about the disruption before leaving increased the number of trip cancellations (Adelé et al., 2019). In this study cancelling the trip was equalled to returning back home since train travellers were assumed to be already at the station or in the middle of their train journey. With the model estimated in this study the smallest percentage of travellers returning home would be 1.2% when the access time is 30 minutes (returning home is made unattractive while making rerouting and waiting as attractive as possible). When rerouting and waiting are made as unattractive as possible returning home can have a share of 60% for an access time of 30 minutes. This shows that the share is very much dependent on the disruption scenario and the other options available but also that returning is much more common than before the COVID-19 pandemic. Ton et al. (2021) found that people with a negative attitude towards teleworking might be glad to return back to the office. In this study this is indeed the case as well since people with a negative attitude towards teleworking are more likely to wait for the disruption to be over than travel back home even though they have the option to work from home. The results are summarized in Table 8.1.

Table 8.1: Comparison of how factors influence travel behaviour according to literature and according to this study.

Characteristics	**Expected influence on waiting tolerance (literature)**	**Influence on waiting tolerance results from research**
Age	+	-
Trip distance	+	+
Travel frequency	+	not found
Trust travel info	+	-
Gender (women more waiting tolerance)	+	not found
	Expected influence on probability of rerouting (literature)	**Influence on probability of rerouting from research**
Travel frequency	+ / -	not found
Positive attitude towards information	+	+
	Expected influence on probability of cancelling trip (literature)	**Influence on probability of returning home / cancelling trip from research**
Trip distance	+	not found
Able to telework	not studied	+
Positive attitude towards teleworking	not studied	-
Conscious of COVID-19	not studied	+

Related to travel information Rahimi et al. (2019) found that travel information can be received differently depending on the attitude of the person towards travel information. This is indeed the case in this study since there is a class of people who trust the information and seem to follow it to reroute and a class of people who are sceptic of information and are more likely to return home. In the Dutch train network when a disruption occurs the cause is always announced. In this study the kind of disruption that people had in mind while participating in the stated choice experiment did not have an effect. This is in agreement with the study by Lin (2017).

Finally, when looking at studies that incorporated COVID-19 perception and train travel behaviour Dirkzwager (2021) found that a higher risk perception of COVID-19 leads to less train travel. In this current study people who perceived COVID-19 as a risk were more likely to belong to the 'Sceptic returners' class and therefore more likely to avoid train travel. C. Chen et al. (2021) found that attributes such as travel time become less significant when making decisions. Decisions were more dependent on COVID-19 infection rates and risk perception. An effect of COVID-19 was found in this current study but the people with a high risk perception still weighed other attributes as well. This could indicate that the effects of the COVID-19 on travel behaviour are starting to subside or that during disruptions other factors are more important than avoiding crowds.

8.2.2. Limitations

This study also has several limitations due to scoping of the project and used methodologies and tools. For example, the context of the disruption scenarios was mostly fixed and assumptions were made. First, in the study only disruptions shorter than one hour were investigated. Longer disruptions may lead to different travel options considering that replacing bus services provided by NS might become an option then if rerouting is not possible. It is expected that the share of people waiting for the disruption to be over decreases while the share of travellers choosing the shuttle bus will increase. Only long trips were considered in this study as well to eliminate the possibility of using other forms of public transport. For shorter trips especially in urban areas other forms of public transport such as the tram, metro or bus might become viable options as well. For short distance trips in urban areas it is expected that more travellers leave the train network and choose a different form of public transport to make their journey assuming that it is a possibility to use other forms of public transport. It was also assumed that in the case of a disruption costs do not play a role. However, if travel expenses are not covered by employers this might influence behaviour possibly resulting in more people returning home since no costs are made for the trip. In this study it is also assumed that all respondents have the ability to reroute when their normal itinerary is disrupted. This is not the case and for this group of people different travel options might be feasible. Lastly, it was assumed that the disruption occurs on the way to work to investigate if people would return home. However, as respondents also indicated, their choices would be very different if the disruption occurs when people return to their home. It is expected that returning back to their workplace whenever a disruption occurs on their way back home will hardly be chosen as a potential travel option. Assuming travellers want to go home, rerouting or waiting for the disruption to be over become more attractive. These limitations due to a fixed stated choice context can be avoided by creating a stated preference survey which adapts context and available alternatives based on input from the respondents which was not possible in this study due to limitations of the survey tool.

The online survey was distributed via the NS panel consisting of approximately 80.000 members. It is expected that people who apply for this panel are experienced train travellers who know the NS network well and want to contribute to better services by filling in questionnaires while some NS panel members participate to complain about services. The high percentage of experienced travellers might lead to an overestimation of the share of rerouting considering their knowledge of the train network. On top of that approximately 97% of respondents indicated that they had experienced a disruption in the past. In the invitation email the topic of the study was announced and people who have experienced a disruption in the past might have wanted to share their opinion on their previous experiences which might explain the high percentage of people having experienced a disruption. Another limitation of the survey tool was that input from respondents could not be used in later questions in the survey. Otherwise a pivoted design in combination with the elimination of non-feasible travel alternatives might have been used to make the disruption scenarios and travel times more realistic for each respondent.

Only commuters were invited to participate in the study because of the defined scope of the study and the trip purpose being fixed to 'travelling to work'. It is expected that for other trip purposes behaviour will also change. For example travelling for leisure purposes can either be time-bound (such as attending a concert) or not at all (shopping) which might have a large impact on the choices people make during disruptions. If people attend a time-bound event rerouting or waiting for the disruption to be over are more likely options than returning home. People could also travel in groups and wait together at the station or share a taxi. For flexible events such as shopping it is expected that the share of people cancelling the trip or possibly changing their destination or travel mode becomes larger since they might also have the ability to perform the activity elsewhere. Apart from leisure travellers a large share of peak-hour travellers are students. A difference between commuters and students is that the trip purpose for students is more complicated than for commuters. Students can travel to schools and universities to attend live lectures which are sometimes obligatory and other times not, sometimes also possible to follow online and sometimes not. They can also travel to their school to take an exam which is a time-bound event. Again, for time-bound and obligatory events it is expected that students will be more inclined to reroute or wait for the disruption to be over. For non-obligatory events they might be more inclined to return back home. The share of students waiting for the disruption to be over could be increased by providing WiFi and study spaces at stations so that students can spend their time effectively.

Lastly and possibly most important, the study was performed by distributing a stated choice experiment. Respondents indicated that they would choose a certain travel option but whether or not their behaviour is the same in real-life is not certain. A disruption is usually a stressful situation where little information, crowding and making fast choices are a reality. The respondents of this study did not experience this stress and had time to rationally weigh their options which might lead to them making different choices in the experiment than in real-life. A solution could be to create a stated choice experiment with some elements that cause a small amount of stress. An example could be to set a time limit for each question so that respondents do not have the time to carefully weigh their options or add elements such as sounds or visual effects. Since asking people at train stations to explain their choice behaviour during disruptions is not feasible, adding stress inducing elements to a stated choice experiment might make the situation a bit more realistic.

8.2.3. Recommendations

Based on the previously mentioned conclusions and limitations practical recommendations can be made specifically for NS and recommendations for further research to increase knowledge on the topic.

Practical recommendations for NS

For NS it is recommended to improve their information provision towards travellers during disruptions. Respondents indicated that the travel information often is not accurate or lacking. People who do not trust the information are more likely to return home and therefore increasing trust in the travel information by making improvements could lead to more train travellers staying in the train network during a disruption. The advice is to provide a rerouting advice whenever possible since respondents indicated that this information is lacking and especially less experienced train travellers might have difficulty finding their way without the additional information. Another recommendation is to make the information provision more transparent by for example indicating that NS also does not yet know what is happening but will shortly provide travellers with more information. Respondents also indicated that they would like to see more staff in the stations who they can approach and ask for extra information. The visibility of staff in the stations is expected to increase the trust of train travellers in the provided information and might therefore increase the share of people rerouting instead of returning home. A possibility could be to ask train drivers and train conductors to help at the station when a disruption occurs.

Results from this study are currently used in a tool by NS to support rolling stock planners to make decisions during disruptions. This shows the importance and relevance of this study. It is however recommended to expand the model used in that tool with more factors such as the disruption length and rerouting travel times since this study shows that those factors have a large effect on travel behaviour. The estimated model is currently incorporated in a self-made tool as well which is expected to be helpful while making predictions of passenger flows during disruptions. However, before making predictions it is necessary that the model is validated using for example smartcard data. To make this validation a model that assigns train travellers to a train based on their check-in and check-out is required.

Currently control strategies such as extending or increasing frequencies of rerouting trains cannot be applied during disruptions since large changes in rolling stock cannot be made on such short notice. This lack of flexibility might lead to passengers returning home during the disruption while control strategies for the rerouting options such as increasing the length of the trains or increasing the frequency has the potential to increase the number of people rerouting. On top of that, because of the COVID-19 pandemic teleworking has led to a less constant work week in terms of traveller demand. Commuters are expected to travel less on Wednesdays and Fridays than before the pandemic and train lengths and frequencies might be reduced on these days. It is therefore recommended to investigate whether it is possible to make a more flexible rolling stock planning in which last-minute changes can be applied proactively.

In the time between the lifting of the COVID-19 measures in March 2022 and the distribution of the online questionnaire in June 2022 train travellers' attitude towards the train became more positive and avoiding crowded places, afraid to get infected with the virus and continuing to wear a facemask less evident. There was a significant interaction between crowding and COVID-19 consciousness but not as large as expected. Based on this conclusion and the fact that consciousness of COVID-19 seems to reduce with time, applying control strategies with the goal of reducing crowding should not be the main focus point during disruptions.

Recommendations for further research

Based on the defined scope of the stated choice experiment many more factors can be investigated in future research. The stated choice experiment could for example be repeated for leisure travellers and students instead of commuters. Longer disruptions where replacing bus services are employed can be investigated as well since people might have a different perception of these bus services than the train services. Shorter trips are also interesting to investigate since other forms of public transport might become feasible options to replace the train journey.

It was assumed that train travellers find out about the disruption either at the station or during their train trip. In reality however many train travellers check travel apps before leaving their house and might already discover the disruption at that moment in time. It is interesting to investigate if more people would stay at home or possibly change their departure time.

In this study a significant effect of the perception of the COVID-19 virus was found on travel behaviour. This study was performed three months after the last COVID-19 restrictions were dropped in the Netherlands but it might be relevant to investigate whether the effect still lasts after longer periods of time.

Another interesting topic for research is what the effect of the train station where the disruption occurs is on the shares of the different travel options. Some train stations have many facilities while others are small and there are no facilities at all. If workplaces are present at stations the disruption time can be spent more effectively and maybe train travellers are less inclined to travel back home. Adding study spaces with WiFi in a recreational area such as a cafe might therefore be interesting since the space can then be used for both leisure and study or work purposes.

After conducting the experiment it was noted that some respondents had difficulty to picture themselves in the given disruption scenarios because they do not have an option to reroute or can also use other forms of public transportation to arrive at their destination while these were not options in the experiment. It might therefore be valuable to perform the study again but using train traveller’s common itinerary and add a disruption to their own journey. This could be done using a pivoted design which takes the attributes of the respondents’ own journeys and multiplies the attributes by a certain factor to create disruption scenarios. This was not possible to do in this study due to limitations of the survey tool.

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A Scientific paper

Capturing heterogeneity in travel behaviour during unplanned train disruptions;
considering the rise of teleworking in the Netherlands after the COVID-19 pandemic

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***Abstract*—The aim of this study is to capture heterogeneity in travel behaviour during unplanned train disruptions focusing on the rise of teleworking due to the COVID-19 pandemic to improve train services and help predict passenger flows during disruptions. To perform the analyses, a dataset is elicited from 815 Dutch train commuters by distributing an online questionnaire. A labelled stated choice experiment was designed and a latent class choice model was estimated. The biggest indicators of travel behaviour are the moment of discovering the disruption, the disruption length and job characteristics. Four latent classes were uncovered: the 'Trade-off teleworkers', 'Sceptic returners', 'Trusting workplace travellers' and 'Endless waiters'. Each class has a different initial preference for a travel option and different sensitivities to the travel attributes as well. Individual characteristics such as age, necessity to arrive at the workplace, ability to telework, telework attitude and the amount of trust in the provided travel information play a role in predicting choice behaviour during unplanned train disruptions. Based on the results advice can be given on how the level of service during disruptions can be improved for people who have to arrive at their workplace and cannot telework.**

Keywords: travel behaviour, disruptions, stated preference, latent class choice model, heterogeneity, teleworking

I. Introduction

Railway systems have the potential to reduce the contribution of transport systems to climate change (Givoni et al., 2009). Especially when private car users and airplane travellers switch to travelling by train. In the Netherlands the number of kilometres travelled by train increased by 14% between 2010 and 2018 (Rijksoverheid, 2020). For the Dutch Railways (NS) this increase was 22% which is explained by a quality improvement of the offered services such as increased frequency, connections between trains and network expansion. In the same period, the travelled kilometres by private cars increased by 7.9% (Rijksoverheid, 2022). Car users can be attracted to public transport if the image and levels of service of public transport are improved. However, if the public transport service is unreliable people are more likely to switch to the car (Beirão and Cabral, 2007). Therefore it is essential that train services are reliable to capture car users and hold onto current train travellers with the goal of making transportation more sustainable.

Service reliability in public transport has a large impact on passenger satisfaction (Soza-Parra et al., 2019). Public transport services are often perceived as unreliable by passengers and in concessions passenger impacts of service unreliability do not receive enough attention (van Oort, 2014). Unplanned public transport disruptions can lead to delays and crowding in stations and vehicles which causes anxiety for passengers (Cheng, 2010). These sudden disruptions force passengers to instantaneously shift their travel strategies and often switch to less familiar alternatives (Drabicki et al., 2021). Control strategies can help to mitigate crowding and also improve regularity of the public transport vehicle trips (Nuzzolo and Comi, 2016). Information such as the vehicle occupancy rate and the number of travellers waiting at stops are important inputs for such control strategy applications by public transport operators. An example of a control strategy is to extend trains on alternative routes which are expected to become more crowded during disruptions. Other practices are deadheading and short-turning which entails skipping stops with low demand and performing shorter cycles to increase frequency respectively (Canca et al., 2012). To apply the control strategies information on travel behaviour during unplanned disruption is required to predict passenger flows as input to assess the effect of the control strategy.

For train operators, it is important to know how many passengers cancel their trip or reroute in the train network to apply appropriate control strategies during unplanned disruptions to better accommodate passengers. Different decisions on control strategies can only be made if passenger flows can be accurately predicted. Currently, NS can predict passenger flows well during during pre-planned disruptions such as maintenance works because travel options are known in advance by both passengers and NS. It is more difficult to predict passenger flows during unplanned disruptions because travellers make decisions in a short time instance and information can be lacking especially in the beginning phase of the disruption.

With the start of the COVID-19 pandemic in the Netherlands in March 2020 government restrictions regarding travelling and working from home significantly changed people's travel behaviour (de Haas et al., 2020). The rise of teleworking during the pandemic is expected to affect travel behaviour during disruptions since train travellers are in general positive about working from home and plan to continue working from home after the end of the pandemic (van Hagen et al., 2021b). Due to this development, during a disruption there is an additional travel option available for train commuters if the disruption occurs during their outbound journey namely; return back home and telework. It is also expected that crowding in vehicles might have a larger impact on passenger's comfort than before the pandemic since larger crowds are associated with more risk of infection. However, this paper solely focuses on the effect of the rise of teleworking on travel behaviour during unplanned rail disruptions. For the effects of crowding on travel behaviour the reader is referred to the complete study by Bickel (2022).

The scientific relevance of this study is that travel behaviour during unplanned disruptions is studied in the context of the aftermath of the COVID-19 pandemic which is expected to have changed people's travel behaviour and has not been studied before to the best of the author's knowledge. The study is also relevant for public transport providers. With this knowledge passenger flows might become better predictable during unplanned disruptions in a robust rail network. By also investigating the different latent classes control strategies can be applied to target relevant traveller groups. Reducing crowding in the vehicles and a better management of disruptions increases passenger satisfaction which might ultimately lead to more public transport users which is relevant for public transport operators and policy makers.

The sections in the remainder of the paper are structured as follows: after the definition of the conceptual framework based on a literature review in section II, the methodology and data gathering process is explained in section III. The results of the latent class choice model aiming to capture heterogeneity in travel behaviour during disruptions are presented in section IV. Lastly, the conclusions and discussion are provided in section V.

II. Conceptual framework

In this section of the paper a conceptual framework is developed to summarize the variables expected to influence travel behaviour during unplanned train disruptions in the aftermath of the COVID-19 pandemic. The conceptual framework is based on expert information from NS and the author as well as an extensive literature which can be found in the study by Bickel (2022). The decision was made to focus on three travel alternatives on an outbound commuting trip which are most relevant to investigate for NS namely; waiting for the disruption to be over and continue on the original route, rerouting in the train network and returning back home. It should therefore be noted that this framework does not give a full overview of all factors influencing choice behaviour but only of the factors that influence the choice for one of the three specified alternatives. First, the included attributes of the alternatives are discussed after which the other factors included in the model such as trip characteristics and sociodemographics are touched upon.

A. Attributes

When looking at literature several attributes are found that influence the choice for a certain travel alternative. Travel time is seen as a relevant attribute in multiple studies (Fukasawa et al., 2012; Lin, 2017; Lin et al., 2018; Auld et al., 2020; Li et al., 2020; Rahimi et al., 2020; Teng and Liu, 2015). In general it is found that a longer travel time reduces the probability of choosing a certain travel alternative. In this study the travel time is specified as the travel time in the train. For the rerouting option the travel time is an addition to the original travel time in the train indicating how much longer the rerouting option is.

The waiting time is also expected to have an effect on travel behaviour and found to be relevant in multiple studies since people dislike waiting (Fukasawa et al., 2012; Auld et al., 2020; Rahimi et al., 2020). The waiting time is specified as waiting time before the train departs so in the case of the alternative 'waiting for the disruption to be over' this equals the disruption length. For the other two alternatives the waiting time is correlated with the frequency of the rerouting and returning trains assuming that those services are not affected by the disruption.

Crowding was already defined as a factor influencing travel behaviour before the start of the COVID-19 pandemic (Fukasawa et al., 2012; Teng and Liu, 2015). It is expected that crowding will have an even more negative influence on choosing a certain travel alternative due to the pandemic which is confirmed by studies investigating the influence of crowding on train choice behaviour during undisrupted situations at the time of the COVID-19 pandemic (Shelat et al., 2021; Shelat et al., 2022). Crowding is defined as crowding on the platforms where the trains will depart giving travellers an indication of what the crowding inside the trains will be like.

Lastly, for the rerouting option the number of additional transfers that travellers would have to make is assumed to have an influence on travel behaviour since transferring often causes a large disutility (Fukasawa et al., 2012; Li et al., 2020). In the Dutch train network rerouting is often possible but an additional transfer is nearly always required.

B. Disruption characteristics

In the remaining part of this section other factors involving choice behaviour are discussed. The first group of factors that is discussed is the 'disruption characteristics'. Among these the time of day when the disruption occurs, the length of the disruption and the information provision are expected to have an effect on choice behaviour according to literature and expert knowledge from NS. The time of day when the disruption occurs is often correlated with the journey direction when focusing on commuters. If a disruption occurs during the morning peak hours cancelling the trip and travelling back home might be a feasible option while when a disruption occurs during the evening peak hours cancelling the trip is often not feasible. The disruption length is another characteristic of a disruption and apart from the waiting time it causes the disruption length itself also has an effect on the rerouting option and returning back home when looking at the total travel times compared to the disruption length. Whether or not information is provided also has an effect on travel behaviour since information on additional travel times for the different alternatives is known to influence people's train choice (Fukasawa et al., 2012; Lin et al., 2018).

C. Trip characteristics

According to literature longer trips have a higher chance of being cancelled (Nguyen-Phuoc et al., 2018). The trip purpose is also assumed to have an effect on choice behaviour since work related trips might be more time constrained than for example leisure trips. People are more likely to wait for disrupted services to resume on homebound journeys than on outbound journeys and therefore journey direction is also included in the framework (Adelé et al., 2019). When the disruption is discovered has different effects according to literature. Finding out about the disruption en-route is assumed to make people more likely to reroute according to the study by Adelé et al. (2019) while the study by Currie and Muir (2017) states that finding out about the disruption beforehand makes the probability of rerouting higher. There however is a consensus in both studies that the probability of cancelling the trip increases when people find out about the disruption before starting their journey (Currie and Muir, 2017; Adelé et al., 2019).

D. Sociodemographics and background variables

Background and sociodemographic variables which are also expected to influence choice behaviour are listed below.

- Increasing age is found to cause an increasing waiting tolerance (Rahimi et al., 2019; Drabicki et al., 2021). A higher probability of cancelling the trip is also found to be affected by an increasing age (Nguyen-Phuoc et al., 2018; Rahimi et al., 2020).
- The ability to telework is added to this study to investigate the effects of the COVID-19 pandemic on travel behaviour during disruptions. It is expected that people who have the option to work from home are more inclined to travel back home during their morning commute if a disruption happens since they can work there. People who do not have this option in fact miss an alternative and therefore are more likely to reroute or wait for the disruption to be over.
- The COVID-19 risk perception is expected to have an effect on the sensitivity to crowding. Since crowding is a phenomenon that occurs often during disruptions it is expected that people who are more aware of COVID-19 or are more afraid to get infected with the virus might avoid crowds.
- Previous experiences with disruptions has not been found in literature to be a factor that influences choice behaviour. However, it is expected that if people have had a negative experience with travelling during a previous disruptions this will have an effect on their travel behaviour during possible future disruptions. These people may be more wary of information provision and therefore be affected by their previous experiences.
- The attitude towards travel information is shown to increase the waiting tolerance when people trust the information (Rahimi et al., 2019). Trusting the provided information also increases the probability of people choosing to reroute (Adelé et al., 2019).
- On the effects of the familiarity with public transport is no agreement in literature. The study by Lin (2017) found that more experience with public transport increases the probability of rerouting because they are more familiar with the system while the study by Drabicki et al. (2021) found that experienced travellers are less likely to reroute because of strong habits. An increasing experience with public transport is found to increase the waiting tolerance (Rahimi et al., 2019; Drabicki et al., 2021; Adelé et al., 2019).

The discussed alternatives, attributes and factors are summarized in the conceptual framework presented in Figure 1.

III. Methods and data

A. Online questionnaire design

The data that is used as input for the discrete choice models is gathered by distributing an online questionnaire among Dutch train commuters. The objective of the questionnaire is to collect data on what travel behaviour during disruptions looks like as well as gathering data on the factors that might influence travel behaviour during disruptions. The questionnaire is structured in three parts defined as follows:

- Job characteristics and normal commuting travel behaviour: Information on respondents' job and ability to work from home is gathered. Detailed information on commuting trips is also gathered including the normal travel time in the train, number of transfers and access times to the train station.

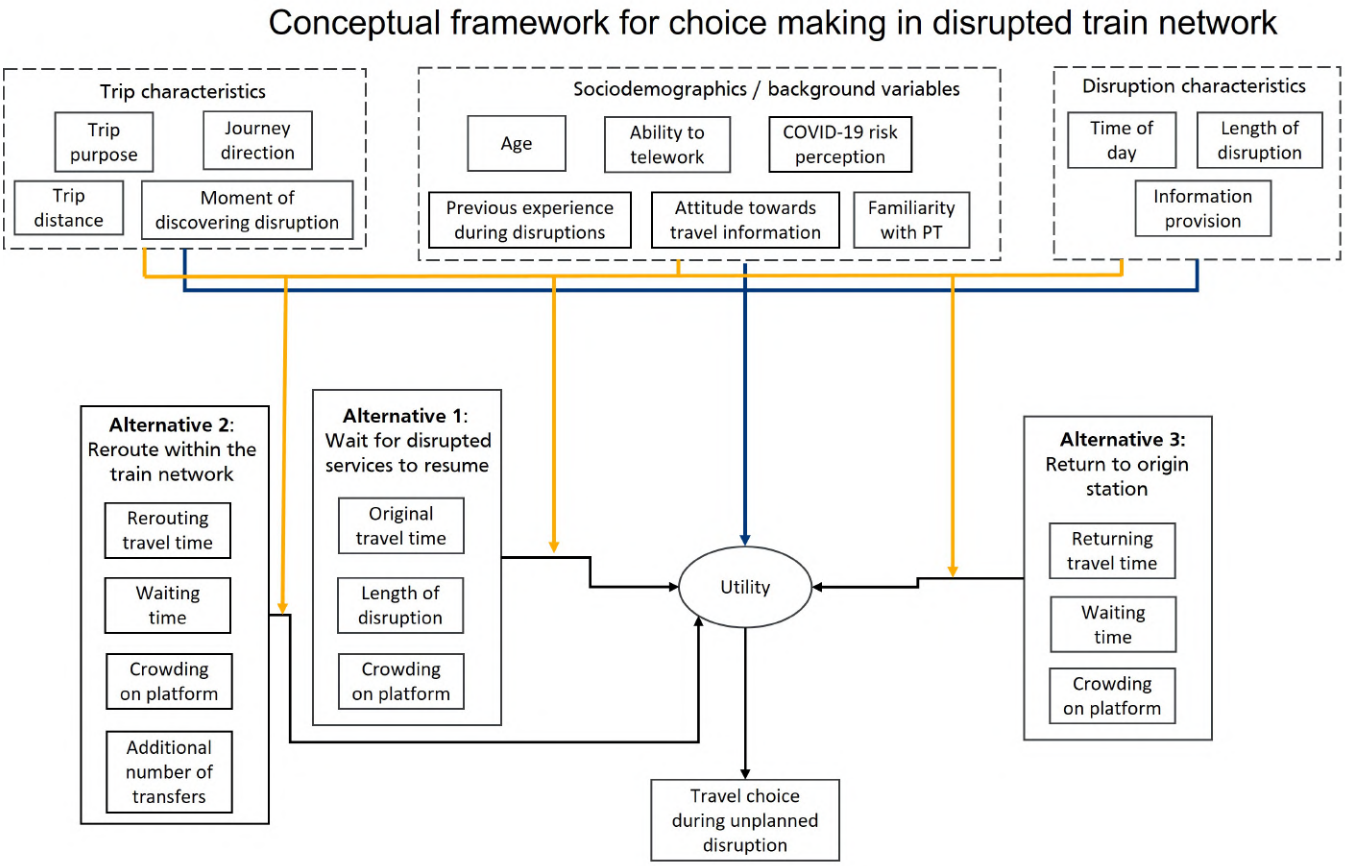

Figure 1: Conceptual framework for the stated choice experiment. Rectangular boxes show observable variables, oval boxes show unobservable variables. The black lines are the main effects of the variables on the utility. Yellow lines indicate interactions between variables and utility of alternatives. Blue lines indicate variables that have an effect on utility. The solid black boxes are the alternatives while dashed boxes contain context variables and sociodemographic variables.

- Stated choice experiment: An experiment with two different disruption context scenarios is included in the questionnaire. Respondents are asked which travel option they would choose for different disruption scenarios among the options 'wait for disruption to be over and continue on original route', 'reroute in the train network' and 'return home'.
- COVID-19 and information attitudes: Statements on COVID-19 perception and attitude towards information during disruptions on a 5-point Likert scale are presented to respondents.

The stated choice experiment is designed based on the procedure by Bliemer and Rose (2006) where first the model is specified followed by experimental design and embedding the experiment in a questionnaire. The alternatives and attribute levels in the experiment are determined after conducting an extensive literature review. A small pilot was conducted to test the comprehensibility of the experiment and the questionnaire. Small changes in the wording of questions were made afterwards but no significant changes to the stated choice experiment were made.

First the context of the labelled stated choice experiment is defined. Two different disruption scenarios are created which both include different attributes and attribute levels. In the first scenario the disruption occurs at the origin station while in the second scenario the disruption occurs during the train journey. The disruption scenarios are shown in Figure 2. It is assumed that there are no COVID-19 measures in place, respondents are travelling to their workplace and they do not discover the disruption before starting their trip. Another assumption is that rerouting is always possible within the train network which might not be the case for a part of the respondents. There is information available on the expected length of the disruption but respondents are notified that this information gives an indication of the disruption length and is therefore uncertain.

The attributes included in the experiment are shown in Table I. The attributes that entail travel time such as original travel time and returning travel time are all defined as travel time in the train. The rerouting travel time is defined as an additional travel time on top of the original travel time, for example plus 20 minutes. The crowding on the platforms is based on the levels of service for pedestrians specified by Fruin (1970).

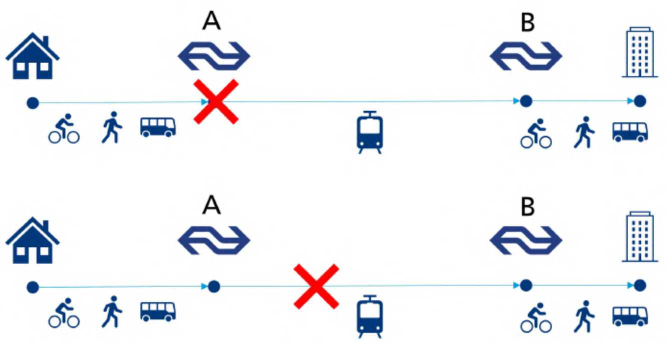

Figure 2: Disruption scenarios. Top: disruption occurs at origin station. Bottom: disruption occurs during train trip.

Table I: Overview of attributes for each of the alternatives. The star sign * indicates that the attributes are only considered in the scenario where the disruption occurs during the train trip.

Attributes / Alternatives	Wait	Reroute	Return home
Disruption length	x		
Waiting time		x	x*
Original travel time	x		
Rerouting travel time		x	
Returning travel time			x*
Access time			x
Crowding on platform	x	x	x*
Additional number of transfers		x	

The attribute levels are chosen based on expert knowledge from NS and an extensive literature review. The focus of this study lies on short disruptions to rule out the alternative of a shuttle bus occasionally deployed by NS. Long distance trips are chosen as another focal point to ensure that other modes of public transport are not a feasible option which would further complicate the experiment. The attribute levels are evenly spaced to make it easier to interpret the estimated effects (Lancsar and J. Louviere, 2006). All attributes have three levels to enable estimating non-linear effects.

Table II: Attribute levels for each alternative in the stated choice experiment. The star sign * indicates that the attributes are only considered in the scenario where the disruption occurs during the train trip.

Attributes / Alternatives	Wait	Reroute	Return home
Disruption length (min)	30, 45, 60	-	-
Waiting time (min)	-	5, 10, 15	5, 10, 15*
Original travel time (min)	25, 40, 55	-	-
Rerouting travel time (additional min)	-	20, 30, 40	-
Returning travel time (min)	-	-	10, 15, 20*
Access time (min)	-	-	Input from respondents
Crowding on platform (Fruin level)	B, D, F	B, D, F	B, D, F*
Additional number of transfers	-	0, 1, 2	-

Since prior values for the parameter estimates are difficult to obtain due to the lack of studies on this topic it is chosen to construct an orthogonal experiment design since it minimizes the variances of parameter estimates

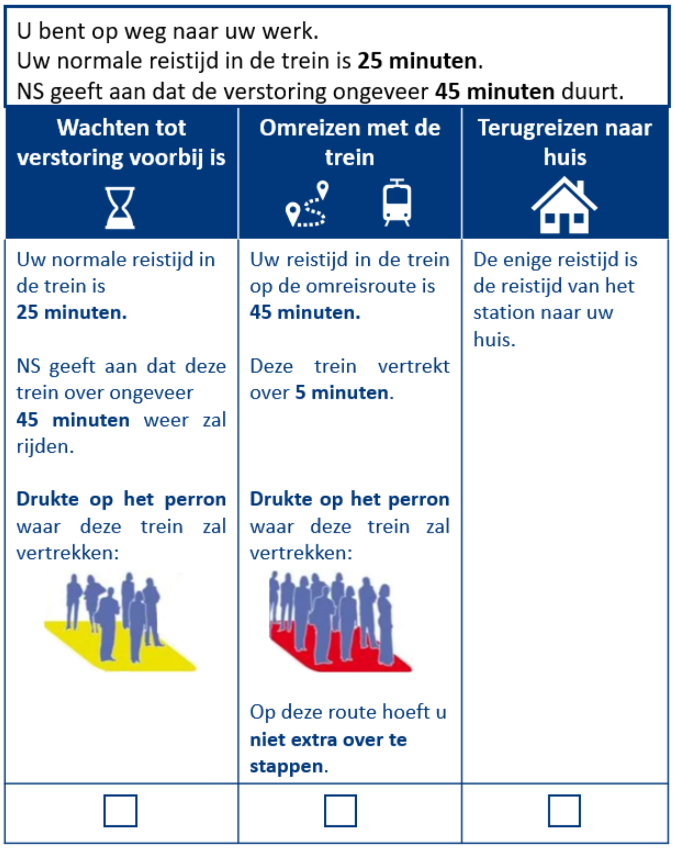

Figure 3: Example of a choice task where disruption occurs at origin station.

(Bliemer and Rose, 2006). The experiment is designed using Ngene software (ChoiceMetrics, 2021). For both disruption scenarios 36 choice tasks are created. Due to the large number of choice tasks blocking is applied leading to six blocks of six choice tasks for each disruption scenario. All respondents therefore are presented with 12 choice tasks in total. An example of the presentation of the choice tasks is shown in Figure 3.
The presentation format of the choice tasks has an impact on the choice that respondents make (Murwirapachena and Dikgang, 2021). It is chosen to provide a mix of text and visuals. Text is still required since the differences in attribute levels across the alternatives are subtle but important to clearly explain to respondents. Crowding on the platforms is presented visually since it increases comprehension of the attribute compared to when passenger densities on platforms are given in numbers.

B. *Descriptive statistics*

Data was gathered between the 7th and 13th of June 2022. During this time period there were no COVID-19 restrictions in the Netherlands. A total of 888 respondents completed the questionnaire of which 73 respondents were removed from the dataset due to unexpectedly small completion times and always giving the same answers for disruption information and COVID-19 statements. Sociodemographic information of the sample is shown in

Table III: Sample description based on sociodemographic characteristics.

Characteristic	Categories	Sample (N=815)
Gender	Female	44.7%
	Male	54.0%
	Prefer not to say	0.7%
	Other	0.6%
Age	18 to 24 years old	1.7%
	25 to 34 years old	15.3%
	35 to 44 years old	24.5%
	45 to 54 years old	26.4%
	55 to 64 years old	32.0%
Household	Living with partner	38.8%
	Living with partner and children	32.9%
	Living alone	20.6%
	Living with parents/carers and/or brothers and sisters	4.1%
	Living with children without partner	2.9%
	Living with multiple adults	0.7%
Education level	Doctorate degree	16.6%
	Master degree	33.5%
	Bachelor degree	30.9%
	MBO	9.7%
	VWO/HAVO/MAVO/VMBO	7.9%
	Other	1.4%
Employment status	Working for employer	67.0%
	Working for the government	24.4%
	Freelancer	3.9%
	Entrepreneur	2.6%
	Student	0.8%
	Retired	0.4%
	Other	0.9%
Travel frequency by train in 2019	4 days per week or more	51.4%
	1-3 days per week	27.6%
	1-3 days per month	12.4%
	6-11 days per year	5.6%
	3-5 days per year	1.8%
	1-2 days per year	0.9%
	Less than one day per year	0.2%
Train subscription	Has a subscription	39.8%
	No subscription	60.2%

Table III. The sample is in general representative of the train commuter population. It should however be noted that due to the method of distributing the questionnaire train commuters under 18 years old and over 65 years old were not approached to participate in the study. These age groups are therefore underrepresented compared to the actual train commuter population. The sample is highly educated and people with a lower education level are underrepresented. The respondents are also very experienced travellers which might lead to an overestimation of people choosing to rerouting since they know the train network well and might rely on their own knowledge to find their way.

A large part of this research consists of looking into travel behaviour during train disruptions in a time where many people can work from home. Questions about teleworking and attitudes towards teleworking are asked to respondents and the results are shown in Table IV. Of all respondents 18.8% responded that they cannot execute their work from home. This is in line with previous research during the COVID-19 pandemic by NS and the TU Delft (van Hagen et al., 2021a;Ton et al., 2021). Approximately 80% of the people who can work from home have a positive attitude towards working from home. This is similar to previous measurements of teleworking attitude (van Hagen et al., 2021a;Ton et al., 2021). After the COVID-19 restrictions and working

Table IV: Sample response to working related questions.

Working characteristics	Answer options	# of respondents	% chosen
Ability to telework (N=815)	Yes	662	81.2%
	No	153	18.8%
Employer permission to telework (N=662)	Yes	658	99.4%
	No	4	0.6%
Teleworking attitude (N=658)	Very positive	260	39.5%
	Positive	266	40.4%
	Not negative / not positive	85	12.9%
	Negative	36	5.5%
	Very negative	7	1.1%
	I never work from home	4	0.6%
Travelling to workplace frequency (N=658)	Each workday	5	0.8%
	3-4 days per week	110	16.7%
	1-2 days per week	428	65.0%
	1-2 days per month	68	10.3%
	Less than 1-2 days per month	47	7.1%
Telework during train ride to work (N=658)	Always	88	13.4%
	Often	92	14.0%
	Regularly	79	12.0%
	Sometimes	181	27.5%
	Never	218	33.1%
Importance of getting to work on time (N=815)	Very unimportant	57	7.0%
	Unimportant	215	26.4%
	Neutral	267	32.8%
	Important	212	26.0%
	Very important	64	7.9%
Necessary to arrive at workplace in mind during experiment (N=815)	Yes	478	58.7%
	No	337	41.3%

from home obligations people start travelling to their workplace again. It seems there is a new balance where most people go to the office once or twice a week instead of each working day which was more common before the pandemic. The largest part of people who can work from home usually do not use their travel time in the train to work. The importance of arriving at work on time is equally distributed between important and unimportant. During the experiment about 60% of respondents had in mind that it was necessary to arrive at their workplace. This mindset can have a large impact on what choices people make during a disruption and the influence is tested when estimating the discrete choice models.

When looking at the choices that are made in the stated choice experiment Figure 4 shows the difference between the responses to the two different disruption scenarios. It should however be noted that these percentages do not take into consideration the choice task and the attribute levels but they give an overview of how often a travel option is chosen among all choice tasks and therefore is descriptive. When a disruption occurs during the train trip the percentage of choice tasks answered with 'returning home' is 30% compared to 46% when the disruption occurs at the origin station. The percentage of rerouting is relatively similar and waiting was chosen in 24% and 34% of the choice tasks respectively. This indicates that the moment of the disruption occurrence during the journey has a large effect on the travel decisions that are made.

C. Methods

Latent class choice modelling (LCCM) is used to capture heterogeneity in travel behaviour during unplanned rail

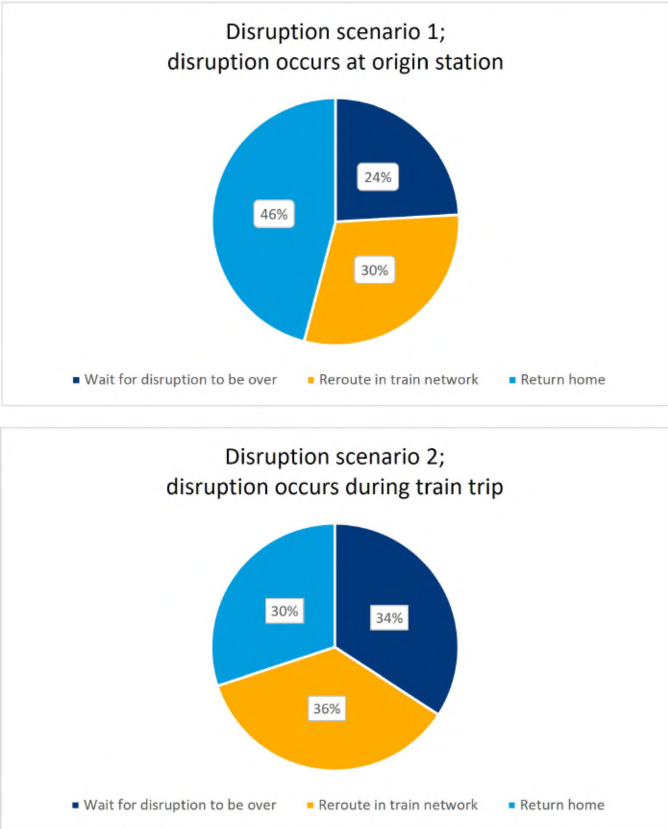

Figure 4: Choice overview of all choice tasks.

disruptions in the aftermath of the COVID-19 pandemic where working from home has become more common. A latent class choice model probabilistically assigns an individual to a discrete mixture of classes (Shelat et al., 2021). It is therefore assumed that the population can be split into a finite, discrete number of groups based on a combination of characteristics (Matyas and Kamargianni, 2021). Traits within the classes are homogeneous but differ between the classes (Coogan et al., 2011). The classification into subgroups makes the latent class choice mode flexible than the mixed logit model and can help with the interpretation of the results (Hess et al., 2008).

The latent class choice model can mathematically be described by Equation 1. The formula shows that the latent class choice model consists of two parts; the class membership function π_{ns} and the class-specific model $P_{in}(\boldsymbol{\beta_s})$.

$$P_{in} = \sum_{s=1}^{S} \pi_{ns} P_{in}(\boldsymbol{\beta_s}) \tag{1}$$

The class-specific model is essentially a multinomial logit (MNL) model and is described in Equation 2. The model describes the probability that alternative i is chosen from a set of alternatives J. V is the utility which consists of a linear addition of attributes multiplied by the to-be-estimated β parameters and an error term.

$$P_{in}(\boldsymbol{\beta_s}) = \frac{e^{V_{in}(\boldsymbol{\beta_s})}}{\sum_{i'=1}^{J} e^{V_{i'n}(\boldsymbol{\beta_s})}} \tag{2}$$

In this study the panel effect is taken into account meaning that one respondent makes multiple decisions and therefore the sequence of choices should be investigated instead of treating each decisions as a decision from another decision maker. The panel effect is accounted for by applying the formula below. It describes the likelihood of observing a sequence of T choices for decision maker n.

$$L_{in} = \sum_{s=1}^{S} \pi_{ns} \prod_{t=1}^{T} P_{in_t}(\boldsymbol{\beta_s}) \tag{3}$$

The large advantage of latent class choice models is that sociodemographics and other relevant characteristics can be added to the class membership function π_{ns} to explain class membership. In the formula below the γ parameters indicate the influence of characteristics on class membership.

$$\pi_{ns} = \frac{e^{\delta_s + \sum_k \gamma_{ks} z_{kn}}}{\sum_{s'=1}^{S} e^{\delta_{s'} + \sum_{k'} \gamma_{k's'} z_{k'n}}} \tag{4}$$

All parameters (β_s, δ_s and γ_{ks}) are estimated simultaneously using the PythonBiogeme package created by Michel Bierlaire (Bierlaire, 2020). Different models have been estimated until arriving at the final model presented in this paper. This includes estimating models with different utility functions, coding of variables, inclusion of variables and the number of classes. Based on a literature review and initial investigation of the results several variables were indicated to possibly have an effect on travel behaviour and were included in the class membership model. Variables that were not significant in any of the classes were removed from the class membership model among which were the variables; gender, education level, travel experience, train subscription, having a specific type of disruption in mind, fear of getting infected with the COVID-19 virus and the type of station where the disruption occurs. The significant variables are shown in Table V along with the way they were coded in the class membership model.

IV. Modelling results

A. *Number of classes*

The first step in estimating latent class choice models is determining how many discrete latent classes there are based on the data. Therefore the model is estimated using different number of classes with a static class membership function. The results are shown in Table VI. For the different models the rho-squared, final log-likelihood and BIC values are reported to compare the models and look for the best fit. Each model is estimated ten times with randomly generated starting values for the parameters since latent class choice models are prone to getting stuck in local optima.

Table V: Coding of variables that are significant in class membership model.

Variable name	Description
Mobility related variables	
Alternative transport available	Dummy (1=yes; 0=no)
Normal travel time in train	Continuous
Work related variables	
Telework possibility	Dummy (1=yes; 0=no)
Necessary to arrive at workplace	Dummy (1=yes; 0=no)
Telework attitude	5-point Likert scale, continuous
COVID-related variables	
Avoid crowds	5-point Likert scale, continuous
Continue to wear a facemask	5-point Likert scale, continuous
Like to travel by train	5-point Likert scale, continuous
Travel information variables	
Trust the disruption length prognosis	5-point Likert scale, continuous
Trust information in travel apps	5-point Likert scale, continuous
Personal variables	
Age	Categorical

Table VI: Different number of classes model estimation. Initial log-likelihood is -10744.43.

# of classes	ρ^s	Final log-likelihood (LL)	# of parameters (k)	BIC
1	0.184	-8767.99	17	17692.17
2	0.291	-7614.82	35	15464.24
3	0.319	-7313.98	53	14983.23
4	**0.342**	**-7070.55**	**71**	**14617.03**
5	0.351	-6970.745	89	14538.07
6	0.358	-6895.548	107	14508.34
7	0.365	-6821.759	125	14481.42
8	0.373	-6734.058	143	14426.67
9	0.377	-6696.677	161	14472.57

The number of classes is chosen based on a number of criteria. First, it is checked whether the classes contribute to the interpretation of the model As a second criterion, the sizes of the classes are investigated whether they are not too large (> 50%) or too small (< 10%). The number of classes to be used for further model estimations is also investigated by looking at the BIC value which penalizes increasing model complexity (J. J. Louviere et al., 2000). When estimating the latent class choice models for an increasing number of classes the BIC value at first drops quickly when estimating models with two, three and four classes. After this point adding more classes does continue to lead to decreasing BIC values but the differences become smaller. The models were investigated to see if the different classes are still distinct enough in behaviour. When investigating the four-class model it was found that the classes are distinct in terms of trade-offs however the five-class model contained two classes with nearly similar trade-offs. Based on this finding it is decided to estimate a model with four classes even though it does not have the lowest BIC value.

B. *Model estimation results*

The final four-class model has a rho-square of 0.36 and a BIC value of 14452.17. The class membership includes sociodemographic variables, individual travel behaviour characteristics and attitudes. The estimated model parameters can be found in Table VII. The parameter for the waiting time is fixed across all classes since the value was similar for all classes with the goal to make it easier to directly compare the classes.

Regarding the significant parameters all signs are as expected across all classes. The access times are only significant in class two and three while parameters such as the additional travel time and the dummy parameters for extreme crowding and two additional transfers are significant in all classes. The linear and/or quadratic components of the disruption length are significant in three classes. The fourth class is not sensitive to the disruption length at all which is quite remarkable meaning that travel behaviour of people in this class does not depend on the expected length of the disruption. The second additional transfer is valued more negatively than the first additional transfer. For some classes the parameter for the first additional transfer is not significant while the second additional transfer is significant across all classes. The same can be said about the crowding parameters. Going from moderate (Fruin level D) to extreme crowding (Fruin level F) is valued more negatively than from no crowding (Fruin level B) to moderate crowding. The behaviour of the four different classes including their travel preference and which traits characterize the classes is explained in more detail below.

Class 1 (39.0%): 'Trade-off teleworkers' The largest class is mainly characterised by making trade-offs between most attributes and not having a clear preference for one travel option over the others. All attributes except for access times are significant for this class. The attribute levels have a large impact on the travel choices for this class. For shorter disruptions this class is likely to choose to wait but when disruption lengths increase the share of rerouting and returning home rapidly increases while waiting becomes less likely. Waiting time is preferred over additional travel time on the reroute option which is not seen in the other classes. Travellers in this class are conscious of crowding and would wait roughly 10 minutes to go from extreme crowding (Fruin level F) to moderate crowding (Fruin level D). The train travellers in this class are likely to not have to go to their workplace (51.3%) and have the option to telework (44%). Travellers with a positive attitude towards teleworking are more likely to be found in this class. Travellers in the age group of 35-44 years old are more likely to be in this class.

Class 2 (19.8%): 'Sceptic returners' Travellers in this class are mostly characterised by their preference to not wait at all. Even for short disruption lengths they are much more likely to return home than wait for the disruption to be over or reroute. For this class the choice between rerouting and returning home mostly relies on the access travel times since the quadratic component of the access time quickly decreases the utility of returning home. However returning home always has a large share independent of the disruption scenario. This class is sensitive to crowding and would travel 15 additional minutes in the train to avoid crowding. The train travellers in this class are likely to be sceptic towards prognosis information and information in travel

Table VII: Class specific models including class membership function parameters. Estimated parameters in bold and italic are significant at the 95% level. Estimated parameters in only italic are significant at the 90% level. 97 parameters, final log-likelihood = -6900.983, rho-squared = 0.358 and BIC value = 14452.17.

Attributes	Class 1 (39.0%)		Class 2 (19.8%)		Class 3 (18.2%)		Class 4 (23.0%)	
	Est.	Robust t-test	Est.	Robust t-test	Est.	Robust t-test	Est.	Robust t-test
Constants								
Reroute; disruption origin station	***-4.58***	***-4.51***	*13.2*	*1.94*	*-2.36*	*-1.7*	-0.397	-0.215
Reroute addition; disruption during train trip	***2.13***	***5.95***	***-4.69***	***-2.03***	***2.64***	***4.41***	***1.4***	***2.28***
Return home; disruption origin station	***-7.51***	***-6.9***	*13.4*	*1.92*	***-9.05***	***-5.89***	***-4.86***	***-2.46***
Return home; disruption during train trip	***-4.28***	***-5.92***	***9.9***	***2.15***	***-4.81***	***-3.91***	-0.79	-0.633
Wait; disruption during train trip	***2.53***	***6.63***	***-4.69***	***-2.04***	***2.82***	***4.41***	***1.71***	***2.67***
Taste parameters								
Access time	-0.0258	-0.947	0.0399	0.977	*0.193*	*1.78*	-0.0871	-1.12
Access time quadratic	-0.00022	-0.481	***-0.00193***	***-2.27***	*-0.00702*	*-1.92*	0.000847	0.578
Additional TT	***-0.1***	***-10.7***	***-0.0517***	***-2.49***	***-0.0799***	***-8.18***	***-0.0655***	***-7.16***
Crowding level D	***-0.279***	***-3.53***	0.0264	0.169	***-0.424***	***-3.91***	***-0.307***	***-2.74***
Crowding level F	***-1.25***	***-10.3***	***-0.763***	***-4.48***	***-1.37***	***-6.18***	***-1.09***	***-5.94***
Disruption length wait	***-0.28***	***-5.4***	***0.77***	***2.06***	***-0.152***	***-2.38***	-0.111	-1.22
Disruption length wait quadratic	***0.00158***	***2.69***	***-0.0123***	***-2.48***	0.000607	0.94	-0.00032	-0.28
1 transfer	***-0.298***	***-2.02***	-0.0296	-0.106	*-0.358*	*-1.84*	-0.171	-0.851
2 transfers	***-1.03***	***-5.57***	*-0.509*	*-1.7*	***-1.3***	***-6.5***	***-0.729***	***-3***
Return TT in train	***-0.0859***	***-4.58***	***-0.0651***	***-2.52***	-0.0676	-1.33	***-0.0938***	***-3.07***
Wait (fixed across classes)	***-0.0929***	***-15.3***	***-0.0929***	***-15.3***	***-0.0929***	***-15.3***	***-0.0929***	***-15.3***
Class membership								
Constant	Base class		0.0587	0.104	-0.22	-0.366	***-2.08***	***-3.26***
Age - continuous			***0.609***	***4.52***	0.0147	0.0944	-0.188	-1.28
Alternative transport - dummy			-0.222	-0.815	***-0.596***	***-2.08***	-0.198	-0.751
Avoid crowd - continuous			-0.0941	-0.695	*-0.254*	*-1.7*	-0.0844	-0.534
Wear facemask - continuous			***0.403***	***2.9***	0.0971	0.48	-0.0514	-0.311
Like to travel by train - continuous			*-0.278*	*-1.91*	0.0985	0.52	***0.407***	***2.7***
Necessary to arrive at workplace - dummy			***-0.981***	***-3.8***	***1.57***	***4.66***	***1.91***	***5.32***
Telework possibility - dummy			-0.517	-0.973	***-1.48***	***-3.8***	-0.643	-1.39
Telework attitude - continuous			0.235	1.47	*-0.329*	*-1.84*	-0.191	-1.25
Normal travel time in train - continuous			***-0.599***	***-3.18***	0.2	0.942	***0.703***	***4.04***
Trust prognosis			-0.0979	-0.696	*0.229*	*1.7*	***-0.336***	***-2.2***
Trust travel app			-0.0954	-0.673	0.0834	0.504	***0.352***	***2.12***

apps. Travellers who dislike travelling by train have a probability of 50.8% to belong to this class. The sensitivity towards crowding is also explained by the probability of COVID-conscious travellers to be assigned to this class. Travellers that indicate that they will continue to wear facemasks, are afraid to get infected with the virus and do not feel free to travel by train because of the crowding are more likely to be in this class. Travellers are also likely to be able to work from home and not having to arrive at the workplace and can therefore easily return home when a disruption occurs. Especially travellers with a normal travel time in the train of below thirty minutes and with an age between 55 and 64 years old are more likely to be in this class.

Class 3 (18.2%): 'Trusting workplace travellers' In behaviour this class is similar to class one but with the difference that this class has a larger initial preference for rerouting and are less likely to return home than the travellers in class one. When disruptions are short they are likely to either wait or reroute but not to return home. This class is however the most sensitive towards additional travel time on the rerouting option and is more likely to wait for the disruption to be over when this additional travel time increases. This is the only class that is not sensitive to travel time in the train while returning home. Contrary to the previous classes this class is characterized by travellers who cannot work from home (43.2%) and have to arrive at their workplace (26.2%). The travellers are likely to be less experienced travellers and trust the provided information on prognoses, follow advice from the travel apps and are guided more by the provided information by NS than their previous experiences with disruptions. Travellers without alternative modes of transport available to them are also more likely to be in this class. People with access times over 30 minutes also have a slightly higher probability of being assigned to this class (22.7%).

Class 4 (23.0%): 'Endless waiters' The travellers in this class are not sensitive to the disruption length at all. Even when the disruption length is 60 minutes and the other travel options are made as attractive as possible, 80% of travellers in this group would wait for the disruption to be over. The main characterization of this class therefore is that they are very likely to wait for the disruption to be over regardless of the disruption scenario. Travellers in this class are likely to not be able to work from home (28.9%), have to arrive at the workplace (32.8%), are between 18 and 34 years old (31.5%), like to travel by train (31.9%), come from rural areas (30.6%) and normally have a train travel time of over 60 minutes (34.7%). However, if they can telework they are more likely to have a negative attitude towards teleworking (30.5%). Travellers that do not trust the disruption length prognosis are much more likely to be in this class (31.4%) which is unexpected since the travellers in this class are very likely to choose to wait for the disruption to be over in each disruption scenario. It was expected that these types of travellers would be more likely to reroute or return home. Travellers with an access time over 30 minutes are more likely to belong to this class as well (27.4%) which makes sense since returning home is less attractive when access times are very high so waiting might be more attractive for this group of travellers.

V. Conclusion and discussion

In this study a latent class choice model was used to investigate heterogeneity in travel behaviour during unplanned rail disruptions in a Dutch post-pandemic context. A dataset consisting of 815 Dutch train commuters gathered via an online questionnaire sent out in June 2022 was utilized. Heterogeneity in travel behaviour was captured by uncovering four latent classes each with their own preferred travel options and sensitivity to attributes. This segmentation provides insight in travel behaviour during disruptions after the COVID-19 pandemic which caused the rise of teleworking. Based on the segmentation control measures can be applied targeting the different classes which contributes to a possible improvement of the level of service during train disruptions.

Of all respondents 81.2% indicated to have the ability to work from home. Of these potential teleworkers 80% stated to have a positive attitude towards teleworking which is line with the study by van Hagen et al. (2021b). Of all the teleworkers 65% indicated that they only travel to the workplace 1 to 2 days per week. Even if a disruption would happen during their journey to work they have an additional travel option compared to the group of train commuters who cannot work from home and have to travel to work each workday. The group of people who have to arrive at their workplace on time is roughly 34% of the sample but for this group of people a disruption has the largest impact.

The four uncovered latent classes are identified as; 'Trade-off teleworkers', 'Sceptic returners', 'Trusting workplace travellers' and the 'Endless waiters'. The 'Trade-off teleworkers' (39%) are likely able to work from home and do not have to be physically present at their workplace. Almost all attributes are significant for this class and their behaviour can therefore easily be influenced by making a desired travel option more attractive. The 'Sceptic returners' (20%) have a very low waiting tolerance therefore their preferred option is to travel back home. The class members do not trust provided information and are still wary of COVID-19 and crowding. Like the previously discussed class, members are likely to be able to work from home and do not have to arrive at their workplace. The 'Trusting workplace travellers' (18%) on the other hand are less experienced travellers who are compliant and follow and trust travel advice provided to them. These class members are likely to not be able to work from home and therefore have to arrive at their workplace. Their preferred option is to reroute unlike the 'Endless waiters' (23%) who have similar characteristics but prefer to wait for the disruption to be over. Members from this class are not sensitive to the disruption length at all, cannot work from home and enjoy travelling by train.

Based on these findings it can be concluded that there is heterogeneity in travel behaviour during unplanned disruptions. Travel choices seem to be mainly affected by commuters' job characteristics which have changed due to the COVID-19 pandemic and the rise of teleworking. The train commuters who cannot work from are affected the most by a disruption since they have do not have the option to return home and must still arrive at their workplace. Therefore most attention should be going towards improving the level of service for this traveller group during disruptions. People who cannot work from home are the most likely to belong to either the 'Trusting workplace travellers' or the 'Endless waiters' class. For the less experienced 'Trusting workplace travellers' class accurate and extensive travel information is required since they are more likely to rely on it. Information provision can be improved by railway operators by for example providing advice on how to reroute and being more transparent when the situation is unclear for the railway operators themselves as well. In the case of a rolling stock malfunction personnel from that train can also be deployed to provide information at the station and increase visibility of the staff. This might also benefit the 'Endless waiters' class since the transparency and improved information might increase their trust towards the information on the expected disruption length. Apart from that, additional facilities on rural stations should be added to increase the comfort while waiting.

A. Limitations and further research

This research also knows limitations which provide a basis for further research. First, in the study only disruptions shorter than one hour were investigated. Longer disruptions may lead to different travel options considering that replacing bus services provided by

NS might become an option then. Only long trips were considered in this study as well to eliminate the possibility of using other forms of public transport. For shorter trips especially in urban areas other forms of public transport such as the tram, metro or bus might become viable options as well. In this study it is also assumed that all respondents have the ability to reroute when their normal itinerary is disrupted. This is not the case and for this group of people different travel options might be feasible. Lastly, it was assumed that the disruption occurs on the way to work to investigate if people would return home. However, as respondents also indicated, their choices would be very different if the disruption occurs while returning home. It is expected that returning back to where they came from is hardly chosen since people want to go home making rerouting or waiting for the disruption to be over more attractive.

The online survey was distributed via the NS panel consisting of approximately 80.000 members. It is expected that people who apply for this panel are experienced train travellers who know the NS network well and want to contribute to better services by filling in questionnaires. This might lead to an overestimation of the share of rerouting. On top of that approximately 97% of respondents indicated that they had experienced a disruption in the past indicating that there might be a self-selection bias for participating in the survey. Another limitation of the survey tool was that a pivoted design could not be implemented. It is suggested to use a pivoted design to create disruption scenarios around the respondents' commuter trip characteristics to make the disruption scenarios and travel times more realistic for each respondent.

Lastly, the study was performed by distributing a stated choice experiment. Respondents indicated that they would choose a certain travel option but whether or not their behaviour is the same in real-life is not certain. A disruption is usually a stressful situation where little information, crowding and making fast choices are a reality. The respondents of this study did not experience this stress and had time to rationally weigh their options which might lead to them making different choices in the experiment than in real-life.

Further research could focus on what facilities train travellers would prefer to make waiting more comfortable or possibly telework from stations during disruptions as well as what kind of information train travellers find important during disruptions and how the information should be distributed to ensure it reaches all travellers.

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B Stated choice experiment

B.1. Experimental design syntax: disruption scenario 1

```
? Scenario 1, a disruption occurs at the starting station (so people have not travelled by train yet)
? This syntax file creates an orthogonal design.
? The attribute levels for the travel time and costs in the rerouting options are additional values.
? They will be added to the original values (from the waiting for disruption to be over option)in
    excel.
design
;alts = wait, reroute, return
;rows = 36
;block = 6
;orth = sim
;model:
U(wait) = b10*tt_wait[25,40,55] + b20*wt_wait[30,45,60] + b40*crowding_wait[0,1,2] /
U(reroute) = b_reroute + b11*tt_reroute[20,30,40] + b21*wt_reroute[5,10,15] + b41*crowding_reroute
    [0,1,2] + b5*transfer[0,1,2] /
U(return) = b_return
$
```

B.2. Experimental design syntax: disruption scenario 2

```
? Scenario 2, a disruption occurs during the train trip and people are dropped at an intermediate
    station
? This syntax file creates an orthogonal design.
? The attribute levels for the travel time and costs in the rerouting options are additional values.
? They will be added to the original values (from the waiting for disruption to be over option)in
    excel.
? The return travel time is the travel time in the train, travel time from the origin station to home
     still needs to be added afterwards
? It is assumed that it does not cost any money to travel back to the origin station
design
;alts = wait, reroute, return
;rows = 36
;block = 6
;orth = sim
;model:
U(wait) = b10*tt_wait[15,25,35] + b20*wt_wait[30,45,60] + b40*crowding_wait[0,1,2] /
U(reroute) = b_reroute + b11*tt_reroute[20,30,40] + b21*wt_reroute[5,10,15] + b41*crowding_reroute
    [0,1,2] + b5*transfer[0,1,2] /
U(return) = b_return + b12*tt_return[10,15,20] + b22*wt_reroute[5,10,15] + b42*crowding_return[0,1,2]
$
```

B.3. Choice tasks: disruption scenario 1

Table B.1: The choice tasks for disruption scenario 1. The colours indicate which choice tasks are assigned to which block.

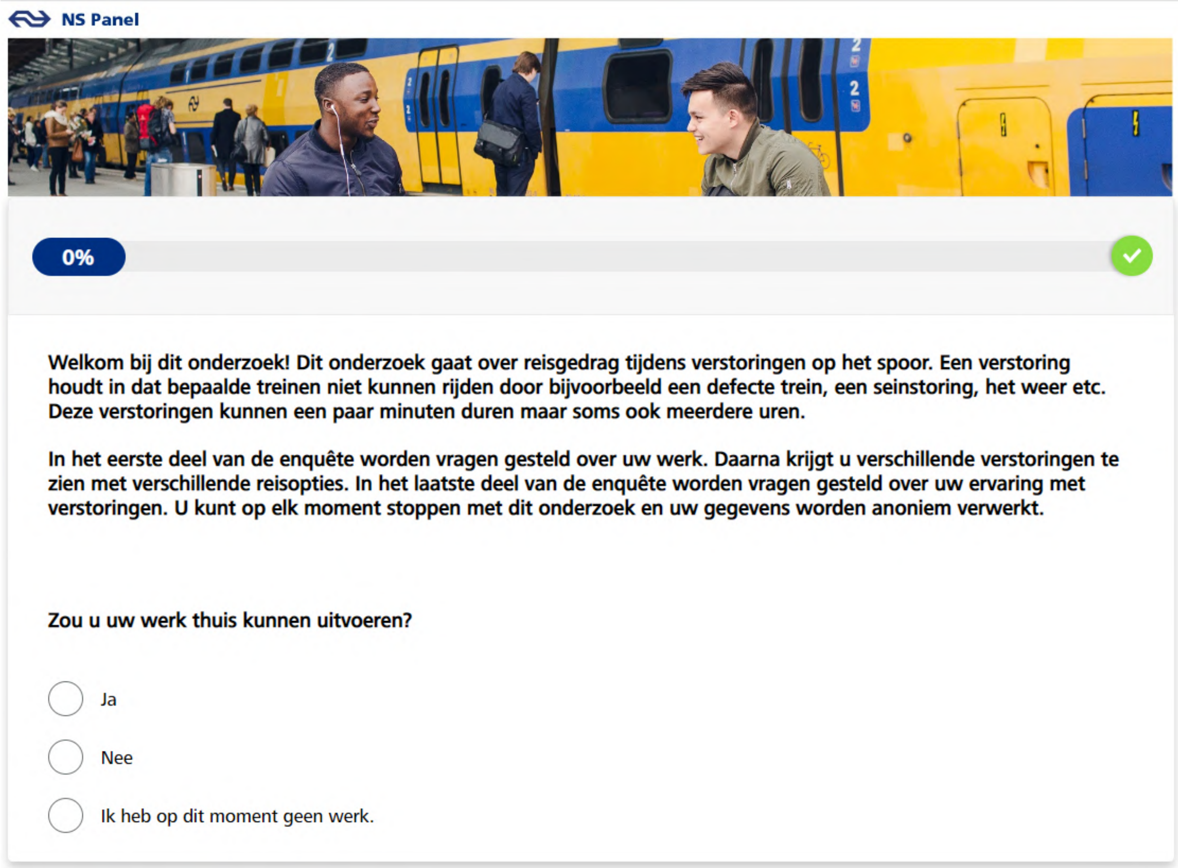
	Wait for disruption to be over			Reroute within train network				
Choice situation	Original travel time	Disruption length	Crowding	Additional travel time	Waiting time	Crowding	Transfer	Block
1	40	45	2	80	10	1	2	2
2	55	60	1	85	15	2	1	5
3	40	45	2	80	15	2	1	6
4	55	60	1	85	10	1	2	3
5	55	30	2	75	5	1	1	5
6	25	60	0	65	10	0	0	5
7	55	30	2	75	10	0	0	3
8	25	60	0	65	5	1	1	6
9	25	45	1	45	15	0	2	5
10	40	30	0	70	5	2	0	2
11	25	45	1	45	5	2	0	3
12	40	30	0	70	15	0	2	3
13	55	60	0	75	15	2	0	3
14	25	30	2	65	5	0	2	6
15	55	60	0	75	5	0	2	4
16	25	30	2	65	15	2	0	1
17	25	45	0	55	10	2	2	6
18	40	30	1	60	15	1	1	6
19	25	45	0	55	15	1	1	1
20	40	30	1	60	10	2	2	4
21	40	60	2	70	5	1	0	6
22	55	45	1	95	10	0	1	3
23	40	60	2	70	10	0	1	1
24	55	45	1	95	5	1	0	1
25	25	30	1	55	5	0	1	1
26	40	45	0	60	10	1	0	4
27	25	30	1	55	10	1	0	5
28	40	45	0	60	5	0	1	2
29	40	60	1	80	15	0	0	4
30	55	45	2	85	5	2	2	4
31	40	60	1	80	5	2	2	2
32	55	45	2	85	15	0	0	5
33	55	30	0	95	10	2	1	4
34	25	60	2	45	15	1	2	1
35	55	30	0	95	15	1	2	2
36	25	60	2	45	10	2	1	2

B.4. Choice tasks: disruption scenario 2

Table B.2: The choice tasks for disruption scenario 2. The colours indicate which choice tasks are assigned to which block.

	Wait for disruption to be over			Reroute within train network				Return home			
Choice task	Original travel time	Disruption length	Crowding	Additional travel time	Waiting time	Crowding	Transfer	Travel time	Waiting time	Crowding	Block
1	25	60	2	55	10	2	2	15	10	2	2
2	25	60	2	65	15	1	1	20	15	1	5
3	35	45	1	65	10	2	2	20	15	1	6
4	35	45	1	75	15	1	1	15	10	2	3
5	35	45	2	75	5	2	0	10	10	1	5
6	35	45	2	55	15	0	2	15	5	0	5
7	25	60	1	65	5	2	0	15	5	0	3
8	25	60	1	45	15	0	2	10	10	1	6
9	35	60	1	55	10	1	0	20	5	2	5
10	35	60	1	65	5	0	1	10	15	0	2
11	25	45	2	45	10	1	0	10	15	0	3
12	25	45	2	55	5	0	1	20	5	2	3
13	35	30	0	75	15	0	0	20	15	0	3
14	35	30	0	55	5	2	2	10	5	2	6
15	15	60	2	55	15	0	0	10	5	2	4
16	15	60	2	35	5	2	2	20	15	0	1
17	15	60	0	35	10	0	1	15	15	2	6
18	15	60	0	45	5	1	0	20	10	1	6
19	35	30	2	55	10	0	1	20	10	1	1
20	35	30	2	65	5	1	0	15	15	2	4
21	15	30	2	45	15	2	1	10	10	0	6
22	15	30	2	55	10	1	2	15	5	1	3
23	35	60	0	65	15	2	1	15	5	1	1
24	35	60	0	75	10	1	2	10	10	0	1
25	15	45	1	35	5	1	1	10	5	1	1
26	15	45	1	45	10	0	0	15	10	0	4
27	25	30	0	45	5	1	1	15	10	0	5
28	25	30	0	55	10	0	0	10	5	1	2
29	25	30	1	55	15	1	2	20	5	0	4
30	25	30	1	65	10	2	1	10	15	2	4
31	15	45	0	45	15	1	2	10	15	2	2
32	15	45	0	55	10	2	1	20	5	0	5
33	25	45	0	65	5	0	2	15	15	1	4
34	25	45	0	45	15	2	0	20	10	2	1
35	15	30	1	55	5	0	2	20	10	2	2
36	15	30	1	35	15	2	0	15	15	1	2

B.5. Online questionnaire



NS Panel

0%

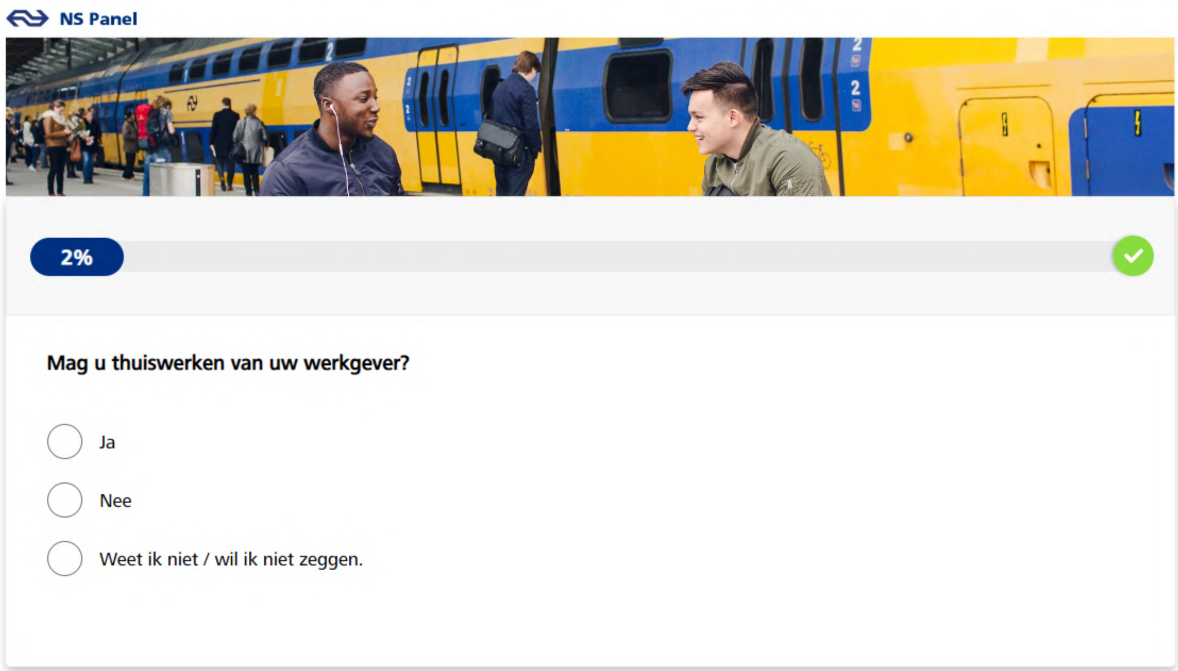
Welkom bij dit onderzoek! Dit onderzoek gaat over reisgedrag tijdens verstoringen op het spoor. Een verstoring houdt in dat bepaalde treinen niet kunnen rijden door bijvoorbeeld een defecte trein, een seinstoring, het weer etc. Deze verstoringen kunnen een paar minuten duren maar soms ook meerdere uren.

In het eerste deel van de enquête worden vragen gesteld over uw werk. Daarna krijgt u verschillende verstoringen te zien met verschillende reisopties. In het laatste deel van de enquête worden vragen gesteld over uw ervaring met verstoringen. U kunt op elk moment stoppen met dit onderzoek en uw gegevens worden anoniem verwerkt.

Zou u uw werk thuis kunnen uitvoeren?

- Ja
- Nee
- Ik heb op dit moment geen werk.

Figure B.1: Questionnaire screen 1.



NS Panel

2%

Mag u thuiswerken van uw werkgever?

- Ja
- Nee
- Weet ik niet / wil ik niet zeggen.

Figure B.2: Questionnaire screen 2.

NS Panel

3%

Hoe ervaart u het thuiswerken?

- ◯ Zeer negatief
- ◯ Negatief
- ◯ Niet negatief / niet positief
- ◯ Positief
- ◯ Zeer positief
- ◯ Ik werk nooit vanuit huis.

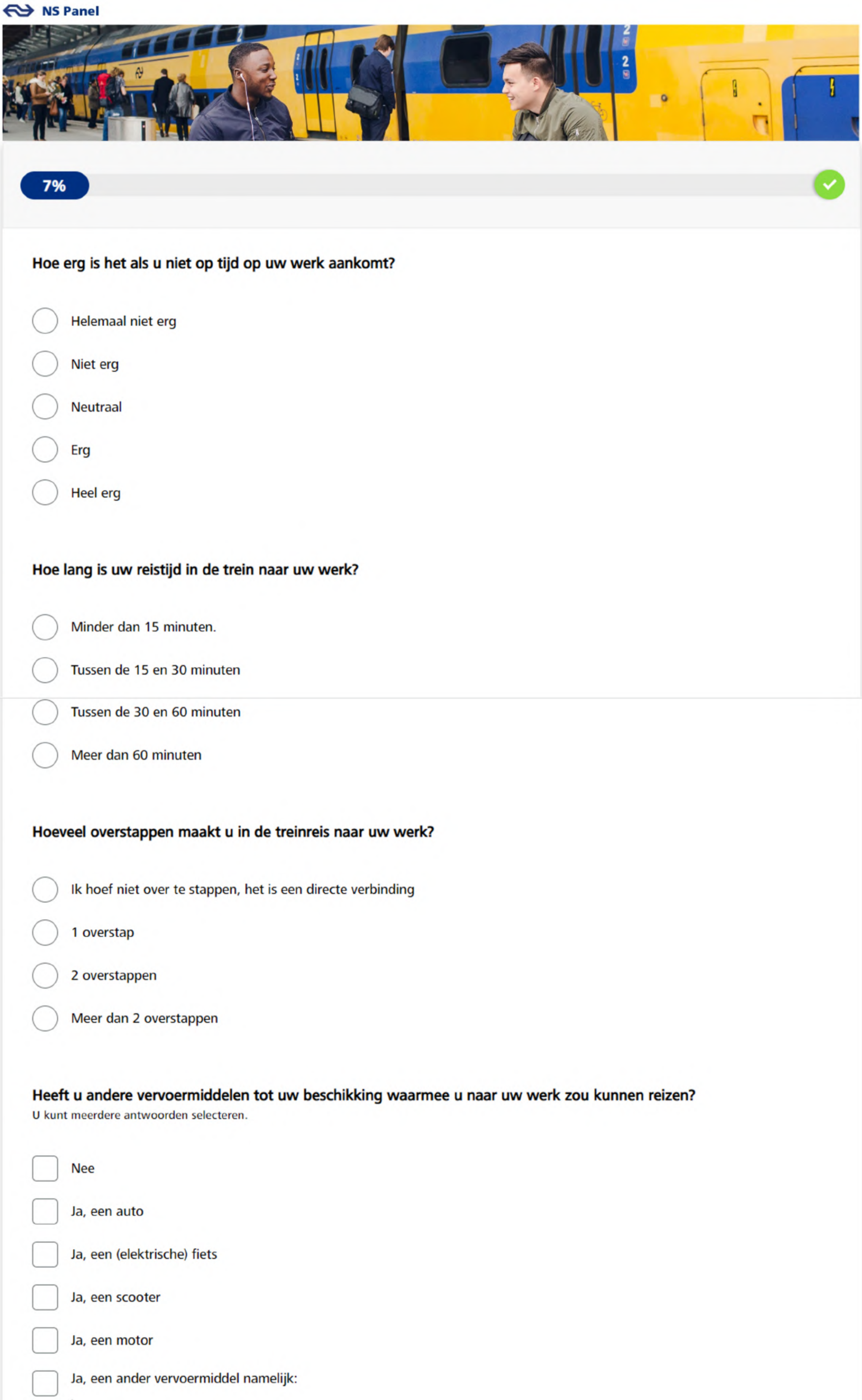
Hoe vaak moet u op locatie aanwezig zijn voor uw werk (voor bijvoorbeeld kantoordagen)?

- ◯ Elke werkdag
- ◯ 3-4 dagen per week
- ◯ 1-2 dagen per week
- ◯ 1-2 dagen per maand
- ◯ Minder dan 1-2 dagen per maand

Hoe vaak werkt u in de trein onderweg naar uw werk?

- ◯ Altijd
- ◯ Vaak
- ◯ Regelmatig
- ◯ Soms
- ◯ Nooit

Figure B.3: Questionnaire screen 3.



NS Panel

7%

Hoe erg is het als u niet op tijd op uw werk aankomt?

- ○ Helemaal niet erg
- ○ Niet erg
- ○ Neutraal
- ○ Erg
- ○ Heel erg

Hoe lang is uw reistijd in de trein naar uw werk?

- ○ Minder dan 15 minuten.
- ○ Tussen de 15 en 30 minuten
- ○ Tussen de 30 en 60 minuten
- ○ Meer dan 60 minuten

Hoeveel overstappen maakt u in de treinreis naar uw werk?

- ○ Ik hoef niet over te stappen, het is een directe verbinding
- ○ 1 overstap
- ○ 2 overstappen
- ○ Meer dan 2 overstappen

Heeft u andere vervoermiddelen tot uw beschikking waarmee u naar uw werk zou kunnen reizen?
U kunt meerdere antwoorden selecteren.

- ☐ Nee
- ☐ Ja, een auto
- ☐ Ja, een (elektrische) fiets
- ☐ Ja, een scooter
- ☐ Ja, een motor
- ☐ Ja, een ander vervoermiddel namelijk:

Figure B.4: Questionnaire screen 4.

NS Panel

11%

Als u reist van uw huis naar het treinstation waar u het vaakst gebruik van maakt om naar uw werk te reizen, wat is dan ongeveer uw reistijd?

Als uw reistijd bijvoorbeeld 20 minuten is, vul dan alleen het getal 20 in.

*Velden met * zijn verplicht*

Uw reistijd in minuten: *

Veld is verplicht

Let op! Onthoud wat u bij deze vraag heeft ingevuld. Uw antwoord moet u in gedachten houden bij het volgende deel van de enquête.

Figure B.5: Questionnaire screen 5.

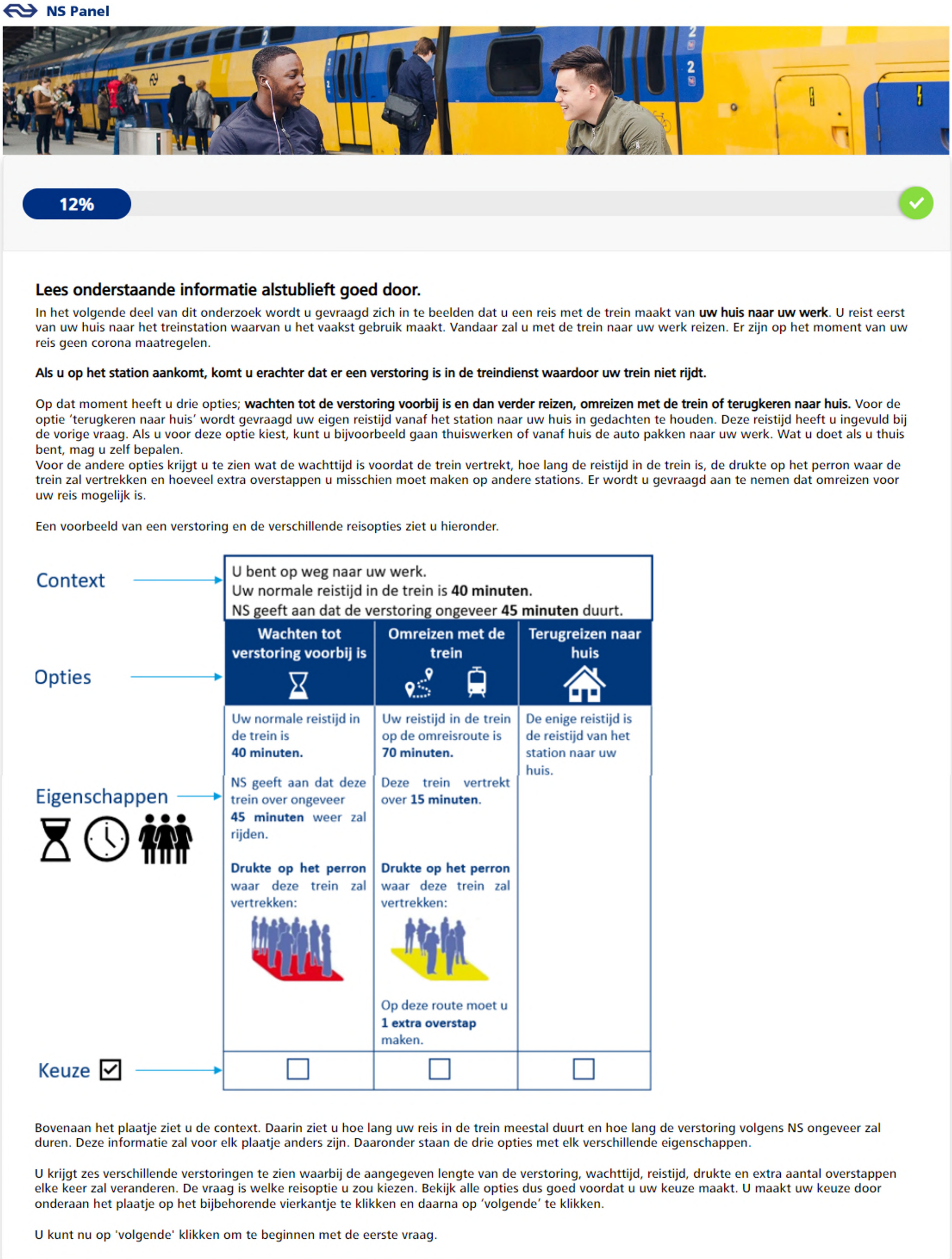


Figure B.6: Questionnaire screen 6.

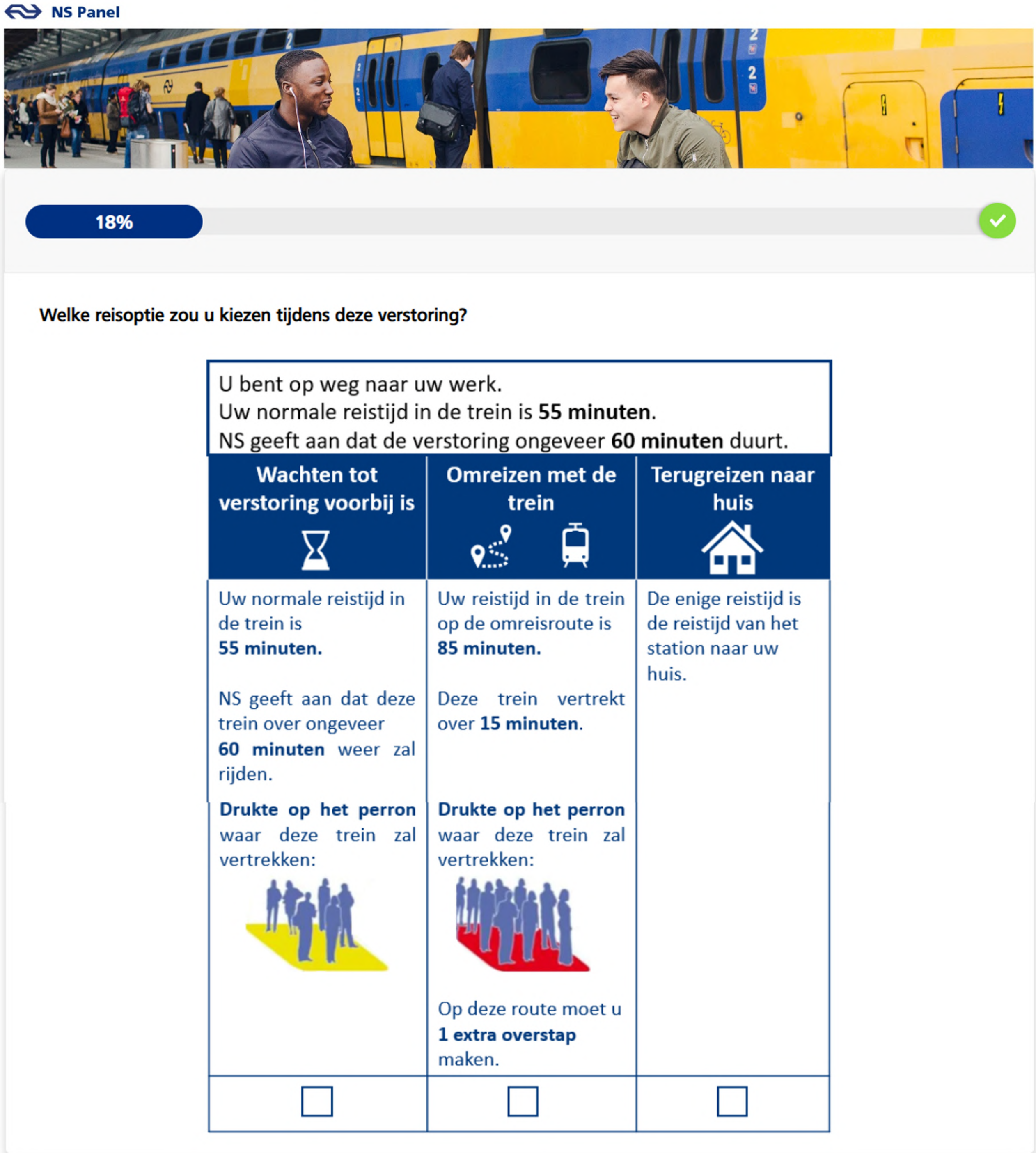


Figure B.7: Questionnaire screen 7.

NS Panel

29%

Lees onderstaande informatie alstublieft goed door.

Bij de vorige zes vragen heeft u aangegeven welke reisoptie u zou kiezen als uw trein niet rijdt. De verstoring gebeurde toen al op het beginstation en u had nog niet gereisd in de trein.

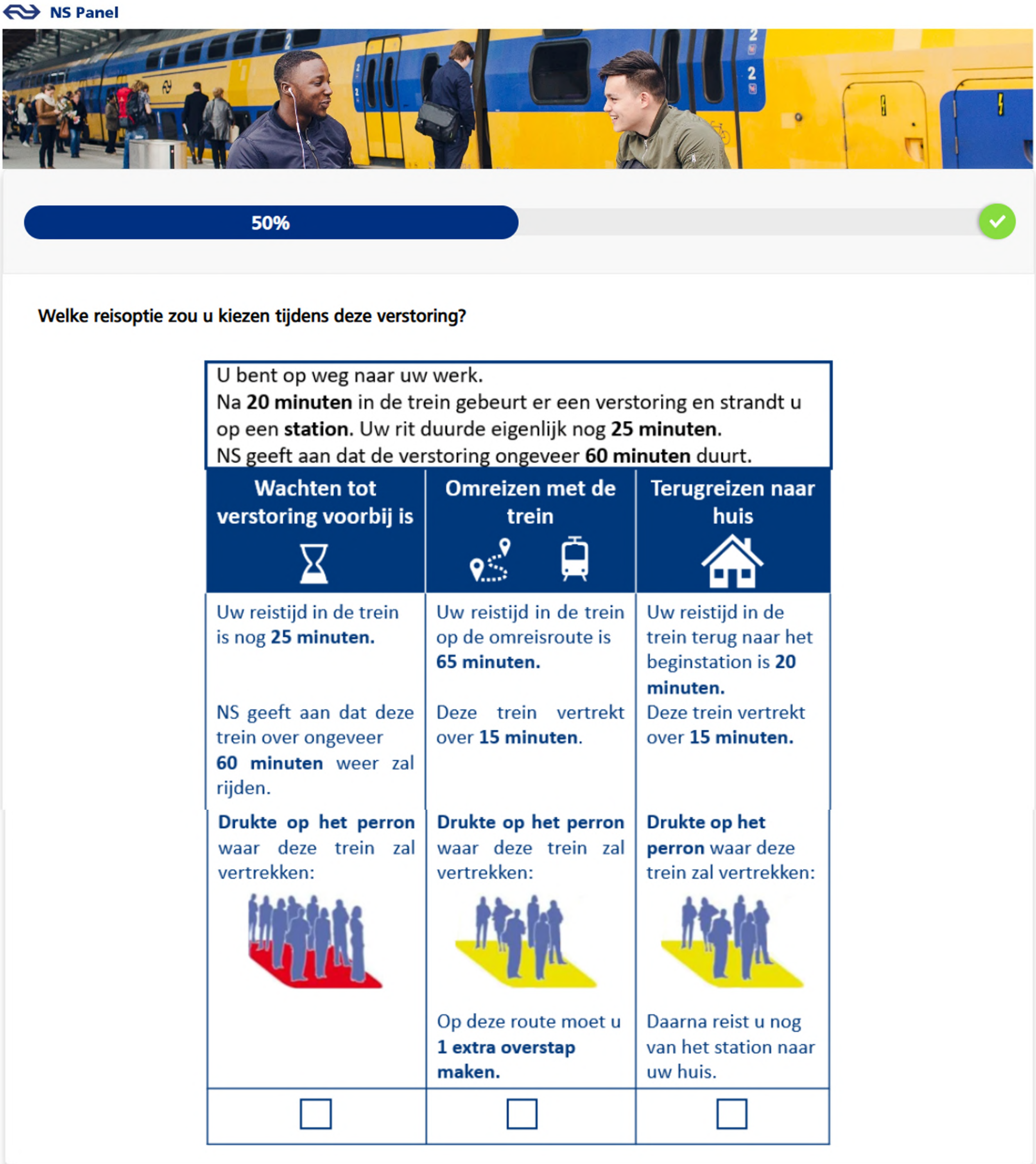
In de tweede situatie reist u al met de trein wanneer er een verstoring gebeurt. U wordt op een tussengelegen station uit de trein gezet. Wat zou u dan doen? Als u terug naar huis zou willen reizen, moet u weer een stuk terug met de trein afleggen in plaats van alleen het stuk van het beginstation naar uw huis. Lees goed de context bovenaan de afbeeldingen door omdat de situatie nu net iets anders is dan bij de vorige vragen. Een voorbeeld van een vraag kunt u hieronder zien.

Context → U bent op weg naar uw werk. Na **15 minuten** in de trein gebeurt er een verstoring en strandt u op een **station**. Uw rit duurde eigenlijk nog **25 minuten**. NS geeft aan dat de verstoring ongeveer **45 minuten** duurt.

	Wachten tot verstoring voorbij is	Omreizen met de trein	Terugreizen naar huis
Opties →			
	Uw reistijd in de trein is nog **25 minuten.**	Uw reistijd in de trein op de omreisroute is **55 minuten.**	Uw reistijd in de trein terug naar het beginstation is **15 minuten.**
Eigenschappen →	NS geeft aan dat deze trein over ongeveer **45 minuten** weer zal rijden.	Deze trein vertrekt over **15 minuten.**	Deze trein vertrekt over **10 minuten.**
	Drukte op het perron waar deze trein zal vertrekken:	**Drukte op het perron** waar deze trein zal vertrekken:	**Drukte op het perron** waar deze trein zal vertrekken:
		Op deze route moet u **1 extra overstap maken.**	Daarna reist u nog van het station naar uw huis.
Keuze ☑ →	☐	☐	☐

Klik op 'volgende' om naar de eerste vraag te gaan.

Figure B.8: Questionnaire screen 8.



NS Panel

50%

Welke reisoptie zou u kiezen tijdens deze verstoring?

U bent op weg naar uw werk.
Na **20 minuten** in de trein gebeurt er een verstoring en strandt u op een **station**. Uw rit duurde eigenlijk nog **25 minuten**.
NS geeft aan dat de verstoring ongeveer **60 minuten** duurt.

Wachten tot verstoring voorbij is	Omreizen met de trein	Terugreizen naar huis
Uw reistijd in de trein is nog **25 minuten.** NS geeft aan dat deze trein over ongeveer **60 minuten** weer zal rijden.	Uw reistijd in de trein op de omreisroute is **65 minuten.** Deze trein vertrekt over **15 minuten.**	Uw reistijd in de trein terug naar het beginstation is **20 minuten.** Deze trein vertrekt over **15 minuten.**
Drukte op het perron waar deze trein zal vertrekken:	**Drukte op het perron** waar deze trein zal vertrekken: Op deze route moet u **1 extra overstap maken.**	**Drukte op het perron** waar deze trein zal vertrekken: Daarna reist u nog van het station naar uw huis.
☐	☐	☐

Figure B.9: Questionnaire screen 9.

NS Panel

78%

Had u tijdens het beantwoorden van de vorige vragen een bepaalde verstoring in gedachten?

- ◯ Nee
- ◯ Ja, een seinstoring
- ◯ Ja, een defecte trein
- ◯ Ja, een aanrijding
- ◯ Ja, een wisselstoring
- ◯ Ja, een andere verstoring namelijk:

Had u tijdens het beantwoorden van de vorige vragen in gedachten dat het noodzakelijk was dat u op de locatie van uw werk zou komen?

- ◯ Ja
- ◯ Nee

Heeft u wel eens een verstoring meegemaakt tijdens uw reis met de trein?

- ◯ Ja.
- ◯ Nee.

Figure B.10: Questionnaire screen 10.

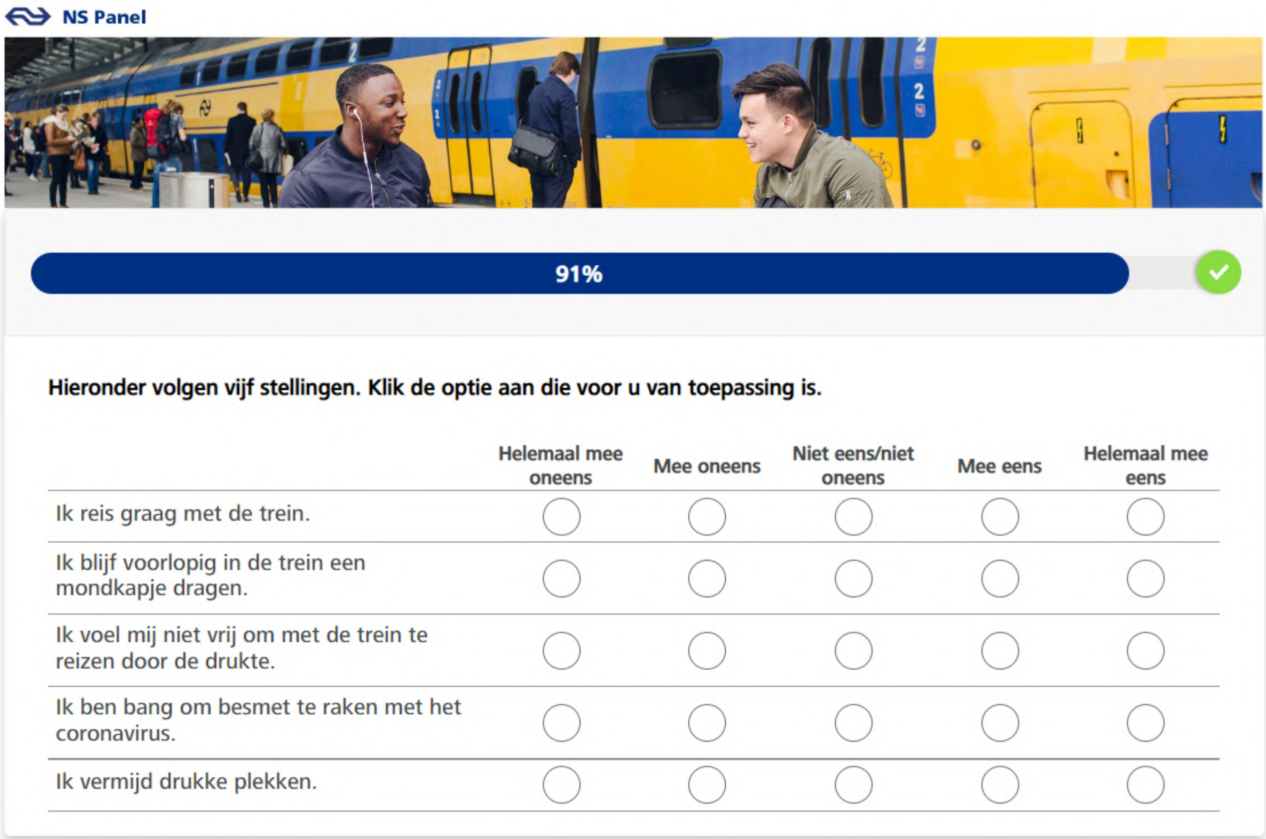
NS Panel

88%

Hieronder volgen vier stellingen. Klik de optie aan die voor u van toepassing is.

	Helemaal mee oneens	Mee oneens	Niet eens/niet oneens	Mee eens	Helemaal mee eens
Tijdens een verstoring vertrouw ik de informatie die NS geeft over hoe lang de verstoring zal duren.	○	○	○	○	○
Tijdens een verstoring volg ik het reisadvies van NS op.	○	○	○	○	○
Tijdens een verstoring vertrouw ik de informatie in de reisplanner app.	○	○	○	○	○
Tijdens een verstoring laat ik me leiden door vorige ervaringen met verstoringen.	○	○	○	○	○
Tijdens een verstoring vertrouw ik meer op eigen ervaringen met verstoringen dan de informatie van NS.	○	○	○	○	○

Figure B.11: Questionnaire screen 11.


NS Panel

91%

Hieronder volgen vijf stellingen. Klik de optie aan die voor u van toepassing is.

	Helemaal mee oneens	Mee oneens	Niet eens/niet oneens	Mee eens	Helemaal mee eens
Ik reis graag met de trein.	○	○	○	○	○
Ik blijf voorlopig in de trein een mondkapje dragen.	○	○	○	○	○
Ik voel mij niet vrij om met de trein te reizen door de drukte.	○	○	○	○	○
Ik ben bang om besmet te raken met het coronavirus.	○	○	○	○	○
Ik vermijd drukke plekken.	○	○	○	○	○

Figure B.12: Questionnaire screen 12.


NS Panel

94%

Hartelijk dank voor uw deelname aan het onderzoek. Heeft u nog opmerkingen over dit onderwerp of onderzoek? Uw opmerkingen kunt u invullen in het tekstvak hieronder.

Als u geen opmerkingen heeft, klik dan op 'volgende' om het onderzoek af te sluiten.

Figure B.13: Questionnaire screen 13.

C Confidential: sample characteristics

D Discrete choice models

D.1. Base MNL model

```
import pandas as pd
import biogeme.database as db
import biogeme.biogeme as bio
import biogeme.models as models
import biogeme.version as ver
from biogeme.expressions import Beta

# Prepare the data
df = pd.read_csv('final_data_dummy_transfer.csv')
database = db.Database('final_data_dummy_transfer',df) #convert dataframe to Biogeme database

# Define the name of the variables as Python variables
globals().update(database.variables)

# Model specification
## Parameters to be estimated
ASC_WAIT = Beta('ASC_WAIT', 0, None, None, 1)
ASC_WAIT_SCE = Beta('ASC_WAIT_SCE', 0, None, None, 0) #to test effect of scenario on ASC_wait
ASC_REROUTE = Beta('ASC_REROUTE', 0, None, None, 0)
ASC_REROUTE_SCE = Beta('ASC_REROUTE_SCE', 0, None, None, 0) #to test effect of scenario on
    ASC_reroute
ASC_RETURN_SCE1 = Beta('ASC_RETURN_SCE1', 0, None, None, 0) #return ASC in scenario 1
ASC_RETURN_SCE2 = Beta('ASC_RETURN_SCE2', 0, None, None, 0) #return ASC in scenario 2

B_DISRUPTIONLENGTH = Beta('B_DISRUPTIONLENGTH', 0, None, None, 0)
B_DISRUPTION_LENGTH_Q = Beta('B_DISRUPTION_LENGTH_Q', 0, None, None, 0)

B_WAIT = Beta('B_WAIT', 0, None, None, 0) #generic waiting parameter

B_ORIGINAL_TT = Beta('B_ORIGINAL_TT', 0, None, None, 0)
B_ADDITIONAL_TT = Beta('B_ADDITIONAL_TT', 0, None, None, 0)
B_TT_RETURN = Beta('B_TT_RETURN', 0, None, None, 0)

B_CROWDING_D = Beta('B_CROWDING_D', 0, None, None, 0) #level B is baseline / reference
B_CROWDING_F = Beta('B_CROWDING_F', 0, None, None, 0)

B_TRANSFER1 = Beta('B_TRANSFER1', 0, None, None, 0) #one extra transfer (zero extra is baseline)
B_TRANSFER2 = Beta('B_TRANSFER2', 0, None, None, 0) #two extra transfers

B_ACCESS = Beta('B_ACCESS', 0, None, None, 0)
B_ACCESS_Q = Beta('B_ACCESS_Q', 0, None, None, 0)

## Definition of new variables
SCE = (Dummy_scenario1 == 0) #is 1 for disruption scenario 2, is 0 for disruption scenario 1

## Specification of the utility functions
V1 = ASC_WAIT + SCE*ASC_WAIT_SCE +\
```

```
    B_DISRUPTIONLENGTH * wt_wait + B_DISRUPTION_LENGTH_Q * (wt_wait**2)/100 + \
    B_ORIGINAL_TT * tt_wait + \
    B_CROWDING_F * crowding_wait_red + crowding_wait_yellow * B_CROWDING_D

V2 = ASC_REROUTE + SCE*ASC_REROUTE_SCE +\
    B_WAIT * wt_reroute + \
    B_ADDITIONAL_TT * tt_reroute + \
    B_CROWDING_F * crowding_reroute_red + crowding_reroute_yellow * B_CROWDING_D + \
    B_TRANSFER1 * transfer1 + B_TRANSFER2 * transfer2

V3 = ASC_RETURN_SCE1 + \
    B_ACCESS * access_time + B_ACCESS_Q * (access_time**2)/100

V4 = ASC_RETURN_SCE2 + \
    B_ACCESS * access_time + B_ACCESS_Q * (access_time**2)/100 + \
    B_WAIT * wt_return + \
    B_TT_RETURN * tt_return + \
    B_CROWDING_F * crowding_return_red + crowding_return_yellow * B_CROWDING_D

## Associate the utility functions with the numbering of the alternatives
V = {1: V1, #alternative 1 is associated with utility function V1
    2: V2,
    3: V3,
    4: V4}
## Associate the availability conditions with the alternatives
av = {1: 1,
     2: 1,
     3: Dummy_scenario1,
     4: Dummy_scenario2}
logprob = models.loglogit(V, av, CHOICE)

# Biogeme
biogeme = bio.BIOGEME(database, logprob)
biogeme.modelName = 'logitMNL_basemodel'
results = biogeme.estimate()

pandasResults = results.getEstimatedParameters()
print(pandasResults)
print(results)
```

D.2. Interactions coding

Table D.1: Coding scheme for individual characteristics.

Gender	Gender	**Education**	Education_level
Male	0	MULO/LBO/MAVO/MBO	0
Female	1	HAVO/VWO/HBO bachelor	1
Other	1	PhD/WO bachelor/WO master/HBO master	2
Alternative mode of transport available	Alternative_transport	**Necessary to arrive at workplace**	Important_event
No	0	No	0
Yes	1	Yes	1
Train subscription	Subscription	**Specific type of disruption in mind**	Disruption_mind
No	0	No	0
Yes	1	Yes	1
Urbanization	Stedelijkheid	**All COVID statements**	COVID_x
More than 2500 adresses per km^2	0	Strongly disagree	-2
Between 1500 and 2500 adresses per km^2	1	Disagree	-1
Between 1000 and 1500 adresses per km^2	2	Not agree / not disagree	0
Between 500 and 1000 adresses per km^2	3	Agree	1
Less than 500 adresses per km^2	4	Strongly agree	2
Nielsen area	Nielsen_gebied	**Teleworking attitude**	Teleworking_attitude
Nielsen I	0	Very negative	-2
Nielsen II	1	Negative	-1
Nielsen III	2	Neutral/cannot telework	0
Nielsen IV	3	Positive	1
Nielsen V	4	Very positive	2
Origin station type	Beginstationtype	**All disruption statements**	Disruption_x
Large station in center of large city	0	Strongly disagree	-2
Large station in center normal-sized city	1	Disagree	-1
Suburban station with node function	2	Not agree / not disagree	0
Station in center small city/village	3	Agree	1
Surburban station without node function	4	Strongly agree	2
Station in rural area near small city/village	5	Never experienced a disruption before	0
Travel experience	Travel_experience	**Teleworking possibility**	Teleworking_possibility
Less than one day per week	0	No	0
More than 1 day per week	1	Yes	1
Age	Age	**Travel time in train**	TT_train
18-34 years old	0	Less than 30 minutes	0
35-44 years old	1	Between 30 and 60 minutes	1
45-54 years old	2	More than 60 minutes	2
55-64 years old	3		

D.3. MNL model with interactions code

```
import pandas as pd
import biogeme.database as db
import biogeme.biogeme as bio
import biogeme.models as models
import biogeme.version as ver
from biogeme.expressions import Beta
import numpy as np

df = pd.read_csv('final_data_new.csv')
database = db.Database('final_data_new',df) #convert dataframe to Biogeme database
globals().update(database.variables)

# Model specification
## Parameters to be estimated
ASC_WAIT = 0
ASC_WAIT_SCE = Beta('ASC_WAIT_SCE', 0, None, None, 0) #to test effect of scenario on ASC_wait
ASC_REROUTE = Beta('ASC_REROUTE', 0, None, None, 0)
ASC_REROUTE_SCE = Beta('ASC_REROUTE_SCE', 0, None, None, 0) #to test effect of scenario on
    ASC_reroute
ASC_RETURN_SCE1 = Beta('ASC_RETURN_SCE1', 0, None, None, 0) #return ASC in scenario 1
ASC_RETURN_SCE2 = Beta('ASC_RETURN_SCE2', 0, None, None, 0) #return ASC in scenario 2
```

```
B_DISRUPTIONLENGTH = Beta('B_DISRUPTIONLENGTH', 0, None, None, 0)
B_DISRUPTION_LENGTH_Q = Beta('B_DISRUPTION_LENGTH_Q', 0, None, None, 0)

B_WAIT = Beta('B_WAIT', 0, None, None, 0) #generic waiting parameter

B_ORIGINAL_TT = Beta('B_ORIGINAL_TT', 0, None, None, 0)
B_ADDITIONAL_TT = Beta('B_ADDITIONAL_TT', 0, None, None, 0)
B_TT_RETURN = Beta('B_TT_RETURN', 0, None, None, 0)

B_CROWDING_D = Beta('B_CROWDING_D', 0, None, None, 0) #blue is baseline / reference
B_CROWDING_F = Beta('B_CROWDING_F', 0, None, None, 0)

B_TRANSFER1 = Beta('B_TRANSFER1', 0, None, None, 0) #one extra transfer (zero extra is baseline)
B_TRANSFER2 = Beta('B_TRANSFER2', 0, None, None, 0) #two extra transfers

B_ACCESS = Beta('B_ACCESS', 0, None, None, 0)
B_ACCESS_Q = Beta('B_ACCESS_Q', 0, None, None, 0)

#interaction parameters
B_DISRUPTIONLENGTH_INT = Beta('B_DISRUPTIONLENGTH_INT', 0, None, None, 0)
B_DISRUPTION_LENGTH_Q_INT = Beta('B_DISRUPTION_LENGTH_Q_INT', 0, None, None, 0)

B_WAIT_INT = Beta('B_WAIT_INT', 0, None, None, 0) #generic waiting parameter

B_ORIGINAL_TT_INT = Beta('B_ORIGINAL_TT_INT', 0, None, None, 0)
B_ADDITIONAL_TT_INT = Beta('B_ADDITIONAL_TT_INT', 0, None, None, 0)
B_TT_RETURN_INT = Beta('B_TT_RETURN_INT', 0, None, None, 0)

B_CROWDING_D_INT = Beta('B_CROWDING_D_INT', 0, None, None, 0) #blue is baseline / reference
B_CROWDING_F_INT = Beta('B_CROWDING_F_INT', 0, None, None, 0)

B_TRANSFER1_INT = Beta('B_TRANSFER1_INT', 0, None, None, 0) #one extra transfer (zero extra is
    baseline)
B_TRANSFER2_INT = Beta('B_TRANSFER2_INT', 0, None, None, 0) #two extra transfers

B_ACCESS_INT = Beta('B_ACCESS_INT', 0, None, None, 0)
B_ACCESS_Q_INT = Beta('B_ACCESS_Q_INT', 0, None, None, 0)

## Definition of new variables
SCE = (Dummy_scenario1 == 0) #is 1 for disruption scenario 2, is 0 for disruption scenario 1

## Specification of the utility functions
V1 = ASC_WAIT + SCE*ASC_WAIT_SCE + (B_DISRUPTIONLENGTH + B_DISRUPTIONLENGTH_INT*Education_level) *
    wt_wait + (B_DISRUPTION_LENGTH_Q + B_DISRUPTION_LENGTH_Q_INT*Education_level) * (wt_wait**2)/100
     + (B_ORIGINAL_TT + B_ORIGINAL_TT_INT * Education_level) * tt_wait + (B_CROWDING_F +
    B_CROWDING_F_INT * Education_level) * crowding_wait_red + crowding_wait_yellow * (B_CROWDING_D +
     B_CROWDING_D_INT * Education_level)

V2 = ASC_REROUTE + SCE*ASC_REROUTE_SCE + (B_WAIT + B_WAIT_INT * Education_level) * wt_reroute + (
    B_ADDITIONAL_TT + B_ADDITIONAL_TT_INT * Education_level) * tt_reroute + (B_CROWDING_F +
    B_CROWDING_F_INT * Education_level) * crowding_reroute_red + crowding_reroute_yellow * (
    B_CROWDING_D + B_CROWDING_D_INT* Education_level) + (B_TRANSFER1 + B_TRANSFER1_INT*
    Education_level) * transfer1 + (B_TRANSFER2 + B_TRANSFER2_INT * Education_level) * transfer2

V3 = ASC_RETURN_SCE1 + (B_ACCESS + B_ACCESS_INT * Education_level) * access_time + (B_ACCESS_Q +
    B_ACCESS_Q_INT * Education_level) * (access_time**2)/100

V4 = ASC_RETURN_SCE2 + (B_ACCESS + B_ACCESS_INT * Education_level) * access_time + (B_ACCESS_Q +
    B_ACCESS_Q_INT * Education_level) * (access_time**2)/100 + (B_WAIT + B_WAIT_INT *
    Education_level) * wt_return + (B_TT_RETURN + B_TT_RETURN_INT * Education_level) * tt_return + (
```

```
    B_CROWDING_F + B_CROWDING_F_INT * Education_level) * crowding_return_red +
    crowding_return_yellow * (B_CROWDING_D + B_CROWDING_D_INT* Education_level)

## Associate the utility functions with the numbering of the alternatives
V = {1: V1, #alternative 1 is associated with utility function V1
    2: V2,
    3: V3,
    4: V4}
## Associate the availability conditions with the alternatives
av = {1: 1,
     2: 1,
     3: Dummy_scenario1,
     4: Dummy_scenario2}
logprob = models.loglogit(V, av, CHOICE)

# Biogeme
biogeme = bio.BIOGEME(database, logprob)
biogeme.modelName = 'logitMNL_interactparam_Education_level'
results = biogeme.estimate()

pandasResults = results.getEstimatedParameters()
print(pandasResults)
print(results)
```

D.4. MNL model with interactions

The two tables below show the estimated interaction effects which are added to the base MNL model. Table D.2 displays the interactions on the ASCs of each alternative while in Table D.3 the interaction effects on the taste parameters are shown. In the tables the upper row of each characteristic is the reference (coded as a 0). For example 'male' for the gender characteristic. The reference for the characteristics 'Teleworking possibility' is 'no' (so people who cannot telework) and therefore the base level for ASC_reroute is -2.9 but for people who cannot telework -0.453 should be added and therefore leads to an ASC_reroute of -3.353. The conclusion can then be made that people who can telework perceive the rerouting option more negatively than people who cannot telework. The characteristics that are not dummy coded are indicated by their second row containing the text 'Interaction parameter'. This means that the corresponding value should be multiplied by the coding to find the proper interaction effect. For example when looking at the teleworking attitude characteristic and one wishes to find the interaction effect when people have a very positive attitude towards teleworking. In Table D.1 it can be seen that this corresponds to a coding of 2. So the interaction effect on ASC_reroute is then -2.77 (reference) + 2*-0.194 = -3.158. In essence it means that when the teleworking attitude becomes more positive, the ASC_reroute parameter becomes more negative. The colours indicate the significance of the interaction effects. Green = significant at 99% interval, yellow = significant at 95% interval and red = significant at 90% interval. When the cell does not have a colour the interaction effect is insignificant.

Table D.2: MNL model interactions on ASCs. Green = significant at 99% interval, yellow = significant at 95% interval and red = significant at 90% interval.

Characteristics	ASC_reroute	ASC_reroute_ SCE	ASC_return _SCE1	ASC_return _SCE2	ASC_wait	ASC_wait _SCE
Gender						
Male	-2.79	1.24	-5.06	-2.72	-	1.48
Female + other	0.0955	-0.0458	0.0272	-0.0328	-0.0898	0.0787
Age						
18-34 years old	-2.58	1.32	-5.31	-2.96	-	1.64
Interaction parameter	-0.148	-0.0502	0.115	0.109	-0.0755	-0.0584
Education						
Low	-2.82	1.22	-5.07	-2.67	-	1.45
Interaction parameter	0.0515	0.00102	0.0235	-0.0486	-0.0264	0.0475
Urbanization						

Very urban	-2.69	1.25	-4.97	-2.75	-	1.5
Interaction parameter	-0.00818	-0.0369	-0.0184	0.0349	-0.00826	0.00204
Nielsen area						
Nielsen I	-2.57	1.18	-4.86	-2.65	-	1.47
Interaction parameter	-0.0215	-0.00562	-0.0257	0.00117	0.046	0.00445
Travel experience						
Not experienced	-2.68	1.23	-5.07	-2.74	-	1.51
Experienced	-0.0524	-0.022	0.0596	0.0166	-0.0238	0.00547
Teleworking possibility						
No	-2.9	1.6	-6.03	-3.5	-	1.91
Yes	-0.453	-0.241	0.538	0.496	-0.581	-0.255
Teleworking attitude						
Neutral/cannot telework	-2.77	1.35	-5.4	-3.03	-	1.68
Interaction parameter	-0.194	-0.0751	0.19	0.186	-0.182	-0.111
Train subscription						
No	-2.85	1.26	-5.17	-2.79	-	1.53
Yes	0.0545	-0.0281	0.0971	0.0104	-0.162	0.0177
Alternative mode of transport available						
No	-2.73	1.24	-5.14	-2.73	-	1.49
Yes	-0.0386	-0.0345	0.132	-0.0129	-0.0809	0.0475
Origin station type						
Very large station	-2.75	1.31	-5.27	-2.82	-	1.5
Interaction parameter	-0.0198	-0.0293	0.0563	0.0052	-0.0417	0.0241
Necessary to arrive at workplace						
No	-2.88	1.06	-4.5	-2.39	-	1.33
Yes	0.609	0.181	-0.723	-0.399	0.513	0.218
Specific type of disruption in mind						
No	-2.68	1.2	-4.95	-2.71	-	1.51
Yes	-0.0191	-0.00702	-0.101	0.0517	0.0688	-0.0447
COVID: 'I am afraid to get infected with COVID'						
Neutral	-2.67	1.13	-4.87	-2.61	-	1.48
Interaction parameter	-0.0325	-0.058	0.0615	0.0535	-0.0825	0.00455
COVID: 'I avoid crowded places'						
Neutral	-2.74	1.21	-5.02	-2.72	-	1.51
Interaction parameter	-0.0673	-0.0443	0.105	0.072	-0.11	-0.0277
COVID: 'I will continue to wear a facemask in the train'						
Neutral	-2.67	1.03	-4.73	-2.43	-	1.39
Interaction parameter	-0.0848	-0.0862	0.0699	0.126	-0.111	-0.0399
COVID: 'I like to travel by train'						
Neutral	-2.76	1.08	-4.69	-2.55	-	1.47
Interaction parameter	0.167	0.0838	-0.209	-0.0786	0.12	-0.00517
COVID: 'I do not feel free to travel by train because of the crowding'						
Neutral	-2.71	1.15	-4.86	-2.62	-	1.47
Interaction parameter	-0.0749	-0.0522	0.103	0.0537	-0.0819	-0.00154
Disruption information: 'During a disruption I trust the information about expected disruption length provided by NS'						
Neutral	-2.83	1.25	-5.13	-2.78	-	1.54
Interaction parameter	-0.101	0.0532	-0.0748	-0.00059	0.176	-0.0526
Disruption information: 'During a disruption I trust the information in the travel planner app'						
Neutral	-2.71	1.19	-4.98	-2.7	-	1.51
Interaction parameter	0.0607	0.039	-0.108	-0.0405	0.0874	0.00149
Disruption information: 'During a disruption I let previous experiences with disruptions guide me'						
Neutral	-2.76	1.19	-4.97	-2.68	-	1.49
Interaction parameter	0.059	0.00782	-0.0278	-0.0222	-0.00898	0.0144
Disruption information: 'During a disruption I rely more on previous experiences with disruptions than the travel information from NS'						
Neutral	-2.75	1.21	-5.04	-2.74	-	1.53
Interaction parameter	0.0306	-0.00295	0.0101	0.0401	-0.0808	-0.0371

Disruption information: 'During a disruption I follow the travel advice provided by NS'						
Neutral	-2.72	1.2	-5.01	-2.71	-	1.51
Interaction parameter	0.000804	0.0779	-0.0838	-0.0879	0.171	0.01

Table D.3: MNL model interaction effects on taste parameters. Green = significant at 99% interval, yellow = significant at 95% interval and red = significant at 90% interval

Characteristics	Access	Access_Q	Add. TT	Crowding level D	Crowding level F	Disruption Length	Disruption Length_Q	Original TT	Transfer1	Transfer2	Return TT	Wait
Gender												
Male	0.0104	-0.000922	-0.057	-0.188	-0.827	-0.174	0.000944	0.00291	-0.185	-0.646	-0.0538	-0.0607
Female + other	-0.0404	0.000831	-0.00617	-0.0126	-0.0517	0.000306	-0.00016	-0.00411	0.000451	-0.166	0.00209	-0.0073
Age												
18-34 years old	-0.0295	0.000149	-0.0542	-0.209	-0.966	-0.147	0.000369	0.000364	-0.154	-0.75	-0.0704	-0.0561
Interaction parameter	0.013	-0.000446	-0.00367	0.00868	0.0613	-0.0157	0.000295	0.000554	-0.0191	0.0135	0.00891	-0.0048
Education												
Low	0.0455	-0.0019	-0.0508	-0.19	-0.634	-0.171	0.00106	0.000589	-0.268	-0.704	-0.0502	-0.0545
Interaction parameter	-0.0378	0.000976	-6.28E-03	-0.00293	-0.154	-0.000817	-0.000151	0.000571	0.0603	-0.0119	-0.00172	-0.0068
Urbanization												
Very urban	0.0119	-0.00127	-0.0598	-0.147	-0.758	-0.181	0.000901	0.00826	-0.0528	-0.73	-0.0679	-0.0694
Interaction parameter	-6.02E-03	0.000216	4.81E-05	-0.0185	-0.0387	0.00352	-0.0000133	-0.00298	-0.0558	0.00352	0.00623	0.00236
Nielsen area												
Nielsen I	0.0318	-0.00193	-0.057	-0.141	-0.762	-0.171	0.000749	0.00297	-0.203	-0.865	-0.0696	-0.0541
Interaction parameter	-1.30E-02	0.000452	-9.75E-04	-0.0167	-0.0303	-0.000587	0.0000391	-0.000559	0.0064	0.0493	0.00562	-0.0033
Travel experience												
Not experienced	0.0274	-0.00205	-0.0605	-0.158	-0.725	-0.177	0.00103	-0.000686	-0.331	-0.821	-0.068	-0.0405
Experienced	-3.60E-02	0.00163	8.64E-04	-0.0411	-0.156	0.00256	-0.000174	0.0023	0.184	0.126	0.019	-0.0297
Teleworking possibility												
No	-4.57E-02	-0.000226	-4.49E-02	-0.324	-0.941	-0.163	0.000945	0.00297	-0.175	-0.704	-0.0608	-0.0631
Yes	0.0366	-0.000234	-0.0195	0.156	0.0943	-0.00878	-0.000169	-0.00266	-0.00465	-0.0175	0.0089	-0.0034
Teleworking attitude												
Neutral/cannot telework	-0.0492	0.000111	-0.0598	-0.202	-0.87	-0.179	0.000997	0.00183	-0.117	-0.613	-0.0547	-0.0697
Interaction parameter	3.50E-02	-0.000618	-5.35E-04	0.00226	0.00291	0.00678	-0.000177	-0.00101	-0.0834	-0.13	0.00283	0.00308
Train subscription												
No	0.0311	-0.00129	-0.0535	-0.101	-0.725	-0.159	0.000753	0.0017	-0.207	-0.745	-0.0645	-0.0507
Yes	-6.44E-02	0.00122	-9.90E-03	-0.148	-0.203	-0.0252	0.000213	-0.000869	0.0339	0.0308	0.0171	-0.0207
Alternative mode of transport available												
No	0.00316	-0.000672	-0.057	-0.145	-0.827	-0.165	0.000814	-5.77E-06	-0.0949	-0.565	-0.0534	-0.0586
Yes	-2.07E-02	0.000313	-4.37E-03	-0.0724	-0.0333	-0.0143	0.000111	0.00175	-0.134	-0.238	-0.000432	-0.0076
Origin station type												
Very large station	0.00158	-0.000692	-0.058	-0.145	-0.83	-0.175	0.000924	5.02E-03	-0.135	-0.817	-0.0606	-0.0487
Interaction parameter	-2.96E-03	0.0000646	-8.73E-04	-0.0225	-0.00979	0.000144	-0.0000197	-0.00185	-0.0253	0.045	0.00321	-0.0071
Necessary to arrive at workplace												
No	-0.00214	-4.82E-04	-0.0769	-0.169	-0.958	-0.19	0.000873	-0.000529	-0.212	-0.957	-0.0517	-0.0845
Yes	-0.0219	0.000191	0.0225	-0.0396	0.142	2.38E-02	-0.0000129	0.00183	0.0461	0.321	-0.0109	0.0306
Specific type of disruption in mind												
No	-0.024	-1.49E-04	-0.0634	-0.201	-0.907	-0.184	0.000965	0.000943	-0.3	-0.809	-0.0527	-0.0706
Yes	0.0909	-0.0024	0.011	0.0261	0.171	2.85E-02	-0.000225	0.000607	0.356	0.276	-0.00149	0.0206
COVID: 'I am afraid to get infected with COVID'												
Neutral	-0.0161	-0.000337	-0.0596	-0.228	-0.916	-0.176	0.000915	-0.00175	-0.197	-0.701	-0.0465	-0.0695
Interaction parameter	-0.00661	0.000224	0.000278	-0.0499	-0.0906	-0.000664	0.0000325	-0.00396	-0.0189	0.0271	0.011	-0.0084
COVID: 'I avoid crowded places'												
Neutral	-0.016	-0.000413	-0.0602	-0.192	-0.843	-0.178	0.000917	0.00101	-0.181	-0.72	-0.0539	-0.0645
Interaction parameter	0.0211	-0.000423	0.00203	-0.0299	-0.187	0.00277	0.0000228	-0.00305	0.00739	-0.0203	0.00332	0.00348
COVID: 'I will continue to wear a facemask in the train'												
Neutral	0.0111	-0.000774	-0.055	-0.245	-0.937	-0.16	0.000741	-0.0055	-0.125	-0.619	-0.0363	-0.0677
Interaction parameter	0.0203	-0.000256	0.00396	-0.0405	-0.0655	0.0121	-0.00012	-0.00524	0.0451	0.0807	0.0154	-0.0032
COVID: 'I like to travel by train'												
Neutral	0.0249	-0.00137	-0.0617	-0.176	-0.786	-0.176	0.000931	-0.00054	-0.122	-0.668	-0.0524	-0.0746
Interaction parameter	-0.0396	0.000964	0.0014	-0.0174	-0.0751	0.000198	-0.0000347	0.00189	-0.0708	-0.0668	-0.00259	0.0115
COVID: 'I do not feel free to travel by train because of the crowding'												
Neutral	-0.0063	-0.000598	-0.0596	-0.229	-0.928	-0.174	0.000917	-0.00135	-0.121	-0.665	-0.0486	-0.0685
Interaction parameter	0.0141	-0.000279	0.000774	-0.0637	-0.129	0.00128	0.0000571	-0.00384	0.0981	0.0873	0.00927	-0.0075
Disruption information: 'During a disruption I trust the information about expected disruption length provided by NS'												
Neutral	-0.0039	-0.000622	-0.0599	-0.206	-0.865	-0.178	0.00094	0.00105	-0.195	-0.716	-0.0529	-0.0644
Interaction parameter	-0.0155	0.000383	-4.37E-05	0.0491	0.0447	0.00698	-0.000146	3.19E-05	0.0436	-0.0161	-0.000414	0.00102
Disruption information: 'During a disruption I trust the information in the travel planner app'												
Neutral	-0.0039	-0.000622	-0.0599	-0.206	-0.865	-0.178	0.00094	0.00105	-0.195	-0.716	-0.0529	-0.0644
Interaction parameter	-0.0155	0.000383	-4.37E-05	0.0491	4.47E-02	0.00698	-0.000146	3.19E-05	0.0436	-1.61E-02	-0.000414	0.00102
Disruption information: 'During a disruption I let previous experiences with disruptions guide me'												
Neutral	-0.0143	-0.000456	-0.0617	-0.229	-0.838	-0.172	0.000843	-0.00076	-0.206	-0.72	-0.0484	-0.0652
Interaction parameter	0.00294	0.0000256	0.00218	0.0427	-0.0131	-0.00321	0.0000475	0.00234	0.025	0.000412	-0.00545	0.00139
Disruption information: 'During a disruption I rely more on previous experiences with disruptions than the travel information from NS'												
Neutral	-0.00667	-0.000499	-0.0595	-0.196	-0.877	-0.168	0.000801	0.000355	-0.179	-0.715	-0.0558	-0.0609
Interaction parameter	-7.15E-03	0.0000634	-4.97E-04	0.00999	0.0603	-1.59E-02	0.000215	1.74E-03	-0.0126	-0.00826	0.00445	-0.006
Disruption information: 'During a disruption I follow the travel advice provided by NS'												
Neutral	-0.0092	-0.000508	-5.95E-02	-0.201	-8.56E-01	-0.179	0.000944	8.46E-04	-0.185	-7.31E-01	-0.0523	-0.0648
Interaction parameter	-0.00966	0.0003	-0.00201	0.0453	0.00264	0.00858	-0.00014	0.00165	0.0204	0.0639	-0.00808	0.00516