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Heterogeneity in route choice behaviour during unplanned train disruptions considering the possibility of teleworking

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ABSTRACT

Unplanned train disruptions are a source of passenger dissatisfaction because they are often accompanied by overcrowding and lack of information. To better accommodate passengers during disruptions and preventing travellers from switching to other less sustainable modes of transport, mitigating control strategies can be applied by railway operators. This however requires predicted passenger flows over all available travel options as an input. Due to the COVID-19 pandemic these passenger flows have become less predictable, as many travellers have gained an additional feasible alternative to cope with unplanned disruptions on outbound commuter trips – they may return home and start teleworking. Because this travel option is only available to teleworkers and now utilized more than before the COVID-19 pandemic, heterogeneity in route choice behaviour has increased. To fill this knowledge gap and provide predictions of passenger flows, an online survey containing a labelled stated choice experiment was carried out among Dutch train commuters. Consequently, a latent class choice model was estimated to investigate the influence of disruption characteristics, teleworking, COVID-19 risk perception and information provision on travel behaviour during train disruptions in the Netherlands and uncover heterogeneity in behaviour. Our results indicate that the strongest predictors of route choice behaviour are the moment of discovering the disruption, the disruption length and job characteristics. Uncovering four latent classes shows the different valuations of crowding, waiting times and additional travel times among commuters. Commuters with the option to telework are more likely to return back home during disruptions as well as commuters who are sceptic towards the provided information and those who are still conscious of COVID-19. Commuters who cannot telework and trust the provided information are more likely to reroute within the train network whereas commuters who cannot telework and do not trust the provided information are more likely to wait for the disrupted services to resume.

1. Introduction

Service reliability in public transport has a large impact on passenger satisfaction (Soza-Parra et al., 2019). Public transport services

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are often perceived as unreliable by passengers and the impact of service unreliability on passengers does not receive enough attention (van Oort, 2014) and is often ignored in behavioural models (Soza-Parra et al., 2022). Unplanned public transport disruptions can lead to delays and crowding in stations and vehicles which may cause discomfort for passengers (Kapatsila et al., 2023). These sudden disruptions force passengers to instantaneously shift their travel strategies and often switch to less familiar alternatives (Drabicki et al., 2021). In order to increase passenger satisfaction and prevent people from switching to other, less sustainable, modes of transport passengers should be accommodated better during unplanned disruptions assuming they cannot be prevented. Control strategies applied by public transport operators can help to mitigate crowding and also improve service regularity (van der Werff et al., 2019). Information such as the vehicle occupancy rate and the number of travellers waiting at stops are important inputs for such control strategy applications. 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 (Schettini et al., 2022). The share of travellers choosing for an alternative route is essential information to make informed decisions on the control strategies. Applying control measures during unplanned disruptions to mitigate crowding has become more important since the COVID-19 pandemic since crowding onboard of the trains is a factor that influences risk perception and therefore also travel choices (Shelat et al., 2022b). To apply the control strategies, information on passengers' coping behaviour during unplanned disruption is required to predict passenger flows as input to assess the effect of the control strategy.

Previous studies on unplanned public transport service disruptions have contributed to increasing knowledge on factors influencing travel behaviour during disruptions which are utilized in this current study. Those factors include the effect of travel information on train choice (Fukasawa et al., 2012) and mode choice (Bai and Kattan, 2014; Lin, 2017; Lin et al., 2018; Nguyen-Phuoc et al., 2018; Auld et al., 2020; Li et al., 2020) and how the information penetration rate and spread speed have an influence on network performance (Hua and Ong, 2018). How different information sources are utilized is studied by Drabicki et al. (2021). Also factors influencing waiting tolerance during unplanned disruptions have been studied (Bai and Kattan, 2014; Rahimi et al., 2019) as well as factors impacting passenger satisfaction during disruptions (Currie and Muir, 2017). Previous studies have also assigned passenger flows during system disruptions (Teng and Liu, 2015) based on stated preference surveys and multinomial logit models. In the study by Lin et al. (2018) revealed and stated preference experiments are combined to make the disruption scenarios more realistic for public transport users. Adélé et al. (2019) uses hierarchical clustering to construct eight behavioural profiles for suburban train passengers based on reported responses to disruptions. The study by Rahimi et al. (2020) investigates the impact of personal attitudes, socio-demographic attributes, information about the trip and the built environment on behaviour during unplanned disruptions. These studies were all performed before the start of the COVID-19 pandemic which has changed travel behaviour (de Haas, 2023). Because of the pandemic, many people have gotten used to working from home which is likely to alter their behaviour during unplanned train disruptions making it relevant to study this topic with the addition of the option to telework. The previous studies mostly focussed on changes in mode choice and route choice during unplanned disruptions however, to the best of the author's knowledge, during outbound commuter trips returning back home to work from home has not been studied as a valid option yet. It is expected that after the COVID-19 pandemic train commuters will partially continue working from home since 72% of respondents in the study by Ton et al. (2021) indicated that they have a high willingness to work from home and will continue to do so after the pandemic. For this group of commuters returning back home might be a viable option during a disruption on their outbound commuting journey and should therefore be investigated to accurately be able to predict passenger flows during disruptions and consequently efficiently apply control measures to mitigate crowding and increase service reliability. To better facilitate different groups of travellers during disruptions it is also relevant to investigate how personal characteristics such as perception of crowding and ability to telework after the COVID-19 pandemic influence the choice for a certain travel option which is currently unknown.

In order to address this knowledge gap, a stated preference method is adopted. A revealed preference study was not deemed suitable for this study since disruptions occur irregularly and passengers might be reluctant to answer questions as mentioned by Li et al. (2020). Smartcard data is widely available however during disruptions it is difficult to assign passengers to certain itineraries or trains because of different rerouting possibilities. With a stated choice experiment travel behaviour can also be related to personal characteristics of travellers. Because of these aforementioned reasons, a stated choice experiment approach is chosen. Based on the stated choice experiment a latent class choice model is estimated to predict passenger flows during an unplanned disruption and gain insight in the behaviour of different groups of Dutch train commuters who might respond differently to control measures.

The paper is structured as follows. The conceptual model based on a literature review which serves as a basis for the development of the SP experiment is described in section 2. The methodology entailing the survey design and model estimation methods used to perform the study are described in section 3. The results of the model estimation and description of the latent classes can be found in section 4. Finally, the conclusions, implications of this research, limitations and suggestions for future research are described in section 5.

2. Conceptual framework

In this section, a conceptual framework is developed to summarize the factors expected to influence travel behaviour during unplanned train disruptions in the aftermath of the COVID-19 pandemic. The conceptual framework is based on an extensive literature review considering unplanned public transport disruptions as well as expert information from NS (Dutch Railways). This framework is the basis for designing the stated choice experiment and help to decide which attributes and factors should be included. First, the different travel alternatives found in literature are discussed followed by the attributes of the alternatives, context factors and sociodemographics.

2.1. Alternatives

During an unplanned public transport disruption, different travel alternatives can be available to passengers depending on the network characteristics, disruption characteristics and context of the trips. Table 1 summarizes the different travel alternatives discussed in literature. The different alternatives include waiting for disrupted services to resume, reroute within the network of the disrupted mode, shift to other modes of transport, change destination or departure time and cancel the trip. All studies, except the research by Fukasawa et al., 2012 which focuses on the influence of travel information on train choice, investigate whether passengers shift to other modes of transport during disruptions. Waiting for the disrupted services to resume is not deemed a viable option in certain scenarios because rerouting within the network of the disrupted mode is a good alternative (Teng and Liu, 2015), disruptions are assumed to last for multiple hours (Currie and Muir, 2017) or because of the assumption that replacement shuttles are available (Teng and Liu, 2015; Currie and Muir, 2017; Rahimi et al., 2020). Rerouting within the network of the disrupted mode is not always possible due to network characteristics (Bai and Kattan, 2014; Auld et al., 2020; Li et al., 2020; Rahimi et al., 2020). Changing departure time or the destination and cancelling the trip is less common in literature. The stated preference survey by Auld et al., (2020) found that 15% of travellers would cancel the trip or change the destination. In revealed preference studies, cancelling the trip only occurred in a small part of the disrupted trips (2.6% (Currie and Muir, 2017) and 0.4% (Lin et al., 2018)). It is expected that due to the rise of teleworking the percentage of cancelled trips has increased significantly.

2.2. Attributes

In literature involving SP experiments, several attributes are found that influence travel behaviour during unplanned disruptions. These attributes are summarized in Table 2. As the travel time of alternatives routes increases, naturally the probability of choosing that travel option during disruptions decreases (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).

Tied closely together with the total travel time, the waiting time for an alternative route has a similar effect as the travel time (Fukasawa et al., 2012; Auld et al., 2020; Rahimi et al., 2020).

Waiting time can be associated with the time until the disruption is resolved and passengers can continue on their original route (Rahimi et al., 2019) or for example the time until a replacement shuttle or taxi departs (Auld et al., 2020). For rerouting in the network of the disrupted mode, additional transfers might have to be made. Transferring causes a large disutility and rerouting options become less attractive with an increasing number of additional transfers (Fukasawa et al., 2012; de Keizer et al., 2015; Li et al., 2020).

When switching to another mode of transport, costs of the trip might no longer be the same. Especially when booking a taxi the costs tend to increase and the studies by Rahimi et al. (2020) and Li et al. (2020) found the costs to have a significant negative utility. The SP survey by Lin et al. (2018) however found the costs to be insignificant for decision making.

Crowding was already defined as a factor influencing travel behaviour before the start of the COVID-19 pandemic since disruptions are often paired with crowded vehicles (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., 2022a,b).

Table 1
Research that investigates behaviour during unplanned services disruptions and the studied alternatives.

Number	Reference	Wait for disrupted services to resume	Shift to other mode of transport	Reroute with same mode of transport	Change destination/ departure time	Cancel the trip
1	Fukasawa et al., 2012			x		
2	Bai and Kattan, 2014	x	x			
3	Teng and Liu, 2015		x	x		
4	Currie and Muir, 2017		x	x		x
5	Lin et al., 2018	x	x	x		x
6	Adel�e et al., 2019	x	x	x	x	x
7	Rahimi et al., 2019	x	x			
8	Auld et al., 2020	x	x		x	
9	Li et al., 2020	x	x	x		
10	Rahimi et al., 2020		x		x	x
11	Drabicki et al., 2021	x	x	x	x	x

Table 2
Attributes in reviewed papers with stated preference experiments.

Number	Reference	Travel time	Travel cost	Number of transfers	Crowding	Waiting time
1	Fukasawa et al., 2012	x		x	x	x
2	Teng and Liu, 2015				x	
3	Lin, 2017	x	x			
4	Lin et al., 2018	x	x			
5	Auld et al., 2020	x	x			x
6	Li et al., 2020	x	x	x		
7	Rahimi et al., 2020	x	x			x

2.3. Context

The study by [Li et al. \(2020\)](#) found that if disruptions occur during peak hours, passengers are more likely to shift to other modes of transport since commuters are assumed to be more sensitive to time. Travellers with time constraints are more likely to reroute ([Adel e et al., 2019](#); [Rahimi et al., 2019](#); [Drabicki et al., 2021](#)).

If a disruption occurs during the morning peak hours, cancelling the trip and travelling back home might be a feasible option. As an example, on outbound journeys [Adel e et al. \(2019\)](#) found that 10.3% of respondents would wait for disrupted services to resume compared to 16.8 % of passengers on return journeys. While when a disruption occurs during the evening peak hours, cancelling the trip is not a feasible option since travellers want to travel back home. [Adel e et al. \(2019\)](#) argues that finding out about the disruption en-route makes it more likely to reroute while [Currie and Muir \(2017\)](#) state that finding out about the disruption beforehand makes rerouting more likely. There however is a consensus in both studies that the probability of cancelling the trip is higher if people find out about the disruption before starting their journey ([Currie and Muir, 2017](#); [Adel e et al., 2019](#)). According to [Adel e et al. \(2019\)](#) finding out about the disruption before the start of the trip encourages waiting, using a different mode of transport or cancelling the trip entirely. Another factor that increases trip cancellations is an increasing trip length ([Nguyen-Phuoc et al., 2018](#)). [Bai and Kattan \(2014\)](#) found that on summer days a shift to other modes was less likely while waiting for the disrupted services to resume was less likely on winter days.

Travel information during disruptions can include the expected length of the disruption and rerouting options. If information on the expected length of the disruption is not provided to passengers, they are more likely to shift to other modes of transport ([Lin et al., 2018](#)). [Fukasawa et al. \(2012\)](#) showed that when there was no information provision, travellers gravitated to a similar travel option while when information was provided travellers split up over different trains depending on their own preferences for crowding and additional travel time.

2.4. Personal characteristics

Background and sociodemographic variables affecting choice behaviour found in literature are listed below. From expert judgement new factors related to effects of the COVID-19 pandemic and their hypothesized effect are included as well.

- Older travellers are found to be more tolerant of higher waiting times ([Rahimi et al., 2019](#); [Drabicki et al., 2021](#)). A higher probability of cancelling the trip is also found to be affected by higher age ([Nguyen-Phuoc et al., 2018](#); [Rahimi et al., 2020](#)). People in the age group 18–35 years old are more likely to walk to their destination if the trip distance allows it ([Lin et al., 2018](#); [Drabicki et al., 2021](#)).
- The ability to telework is added to this study as a viable alternative for disrupted train services 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 outbound trip if a disruption happens since they can work there. People who do not have this option miss an alternative and therefore are expected to be more likely to reroute or wait for the disruption to be over.
- Another factor related to teleworking is if it is necessary to arrive at the workplace. It could be that people have the option to work from home but have an important meeting or event that requires them to travel to their workplace anyways. It is expected that the share of people returning back home will be smaller in that case.
- The COVID-19 risk perception is expected to have an effect on the sensitivity to crowding as discussed in subsection 2.2.
- It is expected that if people have had a negative experience with travelling during a previous disruption 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. [Drabicki et al., \(2021\)](#) found that people who regularly experienced disruptions are likely to change their alighting stop or departure time.
- 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 ([Adel e et al., 2019](#)).
- There is no consensus in literature whether familiarity with public transport has an effect on travel behaviour during disruptions. The study by [Lin \(2017\)](#) found that more experience with public transport increases the probability of rerouting because people 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](#); [Adel e et al., 2019](#)).

- If passengers have a lack of alternatives this increases their waiting tolerance (Rahimi et al., 2019). Similar results were found by Adelé et al. (2019) when people live at the end of a public transport line and therefore have few alternatives. Rahimi et al., (2020) found that waiting for a replacement shuttle is also more likely when travellers have less alternatives.
- People with access to a car are more likely to abandon public transport and switch to the car (Bai and Kattan, 2014; Auld et al., 2020).

2.5. Operationalization

For the case study the decision was made to focus on outbound commuter trips in the Dutch train network since commuters' behaviour is expected to have changed due to increased ability to telework and the possibility to return home and telework can only be investigated for outbound trips. Therefore the travel option of returning home and teleworking is included in the stated choice experiment. The focus of this study lies on short disruptions lasting up to one hour since the most common disruptions tend to have a duration shorter than one hour. One hour is not long enough to offer a replacement shuttle but does allow for waiting for the disrupted services to resume. Rerouting is the final alternative that is included in the experiment as rerouting in the Dutch train network is often possible. Shifting to other modes of public transport is excluded because of the focus on long-distance commuter trips. A comparison between the different alternatives is made based on travel time, waiting time, crowding on the platform and for the rerouting option the number of additional transfers as depicted in the conceptual framework. The attributes having an effect on the included alternatives and the sociodemographics and context variables included in the stated choice experiment are summarized in the conceptual framework presented in Fig. 1. The personal characteristics predict which respondent belongs to which class through the class membership function and each latent class has a different impact of the attributes on the utility. The set-up of the experiment is discussed further in section 3.

3. Methodology

In this section of the paper it is explained how the stated choice experiment is designed based on the conceptual model introduced in section 2. After that, the concept of the latent class choice model is discussed followed by the method of data collection.

3.1. Stated choice experiment

For the stated choice experiment, two different scenarios are created for outbound commuter trips. In one of the scenarios it is assumed that passengers find out about the disruption at the origin train station and in the other scenario passengers find out during the train journey and alight the train at an intermediate station. The two scenarios are visually depicted in Fig. 2. It was assumed that there are no COVID-19 measures in place, respondents are travelling to their workplace and they are not aware of the disruption before starting their trip. Another assumption is that rerouting is always possible within the train network. Although the Dutch train network

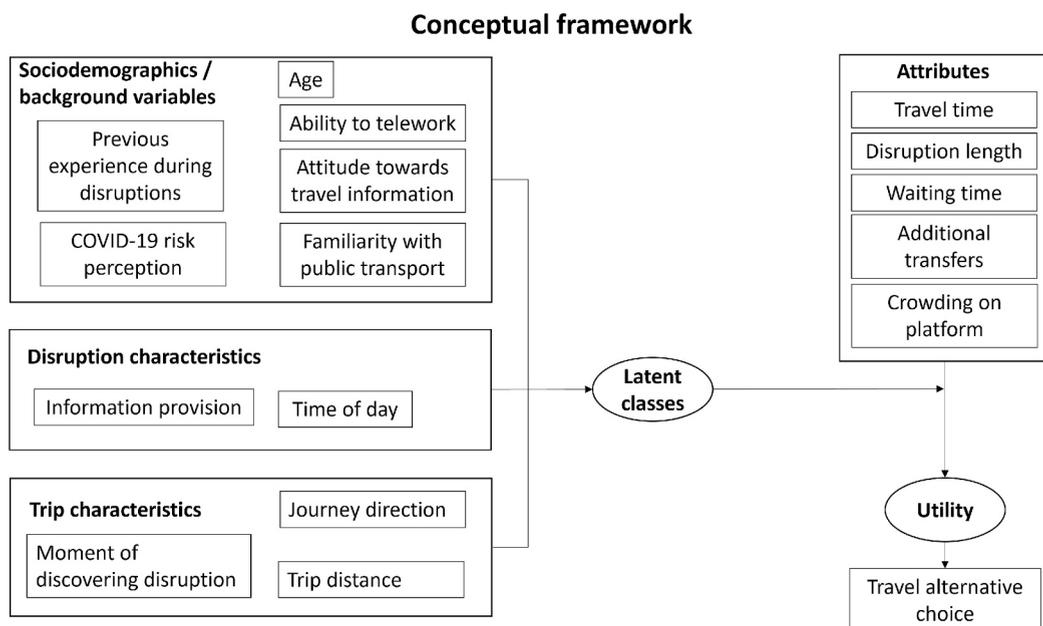


Fig. 1. Conceptual framework for the latent class choice model. Rectangular boxes show observable variables, oval boxes show unobservable variables.

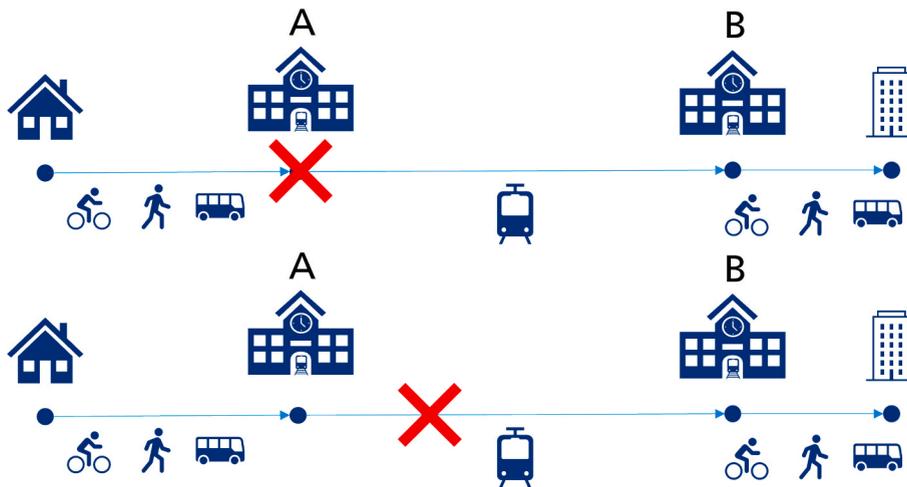


Fig. 2. Disruption scenarios. Top: disruption occurs at origin station. Bottom: disruption occurs during train trip.

is dense, connecting all parts of the country and all major urban areas and offering several rerouting options for many connections, in reality rerouting is not possible for all train travellers. The disruption length in the stated choice experiment is based on disruption data of the Dutch railway operator in 2022. This information is publicly available and shows that in 2022 the most common disruption was caused by rolling stock failure (1707 times out of 5499 disruptions in total) and resulted in a disruption lasting on average 39 min (Rijden de Treinen, 2022). Information on the expected length of the disruption was assumed to be available but respondents were notified that this information gives an indication of the disruption length and is therefore uncertain. Since only short disruptions are investigated in this study, another travel option, waiting for replacement shuttles provided by NS, is not in the scope of this research.

The attributes differ for the two disruption scenarios and are shown in Table 3. Rerouting travel times are specified as an addition to the normal travel time and a range for these values was obtained by using the travel planner in Google Maps (Google, 2022). The waiting time depends on the disruption length but also on the frequency of the trains. The crowding levels are based on the Fruin levels of service which defines crowding as a number of people per squared meter (Fruin, 1970). Level B, D and F are used in the experiment corresponding to low, medium and high levels of crowding respectively. The attribute levels are evenly spaced to make it easier to interpret the estimated effects (Lancsar and Louviere, 2006). All attributes have three levels to enable estimating non-linear effects.

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 compared to a random design (Bliemer and Rose, 2006). The experiment is designed using Ngen 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. Each respondent therefore is presented with twelve choice tasks in total and is randomly assigned to a block. Since the presentation format of the choice tasks has an impact on the choices that respondents make (Murwirapachena, 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. An example of the presentation of the choice tasks is shown in Fig. 3.

After the stated choice experiment, respondents also receive additional statements to measure their attitudes towards information provision, teleworking and crowding which are assumed to have an influence on the class membership model as discussed in section 2. The statements add extra information about the respondent and help explaining what factors influence the decision making. An overview of the statements can be found in Table A1-A3.

The survey is distributed to members of the NS panel which is a group of train travellers who can be approached to voluntarily give

Table 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 disrupted services to resume	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	–	–
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	–

<p>You are travelling to work. Your normal travel time in the train is 25 minutes. NS indicates that the disruption will last approximately 45 minutes.</p>		
<p>Wait till the disruption is over</p> 	<p>Reroute by train</p> 	<p>Travel back home</p> 
<p>Your normal travel time in the train is 25 minutes.</p> <p>NS indicates that this train will run again in approximately 45 minutes.</p> <p>Crowding on the platform where this train will leave:</p> 	<p>Your travel time in the rerouting train is 55 minutes.</p> <p>This train will leave in 15 minutes.</p> <p>Crowding on the platform where this train will leave:</p>  <p>On this route you will have to make 1 extra transfer.</p>	<p>The only travel time is the travel time from the train station to your house.</p>
<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

Fig. 3. Example of a choice task where disruption occurs at origin station (translated from Dutch).

their opinions on train and station services. Because of this construction, asking respondents for personal characteristics and socio-demographic information is not necessary since this is already provided and updated once every six months (NS, n.d.).

3.2. Model estimation

A choice model looks at the trade-offs that people make between different attributes influencing their decision process and aims to predict the choice for a certain alternative. Assuming that not all people have the same choice behaviour, a latent class choice model (LCCM) probabilistically assigns an individual to a latent class which each has their own choice model (Greene and Hensher, 2003). 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). Preferences within the classes are homogeneous but differ between the classes (Coogan et al., 2011).

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 $P_{in}(\beta_s)$ where S is the number of classes.

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

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 systematic utility which consists of a linear addition of attributes multiplied by the to-be-estimated β parameters.

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

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 decision as a decision from a different 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 .

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

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 which makes the models relatively compact compared to mixed logit and regular multinomial logit models. 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 (Bierlaire, 2020). Both disruption scenarios are combined into one model by dummy coding the disruption scenario using a zero for the scenario where the disruption occurs at the origin station and a one where the disruption occurs during the train trip. We tested the influence of the disruption scenarios on the other parameters as well but found this did not improve the model. Therefore, both scenarios are modelled with the same parameters to increase the transferability of the behavioural results. The alternative specific constants in the utility function are then coded as $ASC_{reroute} + ASC_{reroute} * SCE$ where SCE is the dummy variable indicating the disruption scenario as described before. Several different models are tested, varying the different utility functions, coding of variables, inclusion of variables, among which also quadratic components, and the number of classes. Based on the conceptual model described in section 2 and initial investigation of the results several variables were indicated to possibly have an effect on travel behaviour and were therefore included in the class membership model. Class membership parameters that were not significant in any of the classes were removed from the class membership model, namely; 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 4 along with the way they were coded in the class membership model.

The number of classes in the LCCM 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 (Louviere et al., 2000). A lower BIC value indicates a better model fit.

3.3. Data collection

Data was gathered between the 7th and 13th of June 2022. During this time period there were no COVID-19 restrictions in the Netherlands (Rijksoverheid, 2022). The survey was sent out to members of the NS panel who indicated that their main reason to travel by train is commuting. The data is filtered by removing:

- Incomplete responses

Table 4
Coding of variables that are significant in class membership model.

Variable name	Description
<i>Mobility related variables</i>	
Alternative transport available	Dummy (1 = yes; 0 = no)
Normal travel time in train	Ordinal
<i>Work related variables</i>	
Telework possibility	Dummy (1 = yes; 0 = no)
Necessary to arrive at workplace	Dummy (1 = yes; 0 = no)
Telework attitude	Likert scale (−2 Very negative, 2 Very positive)
<i>COVID-related variables</i>	
Avoid crowds	Likert scale (−2 Strongly disagree, 2 Strongly agree)
Continue to wear a facemask	Likert scale (−2 Strongly disagree, 2 Strongly agree)
Like to travel by train	Likert scale (−2 Strongly disagree, 2 Strongly agree)
<i>Travel information variables</i>	
Trust the disruption length prognosis	Likert scale (−2 Strongly disagree, 2 Strongly agree)
Trust information in travel apps	Likert scale (−2 Strongly disagree, 2 Strongly agree)
<i>Personal variables</i>	
Age	Ordinal

- Respondents who indicated that they are currently unemployed since it assumed that they do not travel for work by train anymore
- Responses with completion times smaller than five minutes since it is assumed that seriously answering all stated choice tasks is not possible in that timeframe
- Respondents who gave the same answer to all disruption and COVID-19 statements

4. Results

In this section the estimated models are shown and discussed. First, the survey sample is investigated in subsection 4.1. Determining the number of classes for the latent class choice models is discussed in subsection 4.2.

4.1. Descriptive statistics

A total of 888 respondents completed the questionnaire of which 73 respondents were removed due to the data filtering principles described above. The final sample therefore consists of 815 respondents.

Sociodemographic information of the sample is shown in Table 5. After comparing the sample with data from NS on the train commuter population it can be concluded that the sample is in general representative. It should 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. Of highly educated respondents 48% indicated that they do not trust and 31% that they do trust the communicated disruption length prognosis while for lower educated respondents these percentages are 32% and 43% respectively.

Table 6 shows the sample response to working related questions. The presented statements provide more insight on job characteristics and the statements on ability to telework, teleworking attitude and whether it is necessary to arrive at the workplace are also included in the class membership of the latent class choice model. Of all respondents, 81.2% responded that they can execute their work from home which is in line with previous research during the COVID- 19 pandemic by NS and the TU Delft (van Hagen et al.,

Table 5
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%
	Other	0.2%
Train subscription	Has a subscription	39.8%
	No subscription	60.2%

Table 6
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	65	99.4%
	No	84	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	74	1.1%
	I never work from home		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	21	26.0%
	Very important	264	7.9%
Necessary to arrive at workplace in mind during experiment (N = 815)	Yes	478	58.7%
	No	337	41.3%

2021;Ton et al., 2021). Therefore, for the majority of the respondents returning back home might be a viable option. 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., 2021;Ton et al., 2021). After the COVID-19 restrictions and working from home obligations people start travelling to their workplace again as can be seen in Table 6. 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. 33% of teleworkers indicated that they never work in the train and 27% always or often work in the train. 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.

4.2. 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 before adding different attributes to the class membership function. The results are shown in Table 7. For the different models the adjusted 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 (Masyn, 2013).

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 as shown in Fig. 4. After this point adding more classes does continue to lead to decreasing BIC values but the differences become smaller. The models are investigated to see if the different classes were 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

Table 7
Different number of classes model estimation. Initial log-likelihood is -10744.43.

# of classes	adjusted ρ^2	Final log-likelihood (LL)	# of parameters (k)	BIC
1	0.182	-8767.99	17	17692.17
2	0.288	-7614.82	35	15464.24
3	0.314	-7313.98	53	14983.23
4	0.335	-7070.55	71	14617.03
5	0.343	-6970.75	89	14538.07
6	0.348	-6895.55	107	14508.34
7	0.353	-6821.76	125	14481.42
8	0.360	-6734.06	143	14426.67
9	0.362	-6696.68	161	14472.57

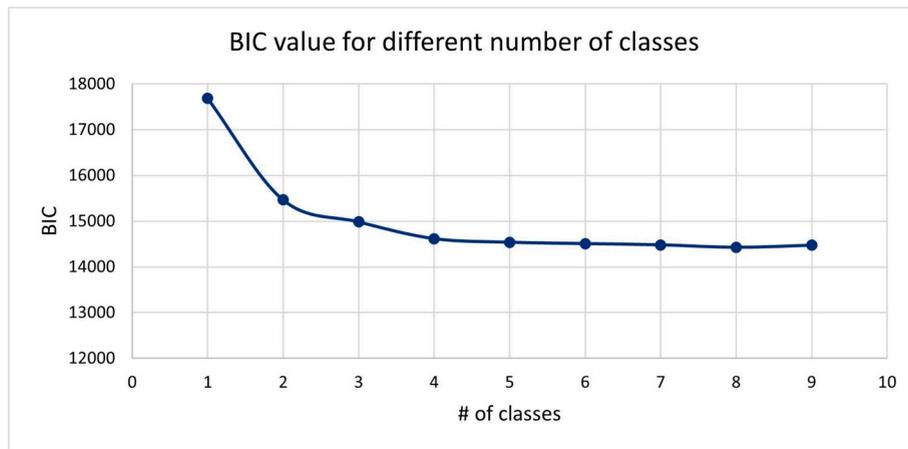


Fig. 4. The BIC-value for estimated latent class choice models with different numbers of classes.

the five-class model contained two classes with nearly similar trade-offs. Although the four-class model does not have the lowest BIC value, it is decided to choose this model since it provides a better interpretation of the results and is more parsimonious.

4.3. Model estimation results

The final four-class model has an adjusted rho-squared of 0.35 and a BIC value of 14452.17. The class membership includes

Table 8

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, adjusted rho-squared = 0.349 and BIC value = 14452.17.

	Class 1 (39 %)		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	-3.00
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			0.609	4.52	0.0147	0.0944	-0.188	-1.28
Alternative transport			-0.222	-0.815	-0.596	-2.08	-0.198	-0.751
Avoid crowd			-0.0941	-0.695	-0.254	-1.7	-0.0844	-0.534
Wear facemask			0.403	2.9	0.0971	0.48	-0.0514	-0.311
Like to travel by train			-0.278	-1.91	0.0985	0.52	0.407	2.7
Necessary to arrive at workplace			-0.981	-3.8	1.57	4.66	1.91	5.32
Telework possibility			-0.517	-0.973	-1.48	-3.8	-0.643	-1.39
Telework attitude			0.235	1.47	-0.329	-1.84	-0.191	-1.25
Normal travel time in train			-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

sociodemographic variables, individual travel behaviour characteristics and attitudes and therefore the final loglikelihood and BIC value are different than shown in Table 7 where a static class membership was used. The estimated model parameters can be found in Table 8. The parameter for the waiting time is fixed since the value was similar for all classes with the goal to make it easier to directly compare the classes. For additional information on the four latent classes, the mean of different attributes has been calculated for the entire sample and for each of the latent classes and can be found in Table 9. This comparison provides a detailed characterization of each of the classes in terms of sociodemographics and attitudes regarding teleworking, COVID-19 and information provision during train disruptions. The MNL model without latent classes is included in Table B4 for further reference.

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 and therefore control strategies during disruptions can therefore make travellers belonging to this class switch to a different travel option. For shorter disruptions this class is likely to choose to wait but when the disruption length increases, 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. This class is conscious of crowding and would wait roughly 10 min extra to go from extreme crowding (Fruin level F) to moderate crowding (Fruin level D). When looking at the personal characteristics of travellers in this class it is likely that they do to not have arrive at their workplace (51%), have the option to telework (44%) and have a positive attitude towards teleworking. Finally, travellers in the age group of 35–44 years old are more likely to be in this class.

Class 2 (19.8%): 'Sceptic returners' This class is mostly characterised by a preference to not wait at all. Even for short disruption lengths this class is 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. On top of that, the class is 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 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. The study by Dirkwager (2021) found that that a higher risk perception of COVID-19 leads to less train travel which is in accordance with the results presented here. 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 usual travel time in the train of below thirty minutes and aged between 55 and 64 years old are more likely to belong to this class.

Class 3 (18.2%): 'Trusting workplace travellers' In behaviour this class is similar to the 'Trade-off teleworkers' but with the difference that this class has a larger initial preference for rerouting and is 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 which is explained by the high share of travellers who cannot work from home and have to arrive at their workplace. 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. 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. The results for this class agree with the study by Adéle et al. (2019) which found that travellers who have a positive attitude towards travel information are more likely to reroute. The results described here indicate that people with less experience with travelling by train are more likely to reroute which is in accordance with the study by Drabicki et al. (2021). Travellers without alternative modes of transport available to them and access times over 30 min are also more likely to belong to this class.

Class 4 (23.0%): 'Endless waiters' This class is not sensitive to the disruption length since the corresponding parameter was not significant in the model. Even when the disruption length is 60 min 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. Travellers in this class are likely to not be able to work from home and therefore have to arrive at the workplace. They are also likely to be between 18 and 34 years old which is in contrast with the results of the studies by Rahimi et al. (2019) and Drabicki et al. (2021) which found that people with a higher age are more likely to wait for the disruption to be over. 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 likely to belong to this class. The study by Rahimi et al. (2019) also found that an increasing trip distance has a positive effect on the waiting tolerance which is also found in this study since people with a normal travel time of over 60 min are more likely to belong to this class. Travellers that do not trust the disruption length prognosis are much more likely to be in this class 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 min are more likely to belong to this class as well since returning home is less attractive when access times are very high so waiting might be more attractive for this group of travellers.

5. Conclusion and discussion

In order to increase passenger satisfaction during public transport service disruptions control strategies can be applied. To estimate the effect of a strategy however, the passenger flows during disruptions should be predicted. A latent class choice model based on a stated choice experiment is utilized to investigate travel behaviour and help predict passenger flows during unplanned disruptions in

Table 9
The mean value of sociodemographic variables, individual travel behaviour and attitudes in the entire sample and in each of the four latent classes.

	Alternative transport available	COVID statement avoid crowd	COVID statement facemask	COVID statement like travelling by train	Important event
Sample	0.67	0.10	-1.23	0.91	0.59
Class					
1	0.70	0.15	-1.28	0.89	0.46
2	0.68	0.33	-0.96	0.66	0.31
3	0.63	-0.11	-1.28	1.01	0.85
4	0.66	0.00	-1.31	1.09	0.84
Sample	0.81	0.90	0.46	0.79	0.64
Class	Telework possibility	Telework attitude	Gender	Travel experience	Subscription
1	0.91	1.05	0.46	0.81	0.64
2	0.90	1.19	0.44	0.80	0.64
3	0.55	0.48	0.48	0.75	0.63
4	0.76	0.73	0.46	0.77	0.63
Sample	0.17	0.25	0.26	0.32	
Class	Age between 18 and 34 years old	Age between 35 and 44 years old	Age between 45 and 54 years old	Age between 55 and 64 years old	
1	0.18	0.28	0.27	0.28	
2	0.07	0.17	0.29	0.47	
3	0.19	0.25	0.24	0.31	
4	0.23	0.25	0.25	0.26	
Sample	0.11	0.32	0.56	-0.22	
Class	Education level (low)	Education level (middle)	Education level (high)	Disruption statement trust prognosis	
1	0.10	0.31	0.58	-0.16	
2	0.12	0.35	0.52	-0.36	
3	0.15	0.33	0.51	0.09	
4	0.10	0.30	0.59	-0.46	
Sample	0.33	0.40	0.27	0.28	
Class	Normal travel time in train less than 30 min	Normal travel time in train between 30 and 60 min	Normal travel time in train more than 60 min	Disruption statement trust travel app	
1	0.33	0.41	0.25	0.27	
2	0.46	0.37	0.17	0.08	
3	0.36	0.41	0.24	0.36	
4	0.19	0.41	0.41	0.41	

the Dutch train network after the COVID-19 pandemic where teleworking has become more popular.

Whereas in previous studies returning back home during disruptions was negligible or not considered, in this study it has proven to be a viable travel option during disruptions on outbound train commuting trips. This is however only the case for people who can telework which in this study was 81% of the sample. Of these potential teleworkers 80% stated to have a positive attitude towards teleworking which is line with the study by [van Hagen et al. \(2021\)](#). 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 and for this group of people a disruption has the largest impact.

Four distinct classes were found by performing a latent class analysis. Teleworkers have a high likelihood of belonging to the 'Trade-off teleworkers' or 'Sceptic returners' class while people who cannot work from home are more likely to belong to the 'Trusting workplace travellers' or 'Endless waiters' classes. For the 'Trade-off teleworkers' class there is no clear preferred travel alternative because the attributes of each travel option heavily influence the chosen travel option. The 'Sceptic returners' have a large share of returning back home for each disruption scenario and are sceptic towards information and still conscious of COVID-19. The 'Trusting workplace travellers' however have a larger initial preference for rerouting and trust the provided information by the train operator. Finally, the 'Endless waiters' are insensitive to waiting time and therefore waiting for the disruption to be over is the preferred travel alternative for all disruption scenarios.

The practical implications of this research are the basis for policy makers and public transport providers to improve the service for passengers during disruptions. The commuters who have the option to work from home have an extra travel option in the case of a disruption compared to commuters who cannot work from home. On one hand, it can be argued that due to more people returning back home the importance of rerouting trains and adequate travel information becomes less important. On the other hand, the group of commuters who cannot work from home still have to arrive at their workplace and can only do so by rerouting or waiting. Therefore travellers belonging to the 'Trusting workplace travellers' and 'Endless waiters' classes should be accommodated by implementing changes in policy. Based on the characteristics of these classes it is recommended that public transport operators further improve the travel information especially clearly communicating the rerouting options and the expected duration of the disruption. Public

transport operator personnel can for example be present in the stations during larger disruptions to help passengers. To prevent teleworkers from returning back home and also to better accommodate people who wait for the disruption to be over, it is recommended to redesign train stations with facilities to telework or comfortably wait.

In order to prevent commuters leaving the train network and increase passenger satisfaction, crowding can also be mitigated during the disruptions. Especially the 'Sceptic returners' class are conscious of COVID-19 and do not feel to travel by train because of crowding. To better accommodate this group, for example, rerouting trains can be extended, though this may not be possible at such short notice when a disruption is unplanned, or the frequency of the rerouting trains can be increased.

One of the limitations of this study is that only disruptions shorter than one hour were investigated. Longer disruptions may lead to different travel options considering that replacing bus services provided by train operators might become an option in that scenario. 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 alternatives 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 mainly 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.

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 is given or known. 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.

Future 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 to mitigate the negative effects of unplanned service disruptions.

CRedit authorship contribution statement

Julia Bickel: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Conceptualization. **Nejc Geržinič:** Writing – review & editing, Supervision, Conceptualization. **Niels van Oort:** Writing – review & editing, Supervision, Conceptualization. **Menno de Bruyn:** Writing – review & editing, Supervision, Conceptualization. **Eric Molin:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

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

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Appendix A

Statements related to working characteristics, COVID-19, experience with unplanned train disruptions and information provision during disruptions.

Table A1
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

(continued on next page)

Table A1 (continued)

Working characteristics	Answer options
Teleworking attitude	Very negative Negative Not negative / not positive Positive
Travelling to workplace frequency	Very positive 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

Table A2

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

Table A3

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

(continued on next page)

Table A3 (continued)

Disruption related questions	Answer options
'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

Appendix B. MNL model

Table B4

Parameter value estimates for the base MNL model. LL = -8767.99, BIC = 17692.17, adjusted $\rho^2 = 0.182$. *** parameters are significant at 99 % confidence interval. Other parameters are not significant.

Name	Description	Unit	Value	Robust t-test
ASC_wait	Alternative specific constant wait for disruption to be over; disruption occurs at origin station	-	0	-
ASC_reroute	Alternative specific constant reroute; disruption occurs at origin station	utils	-2.70	-5.72***
ASC_reroute_SCE	Addition to ASC_reroute; disruption occurs during train trip	utils	1.20	7.27***
ASC_return_SCE1	Alternative specific constant return; disruption occurs at origin station	utils	-4.99	-10.6***
ASC_return_SCE2	Alternative specific constant return; disruption occurs during train trip	utils	-2.70	-8.50***
ASC_wait_SCE	Addition to ASC_wait; disruption occurs during train trip	utils	1.50	9.41***
β_{Access}	Taste parameter access time (time between origin station and home)	utils/minute	-0.0105	-1.43
β_{Access_Q}	Taste parameter quadratic component access time	utils/minute ²	-0.000461	-2.82***
$\beta_{Additional_tt}$	Taste parameter additional travel time rerouting	utils/additional minute	-0.0597	-20.5***
$\beta_{Crowding_D}$	Taste parameter for Fruin crowding level D	utils	-0.192	-5.04***
$\beta_{Crowding_F}$	Taste parameter for Fruin crowding level F	utils	-0.849	-22.2***
$\beta_{DisruptionLength}$	Taste parameter disruption length waiting time	utils/minute	-0.174	-7.90***
$\beta_{DisruptionLength_Q}$	Taste parameter quadratic component disruption length waiting time	utils/minute ²	0.000886	3.50***
$\beta_{Original_tt}$	Taste parameter original travel time in train	utils/minute	0.00115	0.465
$\beta_{Transfer_1}$	Taste parameter for one additional transfer during rerouting	utils	-0.184	-3.30***
$\beta_{Transfer_2}$	Taste parameter for two additional transfers during rerouting	utils	-0.721	-12.3***
β_{Return_tt}	Taste parameter travel time in train when returning home	utils/minute	-0.0531	-6.13***
β_{wait}	Taste parameter waiting time	utils/minute	-0.0637	-13.6***

Table B4 shows the values of the variables for the MNL model. 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. 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. 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. 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).

Data availability

The data that has been used is confidential.

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