Impacts of COVID-19 Risk Perceptions on Train Travel Decisions: A Hierarchicical Information Integration Analysis

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Impacts of COVID-19 Risk Perceptions on Train Travel Decisions: A Hierarchical Information Integration Analysis

Master Thesis

By

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SUMMARY

Travel behaviour has been drastically impacted by the coronavirus outbreak in 2020. Public transport was hit particularly hard as the very nature of mass transit is not compatible with the measures needed to stop spreading of the virus. While there is plenty of research being done about the transmission pathways of the virus there is no wide-spread consensus yet. There is even less known about how risk-enhancing (and -reducing) factors are perceived by public transport travellers. Insights in risk perception related to covid-19 infection in public transport can for instance help in the justification for taking appropriate spread-limiting measures, such as extra cleansing of contact surfaces or the obligatory use of mask. It is furthermore possible to identify if there are certain groups of people who are more likely to avoid the train.

Firstly, a clear definition of perceived risk of covid-19 infection is sought. The perception of risk is often conceptualized as a mismatch between the required outcome and the obtained outcome, multiplied with the weight one attaches to this mismatch and the estimated probability of this occurring (Yates & Stone, 1992). When considering a coronavirus infection as the threat, it is possible to define the mismatch as the personal impact of a covid-19 infection, the estimated probability as the likelihood of contraction (or cognitive risk) and the weight attached as the amount of worry one has about to the virus and pandemic as a whole (or affective risk).

In this research, an experimental set-up is constructed in which we capture how risk-determinant trip conditions are perceived and how important the risk is for travellers in choosing to go by train. We distinguish between different population groups based on sociodemographic, psychometric and travel behavioural characteristics to see if we can observe differences in risk perceptions across public transport users. To this end, a stated preference experiment is created in which a combination of a rating experiment and a stated choice experiment is used. In the top-left of Figure 1, is visualized that risk factors together with psychometric and sociodemographic attributes determine the perceived covid-19 trip risk. This trip (infection) risk forms the bridging element between the rating experiment and the choice experiment. The latter experiment measures the importance of an infection risk with the coronavirus relative to travel time and travel costs. This experimental set-up stems from the Hierarchical Information and Integration theory, first developed by Louviere (1984). The slightly adjusted approach in which one decision construct is used to measure relations of underlying observable attributes with a latent variable is already performed earlier by Molin et al. (2017). In the end, the experiments are combined by calculating the impact of risk factors on the chances of taking the train when these measures are taken and by monetizing the effect of some of these risk factors. The experiment is part of a stated preference survey conducted among 408 frequent and occasional train users (≥6 train trips per year) in the Netherlands.

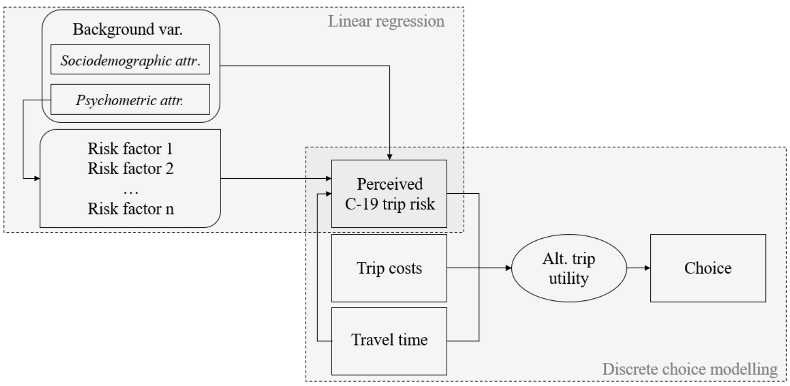

Figure 1. Experimental set-up

With regards to the risk factors that may determine the perceived infection risk, six were identified:

(1) On-board crowding
(2) Transferring
(3) Face masks
(4) Extra cleansing
(5) Infection rate
(6) Lockdown state

The first two are related to the specific train trip conditions. Obligatory face masks and extra cleansing of contact surfaces are two policy measures meant to reduce virus transmission. Lastly, there are two national contextual risk factors. The infection rate is an indication for how many infectious people there are and the lockdown state is a measure for how the government is intervening on a national level. In the rating experiment, respondents are asked to evaluate different train trips with variations of the risk factors in terms of their cognitive risk (likelihood of a virus infection) level. It is then possible to infer the impact of each of the risk factors via a multiple linear regression analysis.

The individual characteristics are also included in the linear regression. Those are not varied by design, but are individual-specific. The selection is based on a literature research on risk (perception) related to virus threats. A wide-range of psychometric predictors is selected which are expected to have an effect on either cognitive, affective or personal impact risk. Among these are health anxiety, the perceived control one has on spreading the virus, prosociality and media consumption. With regards to the sociodemographics, it is known for age that older people are more severely impacted by a coronavirus infection (Dong et al., 2020) and for gender that women are more risk averse in many fields (Weber et al., 2002) and also for covid threats specifically (Brown et al., 2020). Education level is included as it might also play a role in how trip conditions are perceived and how risk is traded off against other trip attributes (in the choice experiment). Differences in trade-offs are even more relevant for work status, given that the trip purpose determines the importance of a trip (Kim et al., 2017).

In the choice experiment, perceived risk has been traded-off against travel time and travel costs. Respondents are asked to choose between two train trips with varying levels of trip time, trip costs and trip risk, measured on a level corresponding to how risky the respondent would rate the train trip. To mimic real-market behaviour it is chosen to divide respondents into two categories, based on their most travelled trips. Travellers usually travelling shorter than 30 minutes are assigned to different choice tasks than travellers who usually travel longer. The respondent can also choose to make neither of the proposed train alternatives. When a respondent chooses to opt out, the intended activity is performed from home, is reached by taking the car or is cancelled. The intended activity (or trip purpose) is not varied by design, but chosen by the respondent and is the same for every choice task. Sociodemographic and some travel behaviour indicators are used to check for differences across the population.

The choice experiment design, which was constructed using a D-efficient design consists of 9 choice tasks, while the rating experiment has 12 rating tasks. The rating tasks are divided into two blocks to reduce respondent load. People are randomly assigned to one of the blocks. After conducting a pilot study (N=56), the main survey was distributed via an online panel. In total, 408 valid responses were obtained.

The first observation from the obtained data is that 27,2% of the responses did not take the train at all since the start of the pandemic, while they did so at least once each two months in the pre-covid era. The second observation is about what people indicate doing when they do not want to take the train (for any reason). Half of the respondents are using a private car instead, in order to be able to partake in the in the intended activity. However, a quarter of the respondents does not have access to a car and is therefore performing the activity from home or obliged to cancel the activity.

The results from the linear regression indicate that on-board crowding is the most important predictor for the perceived likelihood of getting infected with the coronavirus. The influence of crowding on the risk valuation is larger when worried about others or knowing people who have experienced the covid disease. In terms of predictive power, crowding is followed by the national infection rate. The policy measures mask usage and extra cleansing also have a significant effect on the risk perception of travellers. There are several psychometric indicators which are found to have predictive power for the perceived risk. Most important is the indicator that one is afraid to infect a loved one, which is consequently mostly affecting the impact of crowding on risk perception. Less important are being afraid for one's own health (health anxiety), the perception of control one has in spreading the virus and the perceived efficacy of personal actions to prevent spreading. With regards to sociodemographics, only being student is found to have an effect on risk perception. Students estimate the risk of an infection lower compared to other people.

The choice experiment results give insights in the relative importance of perceived risk in choosing between different train trips and not taking the train. Risk is found to be roughly 4 times more important than travel time and 2 to 3 times more than travel costs. The willingness to pay for one scale point (out of 5) reduction of risk (or value of risk) is around 4,64 euros for trips longer than 30 minutes. Interestingly, shorter trips are found to have a value of risk which is less than half (2,17 euros). This is indicative for the fact that the perceived risk increases proportionally with the travel time. However, an interaction effect between travel time and risk is not found to be statistically significant on 95% confidence interval. Trip purposes also did not appear to have any significant effect. The travel frequency did however. Unsurprisingly, people who travel more during the pandemic are less sensitive to the risk attribute.

A combination of both experiment results is used for two practical applications. The first application is a scenario analysis in which the policy measures are varied under different pandemic conditions. For an off-peak (30% seat occupancy) train trip which is longer than 30 minutes with infection rates as they were before the second infection peak in the Netherlands (0,006% of inhabitants is contagious) it is found that obliging everyone to wear a mask increases the probability of taking the train on average with 11,4%. For extra cleansing this is 7,2%. For a more 'dangerous' train trip in which seating occupancy is 60% and the infection rate is 0,010%, the effect of both measures is slightly less (mask usage: 8,1%; extra cleansing: 5,0%).

The second combined model application is the computation of a willingness to pay value for risk reducing factors. This is done for crowding and for the policy measures. The value of crowding for an average respondent in a long trip is calculated to be 0,88 euros per 10% crowding reduction. This means that an average respondent is willing to pay 88 eurocents to reduce the seating occupancy by 10%. This is translated into a time multiplier of 1,43 for easier comparison with other crowding valuation studies. Wardman & Whelan (2011) reported a time multiplier of 1,19, indicating that, however difficult to compare, crowding is valued more heavily in covid circumstances as opposed to normal conditions.

With regards to the willingness to pay for masks a wide range of values is found. The results are depicted in Table 1. The large variation is due to interacting background effects with both risk perception and the weight attached to perceived risk. On average, a traveller is willing to spend around 2 euros extra so that everyone wears a face mask in the train on a trip that takes longer than 30 minutes. For shorter trips this is less than half: 0,92 euros. The willingness to pay for extra cleansing is 1,33 in long trips and 0,61 for short trips.

Table 1. Willingness to pay for risk-reducing measures [euro per trip]

	Long trips average traveller.[a] [bandwidth]	**Short trips** average traveller.[a] [bandwidth]
mask	1,99 [1,11-3,95]	0,92 [0,39-1,32]
cleansing	1,33 [0,74-2,64]	0,61 [0,26-0,88]

[a]Values for an average traveller: age 39, employed, non-student, average frequency, average education level

The results from this study are helpful in making insightful how different trip conditions are perceived by travellers. Public transport operators find themselves in an awkward dilemma having an incentive to transport more people to maintain revenue at a respectable level, but also limiting the number of passengers to reduce the infection risks. Our contributions can help in making informed choices in how to get people back into public transport in a responsible manner while also reducing stress encountered by travellers. There are two important societal recommendations:

- It is important to reduce crowding levels in the train as it is perceived as the most determinative factor for attaining the coronavirus. Objectively speaking, this is probably also the case. Increasing capacity, reducing or spreading demand can help, but are not easily implemented. Better communication to the traveller about crowding levels could also be a solution direction.
- With regards to the safety measures which could be implemented in PT systems it is reported that obligatory mask use and cleansing do have a significant impact on the perceived safety of a train trip. When operators want to seduce people back into the train (if coronavirus allows for it), they might want to consider doing extra cleansing. Most importantly, they also will have to clearly communicate this to their passengers, given that disinfecting contact points is not directly visible.

One should be careful with generalizing the results from this study since risk perception is context-dependent. Other countries than the Netherlands might have other risk aversion cultures (Cornia et al., 2016), and other PT system characteristics. With regards to validity it has to be noted that by the nature of stated preference studies the choices made in the experiment might not be exactly the same as how people would behave in real-life (hypothetical bias). This might be especially true for opting out in this study as the consequences of opting out are not actually felt by the respondents.

It is recommended for future research to further look into the valuation of crowding as it found to be most dominant factor for risk perception in this study. It is possible to extend crowding with the policy measure in which only seats are available next to windows. The effect of different purposes could also be extended since there was no relation found in this study while it was expected. Having an essential jobs was not captured, however might be very important as public transport was in fact only meant for urgent purposes during the stricter lockdown periods. It is furthermore important to note that this study was performed while the context with regards to covid-19 knowledge was rapidly changing and possibly risk perceptions also changed as the pandemic progressed.

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Acronyms

C-19	COVID-19
CE	Choice Experiment
CR	Perceived Covid-19 infection Risk
HII	Hierarchical Information Integration
LR	Linear Regression
MERS	Middle East Respiratory Syndrome-virus
ML	Mixed Logit
MNL	Multinomial Logit
RE	Rating Experiment
RP	Revealed Preference
PT	Public Transport
SARS	Severe Acute Respiratory Syndrome-virus
SARS-CoV-2	Severe Acute Respiratory Syndrome Coronavirus 2
S.D.	Standard Deviation
SP	Stated Preference
TC	Travel Costs
TT	Travel Time
VOC	Value Of Crowding
VOR	Value Of Risk
VOT	Value Of Time
WTP	Willingness To Pay

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PREFACE

Dear reader,

This report is the final result of the TIL5060 thesis graduation project and serves as the finale of the master programme Transport, Infrastructure and Logistics at the Delft University of Technology. The thesis is performed under supervision of Dr. O. Cats (CEG/T&P), Ir. S. Shelat (CEG/T&P), Dr. E.J.E. Molin (TPM/T&L) and Prof. dr. ir. J.W.C. van Lint (CEG/T&P).

We are all affected by the coronavirus pandemic. Some suffered great losses, while others were able to transform their changed life habits into something positive. Nonetheless, it is very likely that this period brings about definitive paradigm shifts for society and possibly how we use public transport.

Diving into the topic of risk perception and the coronavirus pandemic has been a very interesting and above all, educative journey. Especially because of its high relevancy. In general, the whole project was a learning process in which I mastered how to structure a research of this scale. On the downside, writing and thinking about the coronavirus did not stop after working hours since the virus was constantly on the news and remained the number one topic to talk about. In the end, I am very glad to be able to contribute something to the existing body of knowledge concerning covid-19.

This thesis opportunity was given by Oded Cats, together with Sanmay Shelat who provided the general topic. I am grateful that I could perform this thesis as part of the Smart Public Transport Lab at the TU Delft, which granted the necessary funds for the distribution of the survey. Although the supervisors and me were never able to meet in person due to the pandemic, I experienced the supervision as a pleasant process. It showed that Oded took great care in providing all possible means to make the online co-operation as easy as possible. A special word of appreciation to Sanmay as my daily supervisor who was available at any time for feedback or (mental) support throughout the process. I would also like to thank Eric Molin as my second daily supervisor who especially helped me on the methodological choices that had to be made. Last but not least, Hans van Lint knew how to give constructive feedback in such an enthusiastic way that kept me motivated after every official meeting.

Then, I want to thank all respondents who filled in the pilot survey and provided their opinion. Lastly, I would also like to express my gratitude to my family and friends who supported me along the process, even when it was difficult for me. In particular, Adriaan and Siebren with whom I teamed up for structured work sessions

I sincerely hope you enjoy reading this research.

T.W. van de Wiel - 4869265

‘s-Gravenhage, March 17th, 2021

1. INTRODUCTION

The novel coronavirus (SARS-CoV-2) outbreak in 2020 has drastically affected the lives of people all around the world. During the global pandemic, many people are forced to work from home. Moreover, all sorts of (social) activities are cancelled to preserve social distancing and thereby limit spreading of the virus. Unprecedented changes were seen in travel patterns, mainly visible in a reduced number of movements. The usage of public transport (PT) was particularly heavily affected, partially as a consequence of governmental interventions. Because by definition many people are transported simultaneously in PT systems, the coronavirus can be transmitted relatively easily among travellers. During the first peak around April 2020, the Dutch national government encouraged people to avoid public transport as much as possible. A boarding reduction up to 90% was observed during the first month in which the first strict lockdown measures were imposed (Translink, 2021). Even though travellers gradually found their way back to the trains in the months afterwards, the highest PT usage has been around half of the demand observed in the same period one year earlier (Central Bureau for Statistics, 2020).

1.1. Problem definition

The issue with containing the virus and public transport specifically is that due to the highly connected nature of PT networks, many people from various origins and destinations come in contact with each other in enclosed spaces where transmission is easy. A covid-19 infected traveller may transmit the virus to an unknown group of people that spreads out very far to unknown destinations, which is undesirable when the virus needs to be maintained. For illustration, Krishnakumari & Cats (2020) found that on average, one person interacts with 1200 other travellers on a single trip in the Washington metro network.

It seems evident that spreading of the coronavirus is to be prevented in order to mitigate the public health crisis. However, a reduction in the usage of public transport also brings about undesirable effects in both the short and long run. First of all, a continued smaller share for public transport in the modal split results in a bigger share for cars, increasing road congestion and pollution levels. Secondly, public transport is an important link in the freedom of people. Especially to those who do not have access to a private car. Fear of using public transport might decrease the accessibility of certain (disadvantaged) socio-economic groups of people and thereby evoke so-called 'transport poverty', referred to when someone is unable to meet one's mobility or daily activity needs (Lucas et al., 2016). Avoidance is especially expected from people more vulnerable to viruses. When these people also do not have access to other forms of mobility, their accessibility can be severely limited. Therefore, it is highly relevant from a societal point of view to investigate a change in public transport use. If we know which specific factors play a role in risk perception during a train ride, it may be possible to take mitigating actions which reduce these specific factors. Apart from vulnerable groups, travellers not necessarily in the high risk category but perceive those risks as very high are also important to identify. Even when the coronavirus will be no longer be an immediate threat, insights into contamination fear for diseases in public transport remain important to understand. It seems likely that covid-19 will not be the last major virus-related disruption.

1.2. Research gap

While (at the time of writing) there is still scientific debate about the conditions which determine the probability of attaining a coronavirus infection, it is also not studied how dangerous these conditions are perceived by travellers. For example, Hu et al. (2020) studied the relationship between known risk factors and the transmission rates in public transport. Covid-19 was found to have a high transmission risk among train passengers, dependent on the density of passengers in a train and the use of personal hygiene protection. However, they did not investigate whether these conditions are also perceived as dangerous by passengers.

A wide spectrum of literature exists on fear-related effects on travel behaviour (Baucum et al., 2018; Elias et al., 2013; Molin et al., 2017), also caused by (previous) epidemics specifically (Fenichel et al., 2013; Liu et al., 2011; Wen et al., 2005). The coronavirus is not the first virus that has impacted people's daily routines. The closest related epidemics are the first SARS outbreak in 2003 and the more deadly Middle East Respiratory Syndrome (MERS) virus in 2012. The scale of the covid-19 outbreak is however much bigger and has, unlike SARS and MERS, turned into a global pandemic. Kim et al. (2017) already investigated the impact of fear after the MERS-virus outbreak on general travel behaviour in Seoul. They found that fear is able to change travel habits, depending on the adaptability of people. But again, the covid-19 pandemic is different in both scale (regional vs global) and impact. Moreover, it is suspected that covid-19 spreads more easily than the previously mentioned diseases due to milder symptoms which results in people still taking part in daily-life activities whilst contagious (Petrosillo et al., 2020).

While there are already several studies published aimed at covid-19 perceptions specifically (e.g. (Dryhurst et al., 2020; Mertens et al., 2020; Taylor et al., 2020), none of these are aimed at public transport specifically. With regards to studies about perceptions towards previous pandemics, since risk perception is believed to be both time- and spatially dependent (Cornia et al., 2016) another risk aversion culture in the Netherlands is expected as opposed to the countries which are previously studied. Previously mentioned studies also didn't specifically study how fear is traded off against other attributes such as travel cost or travel time, but rather concluded about the impacts and results of fear. A study about fear for contraction of the SARS virus in public transportation in 2003 revealed the exact ridership decrease (Wang, 2014), but again, the underlying trade-off mechanisms are not studied. Besides the knowledge gap in public transport systems, this study also uses a methodological approach which has not yet been applied to fear-related studies other than for safety perceptions in air travel (Molin et al., 2017).

1.3. Research goal

This study will focus on the role of risk aversion towards getting infected with the corona-virus in public transport travel decisions. Furthermore, the goal is to capture the effects of different trip and context conditions, such as the in-vehicle crowdedness and mask use, on the perceived risk. More specifically, this study aims at exploring the role of a perceived covid-19 infection risk in public transport travel behaviour. Secondly, it is about gaining knowledge about what people believe increases the infection risk in a public transport trip and about the personal characteristics that can explain the differences in risk perception among individuals.

1.4. Societal contribution and application

The knowledge about perceived risk increasing trip conditions can be used by operators and governmental bodies to take mitigating actions concerning the trip conditions that are found most important in determining the risk perception. Fear can have detrimental effects on an individual level, but can trigger better compliance for the measures which are taken, benefitting society as a whole. Insights into the perceived effects of the measures and context can therefore be used to ensure the take measures are appropriate, i.e. to ensure a good balance between personal harm, societal costs and control over the virus. Furthermore, the combined approach of the experiment used in this study can be applied for future disruptions.

1.4.1. Problem owners

There are several important actors. First of all, there is the public transport operator who has a dual interest. On the one hand, their profit is affected heavily because of low ridership levels induced by governmental measures and possibly fear. On the other hand, the operators are inclined to transport people in a comfortable and safe way. The expected travel behaviour is important for scheduling, allocating capacity and managing demand. Targeted mitigating measures on the conditions that are found most important in this study might decrease fear and nudge people back into the train. However, if virus transmission is to be prevented, the national government is likely to take measures that reduce the number of people travelling. The government is mostly concerned with minimizing virus transmission on the short term. Still, the government also wants to stimulate public transport use in the long run to prevent congestion on the road and reduce emissions. Lastly, the public transport users who, in normal condition, make trip choices mainly based on travel time, fares and comfort. During the covid-19 pandemic, a new attribute of consideration might come into play. Passengers are likely to avoid high chances of getting infected. Some people may be limited in their activities if they are restrained from public transport due to fear of covid-19.

1.5. Scope

While there are many facets to study, this research is performed in a limited time span. A clear defined scope is therefore needed. First of all, we chose to study effects under the assumption that the covid-19 virus is still contagious whilst vaccines are not widely available. It is important to place this ‘period’ in a wider time-line. We make a distinction between the ‘pre-covid-19’ travel situation and travel behaviour we are interested in, namely during (any form of) lockdown state. Afterwards, we have the phase in which all measures are lifted and lastly the long-term travel behaviour. The collection of data is performed in December 2020, when the virus was still active and stricter lockdown measures were imposed for the second time since the beginning of the outbreak.

This study is scoped towards the micro-scale of influence. This means that perceived risk and the corresponding trade-offs with other trip attributes are measured on the individual level. With statistical analyses it is attempted to make generalization of risk perception and behaviour for the population. The study is aimed at frequent (more than six times per year) train users in the Netherlands. Public transport is considered as one transport modality, but generally includes different forms of PT (e.g. train, bus, metro). The train is the most frequently used PT mode in the Netherlands (Central Bureau for Statistics, 2016). For simplicity sakes, only train trips are considered for this study. There are no major differences expected between risk perception in trains and other forms of public transport.

1.6. Research questions

This study aims at exploring the role of perceived covid-19 related risks in public transport travel behaviour. In order to meet this objective the following research question is put forward:

How does risk perception towards getting infected with the coronavirus influence travel behaviour in public transport systems?

A set of sub-questions is constructed to help reach the research goals and answer the main research question.

SQ1: To what extent influence trip conditions the perceived risk of an infection with the coronavirus?

SQ2: To what extent is the perceived risk of an infection with the coronavirus influenced by individual characteristics?

SQ3: How are travel time and travel costs traded off against the perceived risk of an infection with the coronavirus?

SQ4: How much of the decreased demand for train use in the Netherlands can be attributed to fear of getting infected with the coronavirus?

1.7. Approach

The first goal of this study is to estimate how travellers perceive the risk of getting infected with the covid-19 virus in PT as a function of different trip conditions. Secondly, we want to know how important the (perceived) risk is when choosing between different trips. To this end, an experiment is needed in which not only the risk anticipation of travellers is captured, but also in which the trip conditions are systematically varied. The solution is a stated preference (SP) choice experiment measuring risk perceptions for trips with varying exposure-increasing conditions. This set-up of the experiment has its foundations from the Hierarchical Information and Integration (HII) theory and is earlier used by Molin et al. (2017) to assess safety perceptions in flight choices.

The motivation to use this approach is best explained by pointing out that the perceived risk of a covid-19 infection during a PT ride is an irregular latent attribute. It is dependent on several underlying observable attributes. The underlying attributes are the risk factors (or trip conditions) which are determined by the specific train trip and pandemic context in which the trip takes place. Individual characteristics can also partly determine how someone experiences and weights up risk. The aim is to retrieve the relative contribution of each of the underlying attributes on the risk perception. By means of a rating experiment it is possible to retrieve the relations between the observable underlying attributes and the risk score. When the significant determinants for risk are established, it is possible to measure trade-offs between perceived risk and travel time and travel costs with the help of a choice experiment (CE). A benefit of this approach is that the respondent load is limited compared to regular CE , where all attributes are included in the choice tasks. An overview of the overall experiment is depicted in Figure 1.1.

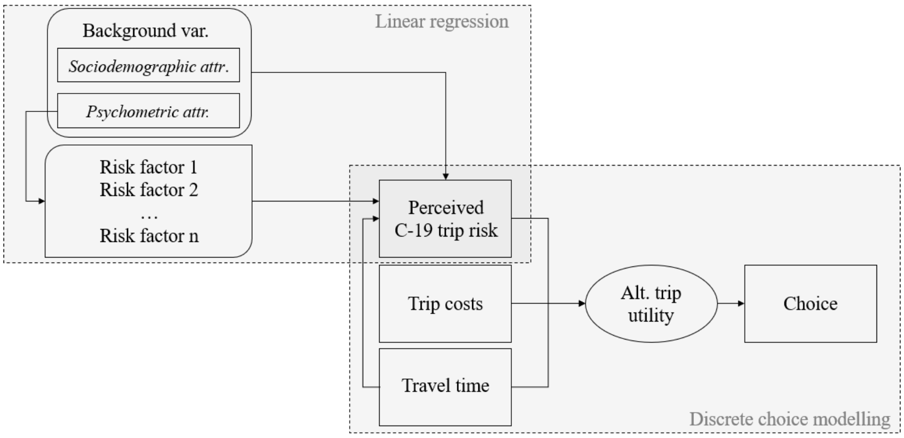


Figure 1.1. Overview experiment

1.8. Thesis outline

To give an overview of how this thesis is structured four research phases are identified which correspond to the chapters in this report. Figure 1.2 illustrates how the research is structured. The remainder of this report is structured accordingly.

In chapter 2, the relevant literature with regards to covid-19 travel pattern impacts (section 2.1) and to risk perceptions in general and for covid-19 risks specifically are reviewed (section 2.2).

An explanation of the used methods and the structure of overall experiment is given in the first section of chapter 3. The gained insights from chapter 2 are used to identify risk factors for public transport trips and relevant individual characteristics able to explain differences in perceptions during the pandemic, in section 3.1. We use the identified attributes to create a rating experiment (section 3.2) and a choice experiment (section 3.3). In section 3.4, the experimental designs for both the rating and choice experiment are constructed. A survey is designed afterwards in section 3.5. Subsequently, the data collection and estimation procedures are described in sections 3.6 and 3.7.

After the data is collected through an online panel, the data is analysed in chapter 4. General observations are done in section 4.1. Then, in section 4.2, the predictors for the perceived risk are estimated using a linear regression model. Secondly, the trade-offs are established via discrete choice modelling in section 4.3. Lastly, in section 3.4, the results of both analyses are combined to exhibit practical applications related to the willingness to pay for mitigating measures, the value of crowding and the travel reductions under varying circumstances.

The final chapter contains the conclusions. The research questions are answered in section 5.1, the limitations of this study discussed in 5.2 and some recommendations for future research are explored in the final section (5.3).

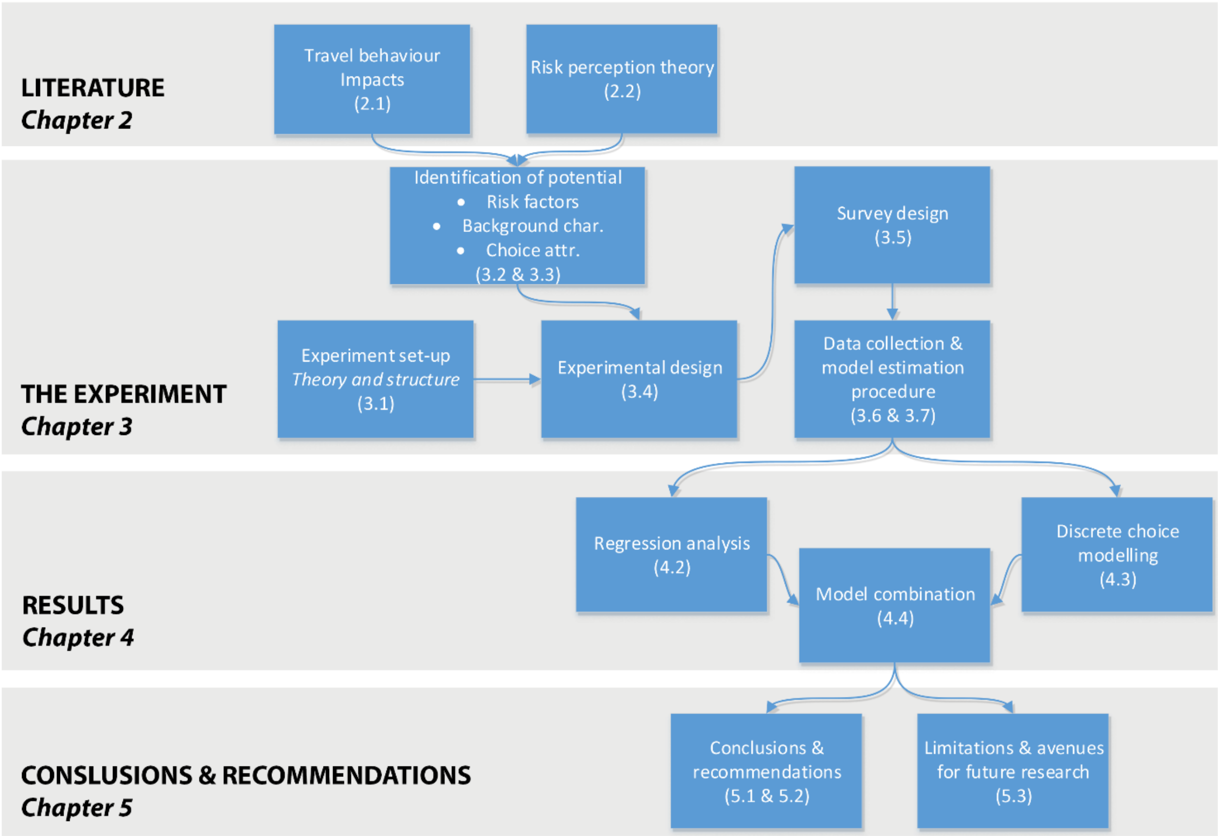


Figure 1.2. Thesis structure

2. LITERATURE

In this chapter, the current body of knowledge regarding covid-19 risk perception and the impact of disruptions is reviewed. The gained insights are used to set up the experiment for this study. Firstly, existing studies on the impacts a pandemic or disruption can have on public transport networks are discussed in section 2.1. Secondly, in section 2.2, we will define the concept of perceived risk and dive into literature about the perception of covid-19 specifically to find relevant individual characteristics.

We searched for scientific literature on covid-19 and other events which were disruptive for public transport (e.g. other epidemics, terror attacks and economic crises) in scientific databases such as Scopus and Google Scholar. Because at the time of writing there is still a lot unknown about the virus, whilst many studies are being performed, we also incorporated some working papers about covid-19. Besides, some non-scientific sources are cited..

2.1. Travel behaviour disruptions

In this subsection the following questions are answered. What are the public transport travel impacts due to covid-19 in the Netherlands? Whose travel patterns are mostly affected? And lastly, what changes are expected to stay permanent, after the virus no longer is an immediate threat to people?

The coronavirus outbreak caused the society to stop functioning as it used to do before. Because of measures imposed by the government, many people worked from home, could not go to their university or were forced to cancel other activities. Travel patterns were thereby changed. From a survey performed during the first wave of the outbreak in the Netherlands, it turns out that approximately 80% of people reduced the number of activities taking place outside their home (de Haas et al., 2020). Ridership rates in public transport systems also dropped dramatically (de Haas et al., 2020; Hu et al., 2020). During the so called ‘intelligent lockdown’ in March-May 2020, PT capacity was limited to 40% by the government and demand was reduced by 90% (Translink, 2021). Later on, in September, when the number of infected people was much lower, PT demand was still at 50% compared to pre-corona times (Central Bureau for Statistics, 2020).

Not all people change their travel habits in a similar way (if they even do so at all), during lockdown measures and after restrictions are withdrawn. These differences are potentially explained by several attitudinal and sociodemographic attributes. With regards to fear attitudes it is known from terrorist threats in public transport (Baucum et al., 2018; Elias et al., 2013), and previous pandemics (Kim et al., 2017; Wen et al., 2005), that fear is an important personal characteristic in travel behaviour changes. Fear of getting infected with the coronavirus depends on one’s health vulnerability (risk sensitivity), but also on the perceived likelihood of getting infected and how risk averse one is. Changes in travel habits are, according to Kim et al. (2017), also related to so-called ‘life fixity’; the extent to which one is able to change their activity patterns. Obviously, one is also less likely to avoid public transport when they don’t have an alternative mode of transportation available. Pawar et al. (2020) found that while PT was perceived as unsafe compared to personal modes in India, mode choice behaviour was not significantly affected. The most likely reason proposed is that people do not have alternative modes. A lack of alternatives can either be caused by the fact that one does not have access to a car or by the fact that travel distances are too long, eliminating active travel alternatives.

It is also to be expected that sociodemographic factors play a role in changed behaviour. For example, regarding gender, it is found in some studies that women are more risk-averse than men (e.g. Weber et al. 2002), and are therefore possibly more likely to avoid public transport. It has to be noted though, that gender could also be a proxy for another unknown variable. Besides individual characteristics, the reason one travels (trip purpose) is also relevant. Activities with higher daily responsibility are less likely to be cancelled or changed (Kim et al., 2017).

Currie et al. (2020, p. 15) developed a new framework for travel behaviour impacts on public transport due to covid-19, based on the theory of Planned Behaviour (Ajzen, 1991). They distinguish between the pre-covid-19 state and impacts during covid-19 shutdown, post-shutdown and long-term post-pandemic impacts. They also distinguish between impacts on different scales of influence. Preliminary results suggest that most changes will not remain permanent (Currie et al., 2020). Also, from Wang et al. (2014) we know that ridership levels recover to previous states as the number of infected people by SARS are decreasing.

2.2. Risk perception

In this subsection, we conceptualize the notion of perceived risk with the help of existing literature on risk perception. Afterwards, this conceptualization is applied to covid-19 as the threat. Already performed covid-19-related studies are reviewed to gain insights in what (individual) factors influence covid risk perceptions.

Perceived risk

The perception of risk is a widely studied topic. Conventionally, risk is measured by a simple multiplication of the probability of an event happening and the corresponding impact (see equation 2.1).

$$Risk = probability \cdot impact \tag{2.1}$$

This can be regarded as an objective definition of risk. Perceived risk however, also captures an individual-specific perception element. The difference in the objectively calculated risk and how threats are perceived is also referred to as the 'perception gap' and can be partly attributed to the one's awareness to the existing threat (Brawarsky et al., 2018). 'Being aware' is however ambiguous and multidimensional. The first one to use the term 'perceived risk' in consumer behaviour experiments was Bauer (1960). Afterwards, numerous studies tried to define perceived risk in different ways (Vlek & Stallen, 1980). Peter & Ryan (1976) argued that differences in risk perception among individuals can be explained by the difference in likelihood judgement of a risk and the degree of negativity attached to it. This is similar to the calculated risk above (equation 2.1), but differs in the fact that the probability and the impact are assessed by people themselves instead of as aggregated terms upfront. In line with this definition, Yates & Stone (1992) conceptualized perceived risk as a multidimensional mismatch between the required and the attained outcome of a service or product. They added an 'importance' factor to the calculation.

Perceived Covid-19 risk

When applying the above described conceptualization for risk perception to a situation in which covid-19 infection is the threat, we arrive at a formula which includes the likelihood of getting infected and the consequences of the illness (or perceived impact assessment) (equation 2.2). The below depicted formula (2.2) is about perceived covid risk on an individual level. Since it focusses on the likelihood of an infection, we talk about cognitive risk assessment. Besides the cognitive, there exists an affective risk dimension which is more about worry with regards to the pandemic on a larger scale.

$$Perceived\ covid\ infection\ risk = \ perc.likelihood\ of\ infection * perc.impact \tag{2.2}$$

It is now clear that perception of risk is a form of risk assessment. Conveniently, risk assessment is in line with the axiom about expected utility theory used in choice experiments. The judgement differences in likelihood, as well as the differences in impact assessment, can partly be explained by socio-demographic differences in society (Boksberger et al., 2007). The differences in impact judgement in light of covid-19 infections can be formulated in terms of how people perceive their personal sensitivity to covid-19, i.e. how heavily an individual is impacted by a potential infection. For covid-19, we know this is mostly influenced by age and underlying health concerns (Dong et al., 2020). Since young people are less severely impacted by a covid-19 infection as opposed to elderly, their impact judgement is also likely to be lower than elderly people. The likelihood judgement can less clearly be attributed to individual characteristics. However, there are various studies performed about perceived risk surrounding covid-19 infections and their psychometric predictors, based on both cognitive and affective risk assessment. Below we review some of these studies. The findings are used to feed into the experiment as background predictors in chapter 3.

Dryhurst et al. (2020) tried to investigate the risk perceptions of covid-19 from people all around the world (Europe, America and Asia). They set out a survey in March and April 2020, when the virus was relatively new to most countries, and measured the risk perception with a risk perception index to look for differences in perceptions all around the world. The index included how serious one thinks the pandemic is (affective), the perceived likelihood of virus contraction (cognitive) (by themselves or friends and family) and the level of worry (also affective). They tried to explain the differences with psychological and demographic predictors, which were largely based on a study about risk perception concerning climate change (van der Linden, 2015). Some predictors were correlated with higher risk perception levels. Among these are experience with the virus and how individualistic someone is. Gender was the only demographic attribute showing a significant relation. Men were found to generally have lower risk perceptions than women.

Gerhold et al. (2020) did a similar study on covid-19 risk perception, but only among German citizens. Data was collected at the end of March 2020. They operationalized risk perception as a scale with a cognitive and an affective dimension. Different from Dryhurst et al. (2020), they measured the effects of several qualitative dimensions of risk perception regarding covid-19. These qualitative dimensions are based on the psychometric paradigm from Slovic (1987). All elements of risk perception were covered in one survey with Likert-scale questions. They found that the elderly perceive a lower probability of getting infected than younger people, while we know the consequences of an infection are generally higher for older people (Dong et al., 2020). Interestingly, they also found that people generally think their relatives and friends are more likely to get infected than themselves. While most people are very worried about the virus and the pandemic, the fear of getting infected was found to be relatively low. This might indicate that some people are reluctant to accept there is an actual risk, thereby not changing their behaviour.

Also Brown et al. (2020) performed a study about experiences of covid-19 health-related risks, executed in the United Kingdom during the strictest lockdown conditions. They found that women perceive covid-19 as a higher risk than men. A relation between employment and risk perception was also found. The lower occupational (lower educated) class reported higher levels of risk than higher occupational class. Furthermore, Mertens et al. (2020) reported a positive relation between media use and fear for covid-19. They performed their study with a survey including a newly tailor-made questionnaire for fear related to covid-19. Besides Mertens et al. (2020), various other studies aiming to capture worry or fear for the coronavirus on a scale, are published. Ahorsu et al. (2020) developed a multidimensional scale to measure fear, worry and anxiety for the covid-19 crisis. Taylor et al. (2020) created a similar scale to capture stress and anxiety levels. Lastly, Engle et al. (2020) performed empirical research about what individual characteristics influence the perceived risk of covid-19 contamination in the US. They concluded that population density and the share of elderly in the population influence mobility reduction during covid-19 restrictions. Interestingly, also political affiliation was found to have significant explanatory power in explaining individual travel reductions to prevent disease spreading.

3. THE EXPERIMENT

In this chapter, the experiment is introduced and explained in detail. In section 3.1, the reasoning behind the use of stated choice experiments is discussed, together with the underlying theory on which choice experiments are based. The overall experiment structure will also be discussed. We will elaborate on how two different (choice and rating) experiments relate to one another and how these are linked. Afterwards, the rating experiment and the choice experiment are covered in detail in section 3.2 and 3.3 respectively. The selection of the alternative attributes and attribute levels is done for both experiments in these sections. The choice tasks are constructed in section 3.4. In section 3.5, the design of the survey is covered and in section 3.6, we describe how the data is collected. Lastly, in section 3.7, the estimation procedures for both experiments are covered.

3.1. Experiment set-up

In this section, the overall experiment set-up is explained. The theory behind discrete choice modelling and the specific method is introduced, after which the methodology is applied to our specific study.

3.1.1 Theory

The theory behind the methodology is explained in this subsection. First, the ideas behind discrete choice modelling are discussed, followed by an introduction on the Hierarchical Information Integration theory.

Discrete choice modelling

To assess the role of fear for contamination in travel behaviour, a stated choice experiment is constructed. We use discrete choice experiments based on the random utility maximization paradigm of discrete choice modelling. This is best explained as the rationale that when an individual is considering different alternatives, the alternative with the highest utility gain will be chosen. In simple words, the alternative which benefits most (or costs the least) for an individual, is chosen. The alternatives' utility (equation 3.1) is derived from the given attribute values and the associated parameter tastes (the systematic utility V_i; equation 3.2), together with a random error component (ϵ_i). The error component contains all attributes left unobserved in the experiment, while the systematic utility includes the choice attributes. The choice probabilities are then calculated using a logit formula (equation 3.3).

$$U_{i,} = V_{i,} + \epsilon_i \tag{3.1}$$

$$V_{i,} = x_i * \beta_i \tag{3.2}$$

$$P_i = \frac{e^{V_i}}{\sum_{i=1}^{I} e^{V_i}} \tag{3.3}$$

Hierarchical Information Integration theory

For this study we use a combined experiment approach stemming from the Hierarchical Information Integration (HII) theory developed by Louviere (1984). This theory assumes that attributes related to one another are combined into subsets by individuals. These subsets are called decision constructs and are usually used in choice situations where respondents are faced with choice alternatives with so many attributes that evaluating becomes difficult. The elegance of this method is that the relation of the (independent) construct variable with the (dependent) underlying attributes within the constructs can be estimated using separate rating experiments (Oppewal et al., 1994). A conventional choice experiment (CE) is then performed where trade-offs between the constructs can be estimated. The hierarchical structure is visualized in Figure 3.1.

An important benefit of this approach is that the respondent load is limited by reducing both the amount of information asked per respondent and reducing the complexity per choice task, as opposed to a regular CE in which all observable attributes are used in the evaluation tasks. This is beneficial because respondents tend to exhibit non-existent behaviour when faced with complex choices tasks or a large number of attributes in SP experiments, as for example depicted in the study from Arentze et al. (2003) where task complexity was found to have a significant effect on data quality.

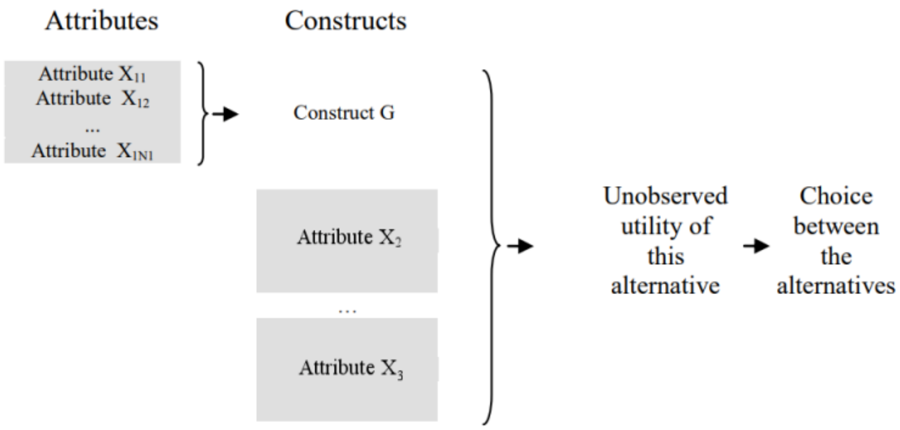


Figure 3.1. HII Construct conceptualization for this study (adapted from Richter & Keuchel (2012))

3.1.2. Experiment structure

The overall experiment set-up for our study is illustrated in Figure 3.2. The left column shows that the 'perceived covid-19 infection risk' is determined by 6 risk factors. At the right side it can be seen that in this study, it assumed that choosing a train trip (with a predefined origin and destination) is solely based on the trip travel time, travel costs and a perceived risk component for contracting the coronavirus. Other variables (e.g. comfort, level of service) may also play a role in real-life, but those are left unobserved in this hypothetical experiment (and thus captured in the error component) as these are not the focus of this study. The considered risk factors and trip attributes are further discussed in subsection 3.2.1 and 3.3.1 respectively.

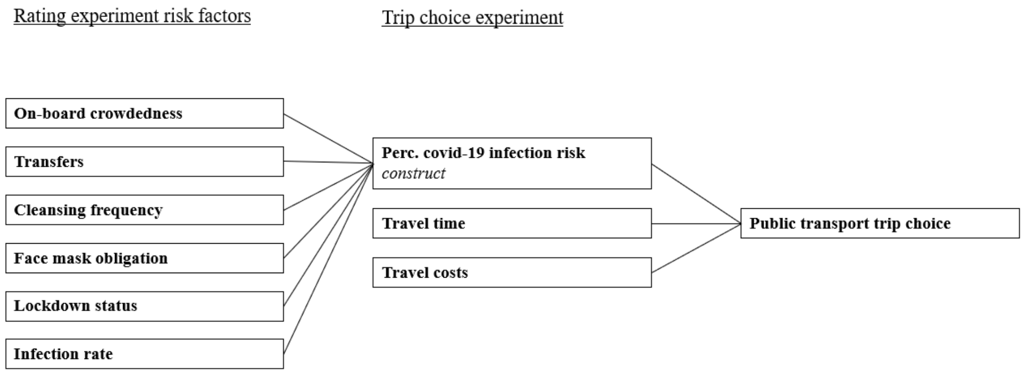


Figure 3.2. Schematic experiment set-up

The experiment is thus a combination of two separate experiments based on the HII theory. These are linked by the perceived covid-19 infection risk attribute, as is illustrated in Figure 3.2. In the rating experiment, the perceived risk serves as the independent variable, while it is one of the dependent variables in the trip choice experiment.

The application of HII theory is different from conventional HII experiments though. Its application is based on a study about safety perceptions in flight choices by Molin et al. (2017). The first difference is that only one construct is used, instead of more. The conceptualization of constructs is only relevant for one set of attributes: the perceived infection risk factors. Moreover, perceived infection risk is not just a gathering of similar attributes with the aim to limit the number of attributes for evaluating a choice alternative. Instead, covid-19 risk is considered to be a complex 'non-tangible' variable, which is dependent on underlying 'tangible' risk attributes. Through combining these underlying risk attributes into one risk construct, a CE reveals the trade-offs between covid-19 infection risk and the other non-risk related attributes (travel time and travel costs). The relative importance of the risk attributes is then measured with a separate rating experiment (RE). The other relevant choice attributes (time and costs) are considered as 'regular' choice attributes, without the use of constructs.

Stated Preference

Choice experiments are usually captured in SP surveys, questionnaires with hypothetical situations in which the respondent is asked to imagine as if it is a real-life situation and make choices accordingly. Revealed Preference (RP) surveys, on the contrary, are about choices respondents already made in real-life. Although RP data usually give more valid results (i.e. no hypothetical bias) it is hard to retrieve RP data in which risk perception is one of the variables. This is caused by the fact that perception variables are not directly observable in revealed choice behaviour. And since one of the goals of this study is to capture the significance of different factors influencing the perception of covid-19 risk in train trips, an SP study is needed. In fact, two different SP experiments are created in order to investigate the role of covid-19 risk perception in trip choices and to measure what is found to be most important for the risk perception.

3.2. Part I: Rating experiment

The first part of the overall experiment is the rating experiment. The attributes travel costs and travel time are quantifiable and easy to operationalize. Perceived covid-19 infection risk however, is not. First of all, it cannot be objectively measured. Secondly, it is dependent on other (underlying) perception-contributing attributes. Because the relation between the underlying attributes and the perceived infection risk is unknown, a rating experiment is created. In addition to different risk factors also individual (psychometric and sociodemographic) characteristics are taken into account. The individual characteristics can however not be varied by design, but only be inferred by the respondents. These are therefore not part of the experiment, but are used in the regression analysis later on. The rating experiment will determine the relative importance of all underlying attributes on covid-19 risk perception in train trips. A schematic representation of the rating experiment being part of the overall linear regression is shown in Figure 3.3.

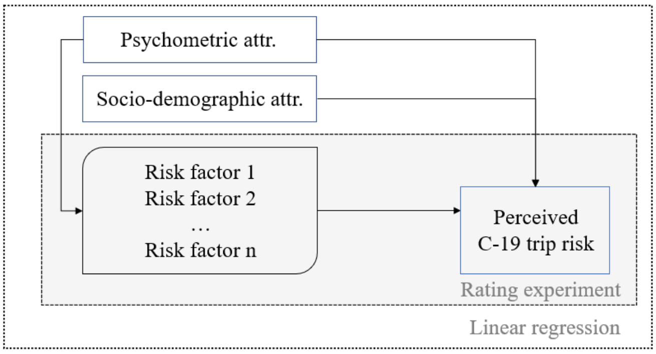


Figure 3.3. Schematic of rating experiment and regression analysis

In the rating experiment, respondents are asked to evaluate train trips with varying levels of the risk factors, in terms of the likelihood of getting infected (cognitive risk). The respondents rate the risk on a scale from 1 (very low risk to get infected) to 5 (very high risk to get infected). A linear regression analysis is then used to estimate the correlations between all risk factors and the perceived risk level.

In the regression analysis, the perceived covid-19 risk is the dependent variable. The risk factors together with the relevant individual characteristics are the independent variables. The most relevant ones are selected and discussed in the following subsections. We based the selection of attributes on current empirical knowledge about covid-19 transmission and risk perception discussed in chapter 2, supplemented with the author's own ideas. The risk factors are subsequently used for setting up the rating experiment in subsection 3.4.1. and together with the individual characteristics in the linear regression as explained in subsection 3.7.1. Some of the individual characteristics are also used for the choice experiment (subsection 3.1.3 and 3.7.2).

3.2.1 Risk factors

The selected risk factors consist of three policy condition attributes, two trip-specific conditions and one pandemic context indicator. These will be introduced together with the associated attribute levels. The number of levels for each attribute is limited to either 2 or 4 to reduce the number of choice sets in the experiment and thereby respondent load (see also subsection 3.4.1). All risk factors are ordinal-scale variables. An overview of all selected risk factors is given in Table 3.1.

- **On-board crowding:** The phase of a train trip in which it is most likely to get infected with the coronavirus is while inside the train. Trains (and PT vehicles in general) are not designed to distance people from each other, but rather to maximize the number of passengers in a relatively small enclosed space. The imposed distance between people to prevent virus spreading (1,5 meters in the Netherlands (Rijksoverheid, n.d.)) is therefore not feasible when vehicles are filled above a certain threshold. Hu et al. (2020) concluded that the infection risk is relatively high in confined spaces, such as trains and recommend to reduce passenger density. McKinsey (2020, June 5th) estimated that capacity is limited to around 15 to 35 percent compared to pre-pandemic levels if social distancing is to be maintained (with 2,0 meters distance in metro systems). Krishnakumari & Cats (2020) even reported that an 80% capacity reduction in Washington's metro system was required in order to adhere to 1,5 meter social distancing. Although estimations vary a lot, it is clear that the capacity reductions are significant.

It is known that crowding in PT is valued negatively by passengers, irrespective of any risk to obtain a disease. The notion that crowding has an increasing effect on the valuation of time is confirmed various times (Li & Hensher, 2011). Cox et al. (2006) proved that crowding can even be a threat to passengers' safety and health conditions (in terms of stress). It is expected that the presence of the coronavirus will make crowding even more important. Crowding is likely to have a positive relationship with the perceived infection risk. After all, encountering more people means a higher risk of meeting someone who's infected. Krishnakumari & Cats (2020) explained this relation by highlighting two exacerbating effects. Firstly, due to crowding, there is an increased likelihood of getting exposed to a contagious passenger. Secondly, closer proximity to others (due to crowding) leads to a higher probability of virus transmission between passengers. Preliminary results from Shelat et al. (2020) show that crowding indeed reduces the willingness to board train vehicles if offered a choice between less crowding and longer waiting times. This indicates that crowding is an important trip condition for risk perception.

There are various ways to represent crowding in public transport (Li & Hensher, 2011). Seat availability is used in this study because it is easy to convey to respondents and is one of the most frequently used ways to operationalize crowding. Next to that, an indication of the possibility to sit alone is given. This is done because it is expected that sitting next to another passenger (other than travel companions) is important in the infection risk perception.

- **Transfers:** Because boarding or alighting causes the most interactions with other passengers during a PT trip, even when it is relatively quiet, the risk of virus transmission is also relatively high. Similar to crowding, it is known that in 'normal' conditions, transfers in public transport are perceived highly negatively by passengers. In literature, this is often referred to as the 'transfer penalty' (e.g. Garcia-Martinez et al., 2018; Horowitz & Zlosel, 1981). Due to covid-19, this transfer penalty might become heavier. Furthermore, a transfer also results in entering a second train with new potentially contagious people inside.

  If we aim to measure an extra 'transfer penalty' it makes most sense to include a possible transfer as an attribute into the choice experiment. Yet, in this research, we model transfers within the rating experiment. This is done because the aim of this study is not to measure transfer penalties directly, but to measure relative contributions of different conditions (including transfers) onto the perceived infection risk. Modelling the effect of transfers in the rating, instead of the choice experiment, allows us to investigate whether the above explained risks associated with boarding/alighting and being in more than one train are also as such perceived by travellers. If we would choose to include transfers in a choice experiment it is not possible to separate the 'penalty' effect from the risk effect.

  The extra exposure risks due to a transfer may not be directly clear to respondents. But since we want to measure how travellers perceive certain conditions it is not wise to explain the associated increased risk with transfers.

- **Face mask policy:** To account for the fact that maintaining a safe distance between passengers is not possible inside trains, many countries have imposed a face mask obligation for PT. In the Netherlands, for all public transport services, wearing a face mask was mandated while inside a PT vehicle as of June 2020. Later, stations were added to this rule. Although the efficacy of this measure is internationally debated at the time of writing, it is clear that face masks are meant to reduce (direct) virus transmission (Greenhalgh et al., 2020). While critics in Greenhalgh et al. (2020) point out the dangers of community use of face masks due to wrong usage, there is evidence that face masks prevent virus spreading, especially by contagious people without symptoms (asymptomatic) (Howard et al., 2020). In the most up to date literature review, Abboah-Offei et al. (2021) conclude that wearing face masks serves a dual preventive purpose: protecting oneself and protecting others from getting a viral infection. Furukawa et al. (2020) highlight the role of presymptomatic and asymptomatic people in virus transmission and Prather et al. (2020) endorse the importance of blocking infectious air droplets from these asymptomatic contagious people, which can be done by wearing face masks.

  Regardless of the objective efficacy of wearing face masks (which is not the aim of this study), subjective safety may increase due to face masks. The rating experiment will determine the effect of mandating face masks in trains on the perception of safety. This attribute is varied as a binary variable: 'face masks are not mandatory inside trains' and 'face masks are mandatory inside trains for all people above age 13'. We chose to specifically state that masks only needed to be worn inside the vehicles because at the time of executing the experiment, this was the imposed rule by the national government.

- **Vehicle cleansing:** As discussed, there is (at the time of writing) still much unknown about the transmission pathways of the coronavirus. We do know that besides respiratory droplets in the air, the role of transmission via contact with contaminated surfaces is endorsed by several researchers (e.g. Guo et al., 2020; Morawska et al., 2020) and the World Health Organization (WHO, 2020). A review of existing literature on surface transmission by Kampf et al. (2020) shows that the coronavirus can persist on inanimate surfaces for up to as much as 9 days. They also concluded however, that disinfection of those surfaces easily inactivates the virus. Cleansing of all contact surfaces may therefore play a key role in the limitation of virus spreading. This will also be true for all chairs, tables, door handles and other contact surfaces in trains.

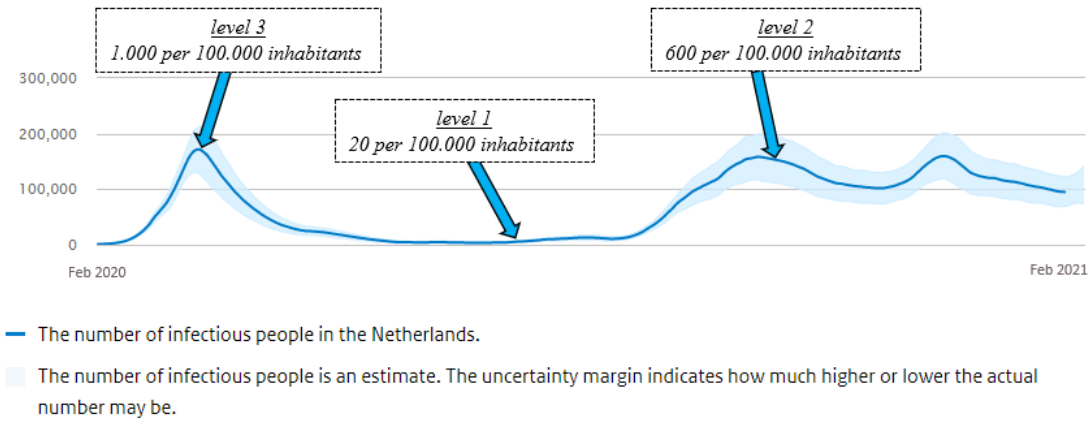
  Some public transport operators around the world did drastically increase their cleansing regime. For example in New York, where all contact points in the metro were extensively disinfected every night (MTA, 2020). Although these measures seem legitimate, some critics claim that indirect transmissions via surfaces are very rare and proper evidence is lacking (Thompson, 2020). The 'hygiene theatre' (as it is called by Thompson (2020)), seemed not so prevalent in the Netherlands (RTL Nieuws, 2020). An explanation may be found in the government's appeal on people's own responsibility. This 'soft' approach is also visible in Dutch PT systems where cleaning protocols from the operators did not change drastically since the beginning of the outbreak. The national rail operator NS indicated that extra attention is given to contact points, but only during cleaning rounds with a frequency similar to the pre-corona era (RTL Nieuws, 2020). Although the role of surface contamination may thus be limited, it does not detract from the fact that the *perceived* infection risk may decrease when travellers know the trains are cleaned regularly.

  In the experiment, the attribute is defined as a binary variable with 'no extra cleansing (regular cleansing protocol)' and 'extra cleansing rounds to disinfect contact surfaces'. We choose to limit the number levels to only two because it expected that the extra cleaning on top of an already increased cleansing protocol will not have a major impact on the rating. The normal cleansing regime of the NS is disclosed in the survey, to give a better understanding of what *extra* cleansing means.

- **Infection rate:** The infection rate is about the number of contagious people in the country. Unlike the other attributes, the infection rate is an exogenous risk factor and can be influenced by neither the operator nor the traveller. Yet, the infection rate is extremely important for the (objective) probability of getting infected during a train trip. With regards to perceived risks, studies on metro ridership in Taipei City during the SARS outbreak in 2003 reveal that the reported number of infected cases was indeed an important predictor for metro use (Wang, 2014).

  Infection rate is included as a risk factor in the rating experiment (and not as a context variable in the choice experiment) because it lets us measure the direct relation with the perceived infection risk. Infection rate is operationalized as the number of contagious people per 100.000 inhabitants. The attribute values are based on previous estimates from the Dutch National Institute for Public Health and the Environment (Ministry of Health, Welfare and Sport, 2020). Although the number of contagious people is always an estimate and may therefore be not entirely accurate, this metric is chosen because of its relative reliability stemming from its independence from changes in testing capacity.

  We chose the attribute levels in such a way that they present specific moments in time to which respondents can relate (see Figure 3.4). Respondents may not have a (good) understanding on how severe a given value for the number of contagious people is. To help interpret these values, we present the infection rates alongside dates for which these infection rates were estimated. The lowest level corresponds to the summer months (July/August 2020) when the number of reported cases was relatively low and virus transmission rather stable in the Netherlands (20 per 100.000 inhabitants). The second level corresponds to the period in time when transmission rapidly increased at the beginning of October 2020 (600 per 100.000 inhabitants) and the third to the highest observed peak in March 2020 (1.000 per 100.000 inhabitants). Lastly, we included an extreme value of 10.000 contagious people per 100.000 inhabitants. This value is unrealistic (has never occurred and will probably never occur), but is included to measure if extreme infection rates also affect risk perception proportionally more heavily.



Based on Dashboard Coronavirus from Ministry of Health, Welfare and Sport (2020)

Figure 3.4. First three attribute levels for infection rate

- **Lockdown state:** Lockdown state refers to the measures imposed by governmental bodies to limit coronavirus spreading across the population. From tap-in data from Translink (2021), a tentative relation can be observed between the governmental interventions and public transport usage. In October 2020 (during moderate lockdown), a 59% boarding reduction was reported, while the first intelligent lockdown caused at its peak a 90% reduction. The relative corona-wise calm summer months experienced the least travel decline relative to one year earlier. The demand reduction is related to compliance with the applicable measures in the given period. There is also reason to believe that the guidelines and rules stated by the government play a role in how people perceive the risks. From research on swine flu in the Netherlands (van der Weerd et al., 2011), and foot and mouth disease in the United Kingdom it is known that government handling is correlated with risk perception (Poortinga et al., 2004).

  Since the exact measures and tone of the government changed over time we need to capture the differences somehow. Strict lockdown measures were imposed during the peak of the pandemic in mid-April, loosened as the number of positive tested people and hospitalizations dropped in the summer and tightened again in September. What 'strict' means is geographical-dependent and relative. Other countries have had stricter lockdown measures. Still, in the Netherlands, social distancing and working from home became the norm during the so-called 'intelligent' lockdown (March-June). Also, measures specifically for public transport were imposed and later relieved again. So was transit use strongly discouraged from the peak (mid-April) until the obligated face masks were imposed (1st of June).

  Because defining demarcated lockdown states is thus somewhat arbitrary we refer to the periods in which specific measures are imposed or withdrawn, listed with a rough time-span. There are four levels ranging from 'normal life' with no restrictions nor social distancing to 'intelligent lockdown' in which working from home is strongly advised and bars, restaurants, theatres and schools are closed. In between is the 'social distancing state' in which social distancing and frequent handwashing are proclaimed, but no far-reaching rules are imposed. Lastly, there is the 'moderate lockdown' corresponding to the measures imposed in October 2020. This state implies that large-scale events are forbidden and a maximum of 30 persons is allowed inside one building.

  Note that the heaviest lockdown level is less drastic then the one experienced at the end of 2020, when all non-essential shops were closed and a curfew which was added in January 2021. However, given the data is collected before these increases, the full lockdown and curfew are not taken into account. Also note there is some overlap with the attribute face mask policy and lockdown state. One might argue that it is not realistic to create a situation in which face masks are obliged, while no lockdown measures are imposed. While the train operator cannot loosen national imposed measures, it may set stricter rules. It is therefore important to stress that the lockdown state is defined on a national level and face mask policy on the operator level.

Other risk factors

The trip travel time is also reviewed as a risk factor. It is widely accepted that the transmission probability of the coronavirus increases with the exposure time (e.g. Prather et al., 2020). Time spent in a train (in-vehicle time) can be seen as exposure time and is thus directly proportional to the actual exposure risk. Hu et al. (2020) proved that co-travel time (sitting inside a PT vehicle, close to a confirmed case) is indeed proportional to the objective infection risk. The notion that longer travel times are also likely to increase the perceived exposure risk is in itself not reason enough to include it in the rating experiment as a trip condition. Unlike transfers and the infection rate, it is chosen to place travel time as a variable in the choice experiment. To still be able to measure a relation, an interaction term is added in the choice experiment between travel time and risk perception.

Table 3.1. Overview risk factors

Risk factor	# levels	Attribute levels (Coding: explanation)	Risk category
On-board crowding	4	1: 10 % of seats occupied, almost empty, easily possible to sit alone 2: 30 % of seats occupied, quite easily possible to sit alone (no one next to you) 3: 60 % of seats occupied, not able to sit alone, but next to others possible 4: 100% (all) seats occupied; only standing places available	trip
Number of transfers	2	0: no transfers 1: one transfer	trip
Face mask policy	2	0: face masks are not mandatory 1: (non-medical face) masks are obligatory inside trains	policy (operator)
Vehicle cleansing	2	0: no extra cleansing of contact points 1: extra surface cleansing rounds during the day (on top of regular interior cleaning)	policy (operator)
Infection rate (number of contagious people per 100.000 inhabitants)	4	1: 20 per 100.000 (1 July 2020) 2: 600 per 100.000 (24 October 2020; 2nd peak) 3 1.000 per 100.000 (24 March 2020; 1st peak) 4: 10.000 per 100.000 (not observed; extremely high)	context
Lockdown state	4	1: Normal life; no restrictions, no social distancing 2: No lockdown: social distancing; urgent advice for frequent hand-washing and no handshaking 3: Moderate lockdown level: no more than 30 people indoors; events cancelled 4: 'Intelligent' lockdown: urgent advice for homeworking; restaurants/bars closed; maximum of 3 people at home	policy (national)

3.2.2. Individual characteristics

Besides risk factors, differences in individual characteristics can also be predictive for perceived risk. When measuring (risk) perception, there is by definition not a single true value, because it varies among people. In this section, the aim is to identify individual characteristics (predictors) which can explain the differences in risk perception. Or in other words, to find the characteristics which are correlated with a higher or lower perceived risk concerning covid-19 in the train. Unlike the risk factors, the individual characteristics are not varied among the profiles within the rating experiment but observed by questions in the survey.

Because there are many individual characteristics which may be correlated with risk perception and because the respondent load is to be limited, a preselection of relevant attributes is necessary. The selection is done based on the literature review about predictors for fear and worry concerning covid-19 as an extension of section 2.2. Many important predictors are found, but only a small selection believed to be relevant for covid-19 risk perception is used in this study. It is also worth noting that although most individual characteristics selected are already proven to be related to covid-19 risk or fear perception, it does not mean these are also correlated with risk perception in public transport.

The individual characteristics are categorized into psychometric, sociodemographic and travel attributes and elaborated upon below. The latter category is discussed in subsection 3.3.3. as these are only relevant for the choice experiment. A complete overview of selected attributes can be found in Table 3.2.

Psychometric predictors

The first category of individual characteristics is the psychometric predictors. The selected predictors are for the most part stemming from the covid-19 studies from Dryhurst el al. (2020) and Mertens et al. (2020). Both studies were performed to retrieve relations between personal characteristics and attitudinal covid-19 risk perception. The selection criteria for our analysis are that the characteristics need to have a significant relation with perceived risk, but also that these should be relevant for public transport in some way. In addition to relevant psychometric attributes, two indicators that directly measure the cognitive (worry) and affective (contraction likelihood) higher level (non-PT specific) risk and one risk attitude metric are included. Because most psychometric predictors are perception-dependent variables (and thus not directly observable), the psychometrics are measured using Likert-scale statements.

- **Prosociality:** One of the most important predictors in the model for covid-19 risk perception from Dryhurst et al. (2020) is prosociality. Prosociality can be explained as all forms of behaviour that are intended to benefit others (Jensen, 2016). Prosociality is supplemented with the notion that benefiting others comes at some sort of personal costs. Translating this to a context for this study it can be explained as follows: limiting the spread of the coronavirus in PT systems is strongly dependent on the behaviour of travellers. To prevent spreading, people need to adhere to some rules and those rules come at a personal cost (e.g. wearing a face mask, giving others sufficient space when boarding, etc.).

  By including prosociality in the experiment, we are able to measure if the willingness to make such sacrifices is correlated with perceived risk in public transport. It is expected that people who are more prosocial are more likely to be in favour of obligatory mask use, given it's a measure that is causing personal nuisance, but serves the main purpose of protecting others. Prosociality is measured with a Likert-scale statement about to what extent the respondent is willing to take actions to benefit others in turn for some (undefined) personal costs.

- **Personal Efficacy** is about the extent to which someone believes he/she can contribute in some way to controlling the pandemic. This attribute rates the believed efficacy of the actions one takes on a scale from 1 to 5. The respondent is asked if the actions they take to limit virus spreading are making a real difference. Low levels of personal efficacy are expected to predict higher risk perception levels. Furthermore, the believed efficacy is expected to correlate with the impact mask usage has on the perceived risk level.

- **Perceived control:** Similar to personal efficacy, perceived control is a measure for the believed effectiveness of personal actions. The difference is that perceived control is about the micro-scale. It relates to reducing the probability of contracting the coronavirus personally, instead of contributing to limiting the spread of the virus for society.

  It is already proven for general risk taking behaviour that people prefer controllable risks over risks that are not in their sphere of influence and thus are assessed as less risky (Weinstein, 1984). Although Dryhurst et al. (2020) did not find a significant relation with perceived risk, we still use this attribute in our regression because the believed effectiveness of the actions that are taken by travellers to limit spreading (e.g. wearing face masks) is likely to be correlated with the perceived infection risk. Higher levels of control will probably mean that lower perceived risks are observed. The impact of the policy measures (mask use and cleansing) is also likely to be affected by perceived control.

- **Governmental trust:** From the global risk review from Dryhurst et al. (2020) it appears that trust in government is correlated with covid-19 risk perceptions in some of the researched countries (Spain and South Korea). The relation exists in such a way that high trust corresponds to lower risk perception for covid-19. If trust is also correlated with perception in our sample, it makes sense to assume that the measures communicated by the government (i.e. lockdown state) are also likely to be correlated with risk perception.

- **Risk for loved ones:** In the study by Mertens et al. (2020), the concern level related not to one's own health, but other people's health is one of the strongest predictors for covid-19 fear. Apparently, many people want to protect others that are close to them. This might also play a role in using public transport. Some travellers might be more cautious or avoid public transport to prevent getting infected and thereby transmitting the coronavirus to other (more vulnerable) family members or friends.

- **Health judgement:** Besides caring about the health of others, Mertens et al. (2020) also found a significant relation between the stated health condition and covid-19 fear, albeit weaker than risk for others. Since it is known that underlying medical conditions (even relatively mild ones) increase the odds of a more severe covid-19 illness (Cai et al., 2020), the health condition is expected to be correlated with risk perception. Yet, there is a mismatch between people who are at higher risk of having severe illness consequences and the observed risk perception (Mertens et al., 2020). Fear of covid-19 is more affected by how people perceive their health than how vulnerable they actually are. The perceived vulnerability appears thus to be very subjective and not necessarily relate to who is factually more vulnerable. In our survey, respondents are asked to rate their health on a scale from very unhealthy (1) to very healthy (5).

- **Health Anxiety:** Health anxiety, the tendency to misinterpret symptoms and believe one is ill while in fact being healthy, is measured for the covid-19 study by Mertens (2020) with the Short Health Anxiety Survey (SHAI) developed by Salkovskis et al. (2002). That people who are anxious about their health will report higher risk perceptions seems eminent. It is interesting to see if one of the risk factors is specifically related to health anxiety. To measure health anxiety, one of statements concerning worry about health from the SHAI is included in the survey (see Appendix E: Survey questions).

- **Virus experience:** It was found all around the world that people who have had direct personal experience with the virus (if someone has had covid-19), perceive higher risks than people who don't have the experience (Dryhurst et al., 2020). This is consistent with literature on risk behaviour in general, as for example with suffering from consequences due to climate change (e.g. van der Linden, 2015). An interpretation of this effect is that attaining the coronavirus strongly affects the affective dimension of risk perception and thereby the overall risk perception. In order to comply with ethical research regulations it is decided to ask respondents only about if they know someone who has had coronavirus.

- **Media consumption:** Media usage is known to influence people's fear levels. More exposure to media is generally associated with higher fear levels. This was for example proved for the Avian Flu with a survey across 23 countries in the European Union (Van den Bulck & Custers, 2009). Mertens et al. (2020) confirm that media exposure is also heavily correlated with fear for covid-19. Media exposure is defined as deliberate information gathering from all sorts of media.

  In our survey, respondents are asked if they deliberately searched or read information about the coronavirus or pandemic. The second option is that one's main source of information is regular media. The last option given is 'I rather avoid information regarding corona'. We might observe differences in risk perception between people whose primary information source is regular media as opposed to people who do their own research as the latter category might be an indicator for people who are more critical-minded towards the coronavirus. Media consumption can be an important predictor for the importance given to mask use and cleansing in particular, since these measures are debated in the media.

- **General covid-19 risk elements:** All (higher level) risk perception elements concerning covid-19 are observed by direct questions. For the affective risk, respondents are asked to rate how much respondents worry about the coronavirus or pandemic. The cognitive risk is captured by a rating about the likelihood of contracting the coronavirus in general (outside PT) on a scale from very unlikely to very likely. Lastly, general covid-19 attitude is covered by asking how serious the pandemic is to society as a whole.

Sociodemographic predictors
Sociodemographic predictors are directly observable individual characteristics which might also influence risk perception or behaviour. Among the demographics are age, gender, education and works status.

- **Age:** Research shows that young people are less severely impacted by an infection with covid-19 (Dong et al., 2020). This is also endorsed by the World Health Agency (2020). One might expect that elderly are therefore more cautious in their behaviour. This expectation is confirmed by a study with a representative sample for the Netherlands which indicated that elderly reduced their activities significantly less than younger during the 'intelligent lockdown' (de Haas et al., 2020). Also, Shelat et al. (2020) found that older respondents were significantly overrepresented among crowd-averse travellers. Moreover, it is expected that younger people are less obedient to the corona measures because they are more likely to prioritize social interactions (Smetana et al., 2006). On the other hand, there is scientific evidence that young people have more dread of hazards (Savage, 1993).

  Studies concerning covid-19 fear so far did also not find the expected relationship between age and covid risk perception (Dryhurst et al., 2020; Mertens et al., 2020). Survey results from a German sample, conducted by Gerhold et al. (2020) even suggest that older people estimate the risk of getting infected as less than younger people do. This could imply the opposite of what is stated above: that younger people behave more cautiously towards serious dangers. The relation between age and covid-19 risk perception (negative or positive) is therefore interesting to investigate.

- **Gender:** There exist numerous studies that indicate women are more risk averse than men (e.g. Weber et al., 2002). Although this might also just be a proxy for another variable, there is also prove that sex matters in risk perception concerning covid-19. Both Brown et al. (2020) and Dryhurst et al. (2020) found that men reported lower levels of perceived risk towards covid-19 than women. This is confirmed by Shelat et al. (2020) in their crowding evaluation study.

- **Education:** Education level could also play a role in risk perception as this might be proxy for how aware people are. Although the results from Dryhurst et al. (2020) indicate a non-significant parameter for education level, Brown et al. (2020) found a negative relation between occupational class and covid-19 risk perception, indicating that people with a university degree perceive the affective risk as lower. We might see that differences in education lead to a difference in awareness for the coronavirus or for the importance of taking mitigating measures.

- **Work status:** Going to school or commuting for a job can determine the need for using public transport services. This is captured in the work status attribute. Activities related to work usually attain a higher priority and are less likely to be cancelled during lockdown measures (Kim et al., 2017). We don't have any expectation regarding a relation between being employed and higher perceived risks though.

Table 3.2. Overview background predictors

Individual background variables	scale	# levels	predictor category
Prosociality	interval (Likert)	5	psychometric
Experience	categorical/binary	2	psychometric
Personal efficacy	interval (Likert)	5	psychometric
Perceived control	interval (Likert)	5	psychometric
Health judgement	interval (Likert)	5	psychometric
Health anxiety	interval (Likert)	4	psychometric
Risk for loved ones	interval (Likert)	5	psychometric
Governmental trust	interval (Likert)	5	psychometric
Media consumption	ordinal	3	psychometric
Gender	nominal/binary	2	sociodemographic
Age	ratio	-	sociodemographic
Education	ordinal	5	sociodemographic
Work status	nominal	2	sociodemographic
Trip purpose[a]	nominal	2	travel
Trip frequency[a]	ordinal	6	travel
Trip length[a]	nominal	2	travel
Car availability[a]	ordinal	4	travel

[a]only relevant for choice experiment (see subsection 3.3.2.)

3.3 Part II: Choice experiment

The choice experiment is constructed in such a way that sub-question 3 can be answered, i.e. that the importance of virus contraction in travel choices is retrieved. The rationale behind choice experiments is to mimic real-market behaviour by letting people choose between similar alternatives with different characteristics. This way, trade-off information about the different characteristics can be obtained. In this subsection, the attributes varied in the choice experiments are discussed.

In order to increase familiarity with the presented choices (and thereby more realistic trade-offs) two different experiments are created with different attribute values. One for people who usually travel longer than 30 minutes by train and one for people making shorter trips. All attributes have 3 different attribute levels (low, medium and high) for each of the two experiment. These are shown in table 3.4 and explained in detail afterwards.

Table 3.3. Overview trip attributes

Choice attribute	# levels	levels (long trips[a] / short trips[b])	Unit
Travel Time (TT)	3	10 / 17 / 24 (short trips) 35 / 45 / 55 (long trips)	minutes
Travel Costs (TC)	3	3,0 / 4,5 / 6,0 (short trips) 9,0 / 12,0 / 15,0 (long trips)	euros
Covid-19 Risk (CR)	3	(1) very low / (3) medium / (5) very high (long & short trips)	rating

[a]for resp. usually taking train trips with TT < 30 minutes.
[b]for resp. usually taking train trips with TT ≥ 30 minutes.

3.3.1. Choice Attributes

For the choice experiment, the trip attributes are discussed which are relevant when choosing between different train options. The following attributes are used in the choice experiment:

- **Travel time (TT)** is a commonly used attribute in choice experiments for transportation. Because travelling is considered as a necessary means (with a negative utility) to get to an activity, travel time is to be minimized. Travel times for public transport trips are usually divided into several parts of the trip: access and egress time, waiting time and in-vehicle-time (e.g. Currie, 2005). In our experiment, we only consider the time passed from origin- to destination station. This includes in-vehicle and possible transfer time. For the sake of simplicity, transfer times are not reported and are captured within the travel time. Access and egress time are disregarded since they are not relevant for this study.

  To increase familiarity, the presented trip alternatives are tailored towards the travel times encountered by the respondents in their ‘usual’ performed train trip. The travel times are varied based on two different base trips: 17 minutes (short trip) and 45 minutes (long trip). Respondents reporting a usual travel time below 30 minutes are assigned to choice tasks with short trips. Similarly, respondents who normally are longer than 30 minutes in the train are confronted with long train alternatives. The lower and upper attribute levels are obtained by subtracting and adding 7 minutes to the base travel times for the short trips and 10 minutes for the long trip. The difference in attribute range has to do with the concavity of the time-utility function. The relation between time and utility is not linear, but concave. It is best explained with the notion that 10 additional minutes on an already long trip are perceived as less bad than 10 minutes on a shorter trip. To deal with this phenomenon, the range for the long trip travel times is slightly widened. This minimizes that respondents are indifferent to trip alternatives in the choice sets.

  As explained earlier in subsection 3.2.1, an interaction term between travel time and perceived risk is included to measure if perceived risk is proportionally increasing with travel time.

- **Travel cost (TC)** is an essential attribute in most choice experiments, not just in transportation. Often in choice experiments, the aim is to retrieve the willingness to pay for an improvement in one of the other attributes of interest. In our case, we can retrieve how price is traded off against a covid-19 contamination risk. To get realistic trip alternatives, the travel costs is (similar to travel time) based on two base values. The ticket price is dependent on how long the train trip takes, however not linearly. Ticket prices from NS (national rail operator) are based on the travelled distance (the relationship is somewhat more difficult which causes some variations in the price per distance). And since the relation between travelled distance and travel time is not linear (can be far off due to transfers), there is quite a wide range of cost-time combinations realistically possible.

  After an analysis on the relationship between travel times and ticket prices of NS train trips in the Netherlands, we decided to vary the short trips with 1,5 euros around the base price and the long trips with 3,0 euros around the base price. The base price for the short trips is 4,5 Euros and 12,0 Euros for the long trips. It is made sure that all time-cost combinations are existent in a real-life for train trip in the Netherlands (with NS). Respondents are asked to disregard any discount cards they may have.

- **Perceived covid-19 infection risk (CR):** This choice attribute acts as the bridging element between the rating experiment and the choice experiment. The perceived covid-19 infection risk (CR) is derived from the evaluation of trips in the rating experiment. The result is a score on a scale from 1 to 5, varying from very low to very high risk. The range of this scale is kept deliberately small to ensure that respondents will use the whole scale (which will be confirmed from the pilot survey). The presented train trips may be rarely rated as very risky or not risky at all in the rating experiment. This is undesirable, since one of the requirements for attribute levels is that all alternatives should be existent in reality. A wrongly scaled attribute causes problems on the individual level too. It might for instance happen that a respondent never rated a trip to be riskier than neutral. In this situation, the respondent will not be familiar with a very high infection risk in a choice profile in the choice experiment. Moreover, seemingly arbitrary precision on the risk scale is prevented and the risk values are easier to interpret by respondents.

3.3.2. Individual characteristics

Similar to the individual characteristics for the rating experiment, there is a group of individual-specific predictors that may influence the trip choice behaviour.

Sociodemographic predictors

These are the same as for the rating experiment (see subsection 3.2.2.)

Travel predictors

We introduce a new category of attributes which are about travel behaviour and the necessity to make a trip. These are only relevant for the choice experiment

- **Trip purpose:** It is expected that the travel purpose partly determines the urgency for making a train trip. For instance, business-related trips attain a higher responsibility value than shopping trips, are therefore more urgent and less likely to be cancelled (Kim et al., 2017). It is also known that business travellers are generally willing to spend more to reduce travel times (e.g. Bates, 2013), which may also apply for the willing to pay for risk reduction. Besides the actual purpose, the respondents will be asked about their ability to work/study form home if they usually travel for work or education-related purposes. For leisure travellers, it is asked how severe they would rate the consequences of cancelling the activity they normally take the train.

The trip purpose is not varied by design, but chosen by the respondent. This is done to account for the fact that not all people will have experience with all possible activities (e.g. not everyone has a job). We ask the respondent what the reason is why he or she normally uses the train. After a respondent has filled in the activity for which most of their public transport trips are made, all choice tasks presented to the respondent will assume this particular trip purpose, ensuring familiarity with the presented choice assignments. Respondents can choose between a wide variety of different reasons to travel. In the analysis phase, these activities are aggregated into three sets of purposes: work-, education- and leisure-related activities.

- **Other travel attributes:** Besides the trip purpose, there are a few other travel behavioural characteristics included in this study. The first is the train travel frequency before and during the pandemic. This makes it possible to see travel reduction patterns. The third travel attribute is about having an alternative transport mode available. In our experiment we ask if people have access to a car, which they can use when they do not want to travel by train.

  The usual reported trip length is the last travel attribute and could also play a role in determining the severity of a trip cancellation. Shorter trips could for instance be replaced by taking the bicycle, whereas this is not possible for longer trips. Moreover, the perceived risk could attain higher weights as a function of the reported trip length. Note that the reported trip length is different from the choice attribute travel time as it is observed from the respondent and not varied in the experiment.

3.3.3. Opting out

In the survey, respondents will be faced with multiple choice situations in which they can you choose between three different alternatives. Two of the alternatives contain train trips with varying levels of the aforementioned attributes. The third alternative serves as the opt-out option, i.e. not performing one of two proposed train trips in a given set.

Opting is out is included in the survey for the following reason. We know that travel demand for public transport during the covid-19 pandemic is lower in the Netherlands, even after the relaxation of lockdown measures in June (Translink, 2021). This is partly a result of a large increase in people who are working from home and a reduction in the number of public and social activities. Infection fear may also play an important role as there is a clear relation between the use of public transport and the acquisition of an acute respiratory infection, such as covid-19 (Troko et al., 2011). In our experiment, we allow respondents to indicate that they don't like either travel options. Hence an opt-out option is included, thereby capturing potential ridership reduction as a function of the risk factors.

The opt-out alternative is not the same for every respondents, but differs according to what someone indicates doing when a train trip is not performed. This leads to three different opt-out scenarios which are related to whether or not the respondent has a private car available to them and whether or not the intended activity (trip purpose) can be performed at home. The scenarios include 1) 'Re-mode': performing the intended activity by taking an alternative mode (car, bicycle or other mode); 2) performing the intended activity from home or 3) cancel the activity.

A downside of adding an opt-out alternative is that it can be considered as an 'easy option' for respondents who do not want to make a decision to save the effort and time associated with evaluating the train alternatives. This may result in many opt-out choices among the respondents, meaning marginal information gains about trade-offs and thereby insignificant parameters. This problem is mitigated by presenting the opt-out option in a sequential manner. Respondents are first instructed to choose one of the train trips. After this is completed, they are asked if they would make the just chosen trip if given the choice to cancel. At the very end of the choice experiment, the respondent is asked what he or she would do if trip was not performed (re-mode, home activity or cancel). This set-up also allows to estimate a dataset in which people are forced to choose and a dataset in which opting out is available. A benefit of the first approach is that it gains more information about trade-offs between the travel attributes while the latter disregards these trade-offs. It is important to consider that this ‘forced’ information is gained from people who do not want to use the train but are forced to choose. The information may therefore be biased (Ben-Akiva et al., 2019).

3.4. Experiment design

This subsection describes how the choice sets for both experiments are obtained. The objective is to create a survey which is efficient in terms of the amount of information it can retrieve (on trade-offs and the importance of the identified risk factors) while limiting the number of required respondents and also without exhausting those respondents. The choice tasks are retrieved from experimental designs which are generated with the software package Ngene (ChoiceMetrics, 2012). The syntax used to create the can be found in Appendix B:Ngene syntax. Table 3.4 gives an overview of the experimental characteristics of both experiments.

Table 3.4. Overview of experiment characteristics

Survey part	Design type	# Options to choose from	# Versions	Respondent assignment	# Choice tasks generated	# Choice tasks shown to resp.
Rating experiment	orthogonal	5 (ordinal)	2	random	12	6
Choice experiment	D-efficient	3	2	based on respondent's usual travel time	9	9

Before the main survey is distributed, a pilot survey is created. The pilot serves several goals. Firstly, the pilot is used to check if all questions are clear and the attribute levels are realistic for respondents. Secondly, results from the pilot show whether the risk perception scale for the rating experiment is properly designed (as explained in subsection 3.3.1). Most importantly, the pilot choice experiment is used to obtain the prior parameter information for a D-efficient final choice experiment design. Lastly, feedback from the respondents is gathered.

3.4.1. Rating experiment

In the survey, the respondents are asked to rate different train trips in terms of perceived risk. Unlike the choice experiments, the rating is done one train trip at a time to ensure the rating is solely based on the trip characteristics. The evaluation tasks for the rating experiment are sequentially constructed with an orthogonal design. An orthogonal design with three 4-level and three 2-level attributes results in a total of 12 unique profiles. To limit the respondent load, the choice situations are split up into two separate blocks. Respondents are randomly assigned to one of the blocks and only need to rate 6 train trips in total. An example question for the rating experiment (from the survey) can be seen in Figure 3.5.

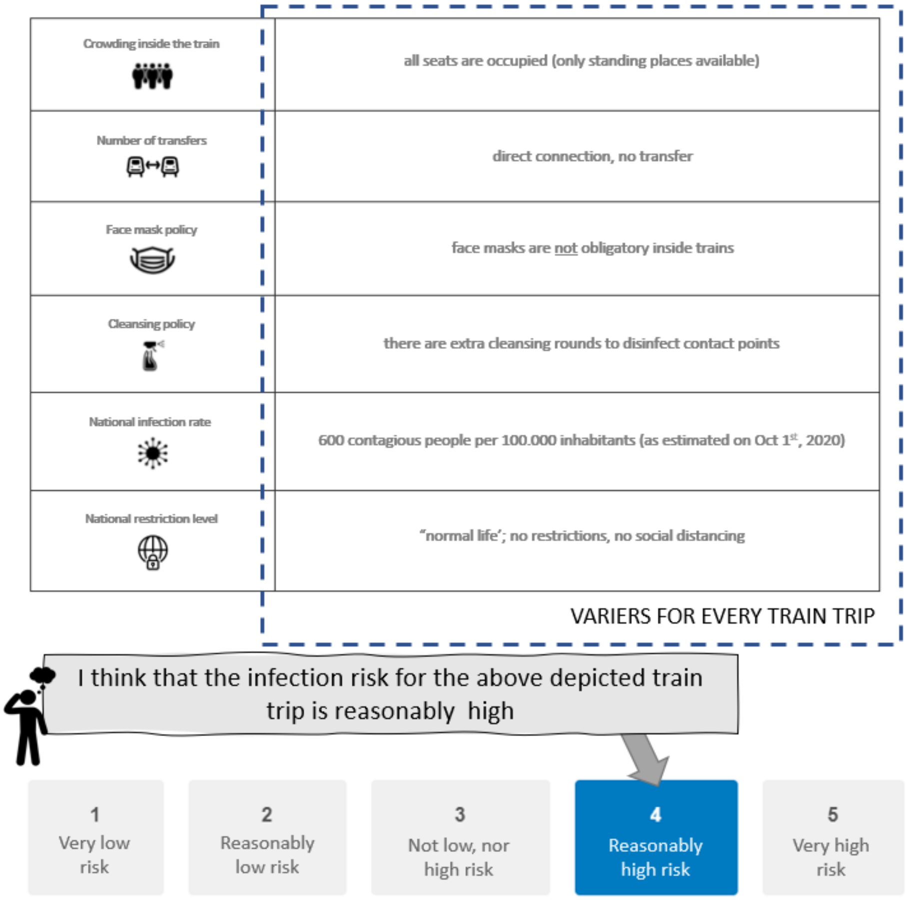


Figure 3.5. Example rating task in rating experiment (translated into English)

3.4.2. Choice experiment

The choice experiment tasks consist of two train options of which respondents need to pick one. For the main survey, a D-efficient design is used to prevent dominant choice alternatives which do not provide additional information about the trade-offs. An added benefit is that the reliability of the model parameters improves with efficient designs because such designs aim to minimize the standard errors. To find reliable parameters however, the model needs to be fed with best estimates (priors) for the parameter beforehand. We obtained the parameter priors by estimating a (MNL) choice model with the observed choices in pilot survey. The choice experiment design for the pilot was also constructed with a D-efficient design. Because no a priori information was available before the pilot was caried out, very small priors with the expected sign (all negative) were used for the pilot experimental design. The magnitude of the signs for the prior information is less significative because the outcomes solely serve as priors for the final model.

Because experimental designs created with a D-efficient method are partially determined by the attribute values, we end up with a different final design for long and for short trips. The respondents are faced with either one of the experiments, based on their usual trip lengths. The final experimental designs can be found in Experimental designs. An example question can be seen in Figure 3.6.

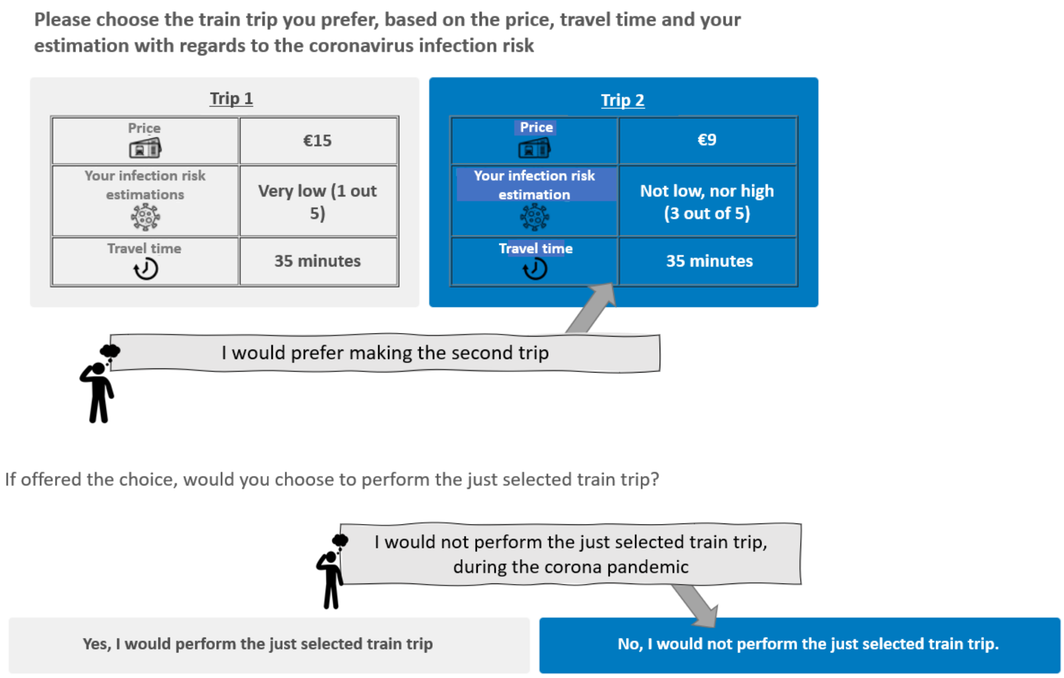


Figure 3.6. Example choice task for long trip choice experiment (translated into English)

3.5. Survey design

In this section, the set-up of the online survey is explained by introducing the survey flow and how a pilot study helped to improve the final design.

3.5.1. Survey structure

The survey consists of three main parts and some introductory/screening questions regarding pre-covid and during pandemic travel behaviour, most used trip purpose and whether one as other transport modes available. This information is used to tailor the remainder of the survey towards the specific circumstances of the respondent. In total, the survey has a total of 41 questions. The first main part of the survey contains the rating experiment, where respondents evaluate 6 different train trips. In the third part of the survey, the respondents choose between different train alternatives as part of the choice experiment, 9 times in a row. The questions are randomized for both experiments to prevent survey bias due to survey fatigue. Finally, in the last part of the survey, the background questions are stated. The background questions cover the psychometric and sociodemographic attributes. An overview of questions can be found in Appendix E: Survey questions and a copy of one of the survey versions in Appendix F: Final Survey.

3.5.2. Pilot results

As explained earlier, a pilot survey is carried out to check if all parameters signs make sense, to observe the risk rating range, to obtain the priors for the D-efficient design of the choice experiment and receive feedback. The pilot survey was distributed among a small group of acquaintances. With a snowballing method, 56 responses were collected. We observed that all parameter signs for the risk factors had the expected signs as well as the trip attributes which all were negative. The parameters for the risk factors transfer and intelligent lockdown level were non-significant. We deliberately chose to keep these in the experiment, to check if a larger sample size would disclose a correlation between perceived risk and these factors. The risk rating range was observed and we concluded that all risk levels were used relatively equally, albeit that the average rating was slightly higher than the middle level. The priors were fed into the into final experimental design. With regards to the received feedback only minor improvements had to be caried out. The infection rates were changed to updated estimates from the Ministry of Health, Welfare and Sport (2020). Furthermore, the direction of the risk scale was changed for clarity reasons and the introductory section for both the choice and rating experiment were extended with some additional information.

3.6. Data collection

We used an online panel (PanelClix) to distribute the final survey. The data collection took place in the first week of December in 2020, just before the start of newly imposed measures by the government (see Figure 3.7). In the end, 513 responses were collected of which 408 are considered to be valid. Responses were eliminated from further analysis if they were incomplete or have a fill-in time shorter than 5 minutes. This to ensure response validity. Data from the pilot survey showed that the average fill-in time was around 12 minutes. The average fill-in duration for all valid responses from the final survey is found to be about 17 minutes. It has to be noted that the average gives a distorted view due to some outliers. These outliers are attributed to people who paused filling in the survey and continued at a later moment. The median fill-in time is 10 minutes which is more reasonable. Although this is shorter than was expected from the pilot results, we believe that it is in the range of to be expected results since the respondents are mostly experienced survey-takers.

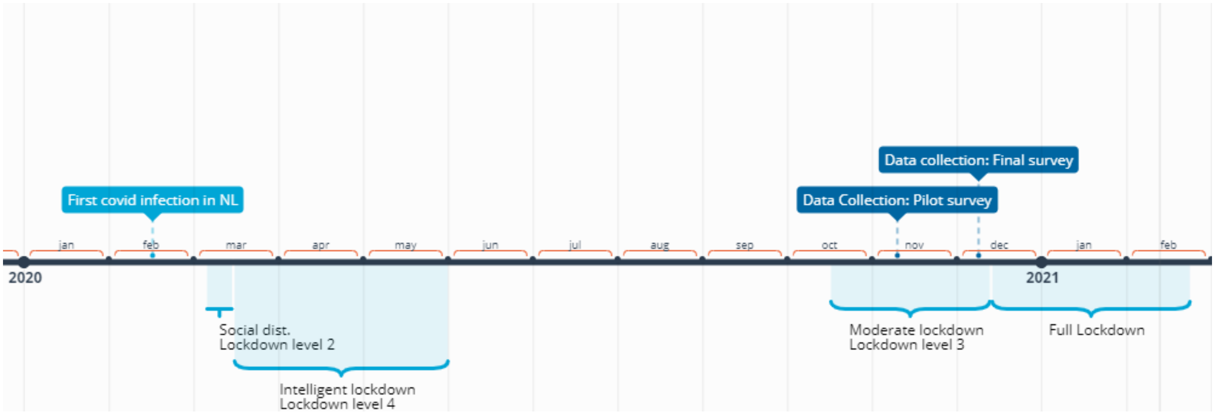


Figure 3.7. Timeline with lockdown levels and data collection

3.6.1. Target population

The population for this study contains train users in the Netherlands. In order to make sure that that all respondents are able make thoughtful trade-offs between train trip characteristics, there is a minimum threshold set for the number of train trips one made before the covid-19 pandemic (before March 2020). The frequency threshold is set to 6 times a year. With this frequency we ensure that every respondent is sufficiently familiar with making train trips, while we also capture the occasional train user who only uses the train once in a while. This last group is important because they mainly travel for leisure purposes and we also want to capture them.

To ensure the representativeness of the sample, we strived to have sociodemographic sample distributions similar to the Dutch train user population. Quotas were set for age and gender. The required distribution were obtained from a survey conducted by the Dutch Central Bureau of Statistics (2016).

3.6.1. Sample characteristics

Table 3.5 gives an overview of the sample characteristics in terms of sociodemographic and travel data. The gender distribution is nicely spread according to the reference population of Dutch train travellers, even if there is a slight overrepresentation of people between 18 and 24. There is also a slight overrepresentation of females in the sample (53,9%). With regards to work status it can be noted that most respondents do have a paid job. The trip purposes are evenly spread over work, education and leisure. The most important observation related to travel frequencies is that 27,2% of the sample did not travel once since the start of the pandemic, while they used the train at least 6 times per year before the pandemic.

Table 3.5. Overview sample characteristics

Background variable	Category	Observations #	Relative %	Reference population[a]
Gender	male	188	46,1%	50%
	female	220	53,9%	50%
Age	0-18	0	0%	-
	18-24	115	28,2%	36%
	25-34	75	18,4%	17%
	35-44	59	14,5%	13%
	45-54	71	17,4%	16%
	55-64	61	15,0%	12%
	>64	27	6,6%	6%
	average: 39,2			
Education	primary school	4	1,0%	
	secondary school	79	19,4%	
	MBO	135	33,1%	
	HBO/WO bachelor	109	26,7%	
	HBO/WO master or higher	79	19,4%	
	other	2	0,5%	
Work status	employed	260	63,7%	
	unemployed	27	6,6%	
	student	76	18,6%	
	retired	23	5,6%	
	other / rather not say	22	5,4%	
Trip purpose	commute (work)	144	35,3%	
	business (work)	27	6,6%	
	education	75	18,4%	
	family/friends (leisure)	80	19,6%	
	shopping (leisure)	29	7,1%	
	holidays (leisure)	43	10,5%	
	sports/leisure (leisure)	10	2,5%	
Train travel freq. before pandemic	<1 per year	0	0,0%	
	1-5 days per year	0	0,0%	
	6-11 days per year	83	20,3%	
	1-3 days per month	105	25,7%	
	1-2 days per week	70	17,2%	
	3-4 days per week	84	20,6%	
	5-6 days per week	41	10,0%	
	every day	25	6,1%	
Train travel freq. during pandemic	never	111	27,2%	
	<1 per month	116	28,4%	
	1-3 days per month	65	15,9%	
	1-2 days per week	68	16,7%	
	3-4 days per week	30	7,4%	
	5-6 days per week	9	2,2%	
	every day	9	2,2%	
	more than once	297	72,8%	
Regular train trip length	< 30 minutes	117	28,7%	
	30-120 minutes	250	61,3%	
	>120 minutes	41	10,0%	
N=408				

[a] Based on travel data from Central Bureau of Statistics (2016)

3.6.2. Experiment characteristics

The 408 respondents did not all complete the same survey version. In order to reduce respondent load two versions of the rating experiment were created and to increase familiarity with the trip attribute values also two versions of the choice experiment were created, resulting in 4 different versions. The respondents were assigned to different versions of the rating experiment randomly, while preserving an even spread. For the choice experiment this is different because the version they were assigned to was determined by the respondent's usual trip length. Since only 28,7% of respondent answered this question with less than 30 minutes, the distribution of respondents over the different survey versions is quite uneven (see Table 5.2).

Table 5.2. survey versions

Version	**Observations #**	**Relative**
RE part 1, CE short	55	13,5%
RE part 1, CE long	142	34,8%
RE part 2, CE short	62	15,2%
RE part 2, CE long	149	36,5%
All	408	100,0%

RE= Rating Experiment, CE= Choice Experiment

Rating tasks

To gain maximum information about the relative importance of different factors it is important that the ratings given in the rating experiment are nicely spread across all rating values (see subsection 3.3.1.). To see if amongst the trips showed, the assessed risk is indeed evenly balanced, an overview is created and shown

Table 3.6. The average perceived risk is slightly higher than the middle value (3,37 out of 5), indicating that, in general, people assess the trips as more unsafe than safe. Please note that it is assumed that the rating is of interval-measurement scale. Besides average ratings, the lowest and highest individual ratings are reported. This gives an indication about whether or not the whole range of ratings is used by the respondents and thus if the scale was appropriate. Ideally, we want the majority of respondents having a lowest rating of 1 and a highest rating of 5. For the lowest rating this not the case, indicating again the trips are viewed as relatively risky. Looking at the distributions it can be seen that most respondents have a highest individual rating higher than 4, showing that most people evaluate at least some of the trips as unsafe. On the other hand, 133 respondents (32,9%) did not rate any of the trips as low or very low risk. This is indicative for the fact that some people will not feel totally safe in the train while covid-19 is still active (at least in the trips we provided).

Table 3.6. Survey characteristics

Characteristic	Category	Observations #	Relative
Ratings	1	145	5,9%
	2	449	18,3%
	3	648	26,5%
	4	773	31,6%
	5	433	17,7%
	total	2448	100,0%
Rating average per individual	1-2	9	2,2%
	2-3	73	17,9%
	3-4	254	62,3%
	4-5	71	17,4%
	average	3,37	
Lowest individual rating	1	94	23,0%
	2	180	44,1%
	3	104	25,5%
	4	26	6,4%
	5	3	0,7%
Highest individual rating	1	2	0,5%
	2	6	1,5%
	3	24	5,9%
	4	140	34,3%
	5	233	57,1%

Choice tasks

With regards to the choice experiment, it is relevant to look if opting out is not chosen extremely often and if there are choice tasks with clearly dominating alternatives (>90% times chosen). When looking at the observed choices which are depicted in Figure 3.8, we are able to conclude there are no strict dominant alternatives in the survey. Opting out is however chosen often. Choice tasks A,C and E in the long trip survey have around 80% opt-out responses. These sets have in common that they all have high risk levels (5 out of 5) for both train alternatives. For the short trips, the choice tasks with high risk levels in both train trips (C & H) show only about 65% opt out responses. This is an early indication that the covid risk is more important in the long trips.

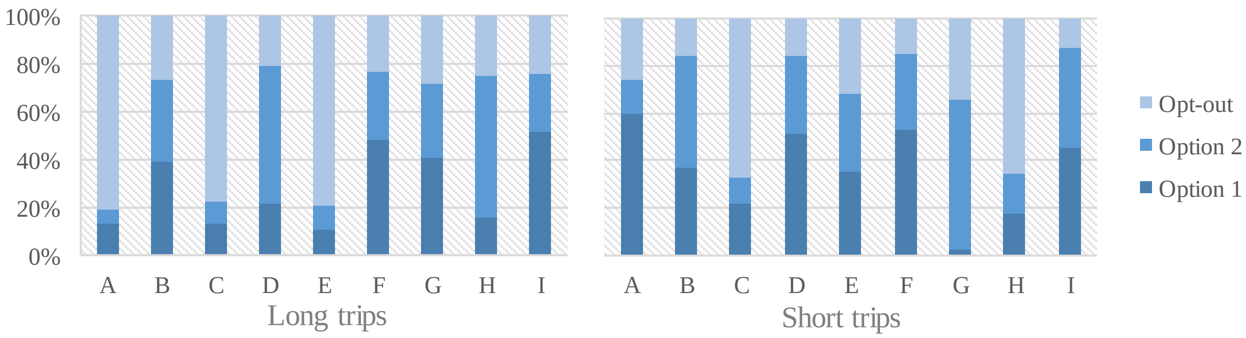


Figure 3.8. Choice task responses (see Appendix C: Experimental designs for the characteristics of each choice task)

3.7. Model estimation

In this section, the estimation procedures for both the rating and choice experiment are introduced. We start by explaining the linear regression for the rating experiment as depicted in the upper-left box of Figure 3.9, followed by the logit models for the discrete choice modelling (lower-right part).

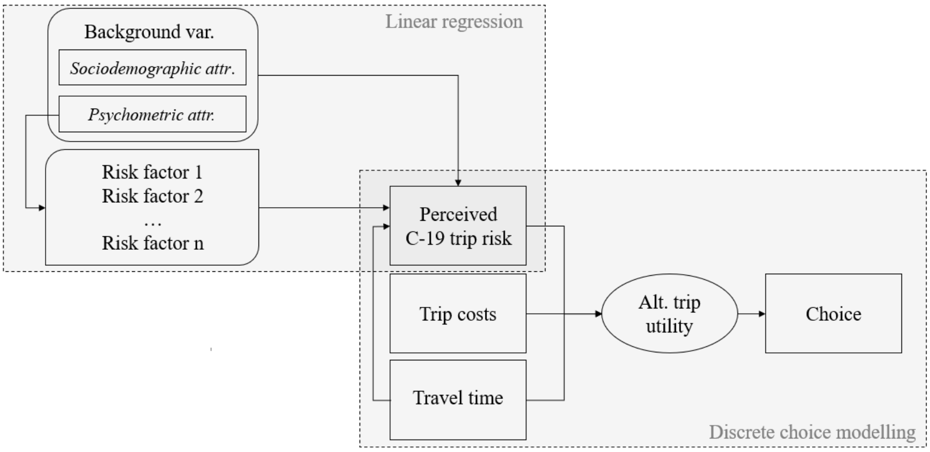


Figure 3.9. Simplified overview of model estimation procedure

3.7.1 Linear regression

The estimation of risk factors is done simultaneously with the background variables in a multiple linear regression analysis. The regression aims to find coefficients (β) for the risk factors, background variables and interaction effects to predict the ratings, as shown in equation 3.1. For a linear regression, all attributes need to be on an interval measurement scale. This prerequisite is however debatable for Likert-scale attributes. The distance between the individual ratings levels might not be interpreted as the same by different respondents. Because we want to use ratio variables in the choice experiment it is however chosen to simplify the rating variable and consider it to be on a continuous scale, which finally makes a linear regression possible.

$$Y = \beta_0 + \beta_i * x_i + \beta_j * x_j + \beta_{ij} * x_i * x_j \tag{3.1}$$

constant 0, risk factor i, background var j.

The regression is performed using SPSS software version 26 (IBM Corp, 2019). The model estimation is performed in a step-wise manner. The first step is a regression model with only main attributes. Afterwards, background variables and interaction terms are added to the model. The linear regression for each individual model is based on a different step-wise method, namely backwards elimination. For each of the different models, the procedure starts by including all of the relevant attributes (including the ones removed in previous steps since they might later appear significant due to interactions). Statistically non-significant parameters are then removed one by one starting with the parameter with the highest p-value. The final model will contain only parameters that are statistically significant on a 95% confidence interval. It has to be noted that main effects are prioritized above interaction effects. This means that when a main effect and an interaction effect parameter with that same attribute are both non-significant, the interaction term is first removed, irrespective of the p-value for the main effect. Also note that the p-value threshold of 0,05 is arbitrary, but commonly used in statistical studies. We therefore also report the statistical non-significant effects.

Besides main effects, we also estimate for some non-linear relations by including quadratic components for crowding and infection rate. Finally, after the final model is estimated, general risk perception components form the risk perception index as explained in subsection 3.2.2. are estimated in a regression model. This is done in a separate model to avoid multicollinearity with the psychometric background variables.

Interaction effects
As mentioned above, we also estimate interaction terms between main and background variables (represented by β_{ij} in equation 3.1). Adding all possible interactions to the model will most probably not result in a valid model. Because there are 8 main attributes (including dummy variables) and 19 background attributes, estimating all interaction effects will end up in a huge amount of interaction terms. If one would choose to estimate all, there is high likelihood that we will find some of the 158 terms to be significant while in fact these may resemble peculiarities in the dataset that are not valid for the population. A careful selection of to be expected interaction terms is therefore needed. An overview of all estimated (and thus to expected) interaction terms is given in Table 3.7. First of all, because we do not have reason to believe that sociodemographic data will correlate with one of the main attributes (trip conditions) specifically, it was chosen to only estimate interaction effects between main attributes and psychometric attributes. Interactions with 'transfer' are also discarded because this risk factor is later found to be statistically non-significant. The argumentation for the estimated interactions is given below.

Table 3.7. Expected interaction effects

Backgrounds ➡ **Main effects** ⬇	Health att.	Health anx.	Prosociality	Perc. control	Pers. efficacy	Risk for loved ones	Trust in gov.	Media consump.	Virus experience
Crowding	x	x							
Mask	x	x	x	x	x			x	x
Cleansing	x	x		x				x	x
Infection rate	x	x				x			x
Lockdown level							x		

- **Health attitude and anxiety**: People who consider themselves as unhealthy might attain more value to the risk factors because they are in general more careful when it comes to their health. It is already known that anxious people will prevent an infection with the coronavirus at larger costs (Mertens et al., 2020) and that unhealthy re believed to more vulnerable to the virus (Dong et al., 2020). These indicators might therefore have an additional effect on the perception of crowding, infection rate, wearing a face mask or extra cleansing.

- **Prosociality** is about the willingness to sacrifice something for society. Wearing a face mask is a typical example of an action which causes personal nuisance, but is done to benefit others. By estimating an interaction effect it is possible to see if willing to sacrifice yourself for the greater good also translates into a higher attained believed effectiveness of wearing face masks.

- **Perceived control:** To what extent individuals can prevent spreading the virus with their own actions is captured in the perceived control variable. As explained earlier, virus spreading can be prevented by wearing masks and (arguably) also by disinfecting contact surfaces. It is therefore expected that people who in general think spreading of the coronavirus can be prevented also think that wearing face masks and regular cleansing will reduce the likelihood of attaining an infection in the train. With a similar line of reasoning, a lower level of perceived control can cause that one thinks that infection rates determine the infection risk more.

- **Personal efficacy** is unlike perceived control only about limiting spreading by taking personal actions. An interaction effect is therefore only included with wearing face masks.

- **Risk for loved ones:** When one is not per se afraid of an infection for themselves, but rather afraid to pass the virus on to vulnerable family members or friends, he or she probably avoids crowded places and restricts their movements when infection rates are higher. An interaction between risk for loved ones and crowding and between infection rate is therefore estimated.
- **Governmental trust:** Since trust in the government is an indicator concerning the opinion regarding governmental actions we expect that low trust in government also affects the lockdown state indicator proportionally heavier than the others.
- **Media consumption:** As explained, wearing face masks and disinfecting contact surfaces are both debated in their effectiveness to prevent spreading of the virus. This discussion was also widely reported in the (Dutch) media. It is expected that the consumption of media sources will have an effect on the believed effectiveness of these measures and thereby an extra effect on risk perception. Especially 'doing own research' might be an indicator for more critical viewpoints regarding these safety measures.
- **Virus experience:** Knowing people who have had the coronavirus might increase awareness and therefore change the perception of all of the risk factors.

Coding

To account for ordinal and nominal variables in the linear regression, some coding has to be performed. The coding schemes are based on effect coding. A benefit of effect coding is that it is easier to interpret the main effect and the interaction effect separately when interaction terms are estimated. Besides, it is easy to capture the mean effect of a binary variable, by setting all dummy variables to zero. By error, work status is included as a dummy coded variable. All coding schemes are shown in Table 3.8.

Table 3.8. Coding of categorical and ordinal variables

Attribute	**Level**	**Effects/dummy coding**		
Main attr.		*parameter*		
Transfer		transfer		
	no	-1		
	yes	1		
Mask		mask		
	no	-1		
	yes	1		
Cleansing		cleansing		
	no	-1		
	yes	1		
Lockdown status		social dist.	moderate	intelligent
	normal life	-1	-1	-1
	social distancing	1	0	0
	moderate lockdown	0	1	0
	intelligent lockdown	0	0	1
Psychometric attr.		*parameter*		
Media exposure		regular	deliberate	
	avoid media	-1	-1	
	regular consumption	1	0	
	deliberate search	0	1	
Experience family/friends		experience		
	no	-1		
	yes	1		

Socio-demographic attr.		*parameter*		
Gender		sex		
	male	-1		
	female & other	1		
Age		age		
	18-87	real values		
Education level		edu_high		
	lower & other	-1		
	higher (bachelor or master)	1		
Work status		employed	student	retired
	unemployed & other	0	0	0
	employed	1	0	0
	student	0	1	0
	retired	0	0	1

3.7.2. Discrete choice modelling

To estimate the parameter tastes for the choice attributes we use discrete choice modelling. We estimate discrete choice models using two different estimations methods with a varying number of parameters, namely a Multinomial Logit (MNL) and a Mixed Logit (ML) model. A variety of models are then used to test for different correlations, based on the research questions and hypotheses. All models are estimated with Apollo (Hess & Palma, 2019a, 2019b) using R. The syntax for the model specification in Apollo can be found in Apollo syntax.

Model specification

Due to the survey set-up in which a distinction is made between people usually travelling shorter and people usually travelling longer than 30 minutes there are two separate datasets for the choice model. We estimate all choice models for the datasets separately. Combining the long and short datasets (and thus estimating the models simultaneously) is tried, but resulted in unexpected parameter values, most probably caused by the introduction of correlations between the attribute values for travel costs and travel time. Separation of the datasets allows for analysing differences in behaviour between long and short travellers.

The first step in the choice modelling is to estimate a simple MNL model with only main effects. This is done for the 'normal' dataset and a version of the dataset in which respondents are forced to choose between the two train alternatives (thus are not allowed to choose to opt out). As explained in subsection 3.4.2., respondents were asked to choose between two train trip alternatives with varying levels of travel time (TT), travel costs (TC) and covid infection risk (CR). The utility function for a train alternative is shown in equation 3.2. After this task was done, a respondent had the possibility to opt-out, being the third alternative. The opt-out alternative is constructed in such a way that it has different meanings to different people, depending on what they indicate doing if the trip was not performed. The opt-out scenarios include switching modes, performing the intended activity at home or cancelling the activity. However, because the opt-out scenarios are captured outside of the experiment, these cannot be modelled directly in the choice experiment. The utility for opting out is thus equal to the alternative specific constant (ASC) (equation 3.3). Separate analyses for the opt-out scenarios are done.

$$V_{train\,alt.\,j} = \beta_{x_i} * x_{i,j} = \beta_{TC} * TC_j + \beta_{TT} * TT_j + \beta_{CR} * CR_j \tag{3.2}$$

$$V_{opt\,out} = ASC_{optout} \tag{3.3}$$

Besides the main effects, several other tests are performed. These include checking if the infection risk parameter is non-linear. We do this by including a quadratic component (CRsq) in the utility equation (equation 3.4). Furthermore, an interaction effect between travel time an covid risk is included to test the hypothesis that infection risk is more important in longer trips (see subsection 3.3.2). The influence of different trip purposes on the trade-offs is estimated by adding interaction terms with the main effects (equation 3.5). Lastly, the background variables are included as interaction terms with the main effects to measure the impact they have on choice behaviour. It is decided to exclude psychometric background variables because these are indicators for latent variable (in this case covid risk perception) and believed to be merely an expression of underlying personal characteristics and therefore do not present a causal relation (Ben-Akiva et al., 2002).

$$V = TC * \beta_{TC} + \beta_{TT} * TT + \beta_{CR} * CR + \beta_{CRsq} * CRsq + \beta_{TT.CR} * TC * CR \quad (3.4)$$

$$\begin{aligned} V &= TC * (\beta_{TC} + \beta_{edu.TC} * edu + \beta_{leisure.TC} * leisure) + TT * (\beta_{TT} + \beta_{edu.TT} * edu \\ &\quad + \beta_{leisure.TT} * leisure) + CR * (\beta_{CR} + \beta_{edu.CR} * edu + \beta_{leisure.CR} * leisure) \end{aligned} \quad (3.5)$$

edu=education

Similar to the rating experiment, all forementioned effects are tested for statistical significance on a 95% confidence level and are removed in a stepwise manner: non-significant parameters are excluded sequentially in order to arrive at a final model with only significant parameters.

Model estimation

For all analyses, firstly the multinomial logit (MNL) is applied. The estimation of MNL is based on the maximum likelihood principle which can be calculated using equation 3.6. This is a multiplication of all logit choice probabilities. The MNL model is considered to be the most basic choice model. This model assumes there is no correlation among alternatives and uses fixed parameter values. Although the MNL model is a robust and convenient to use model, it could be argued that it is oversimplified and does not resemble real-life behaviour. The main issue for this study's experiment is that observations made by one individual are considered independent choices, while in fact they are likely to be dependent on each other, i.e. the error terms are correlated.

An alternative method is the mixed logit (ML) model which is able to incorporate a panel effect, allowing for correlations between choices made by the same individual, while conserving utility maximization behaviour. This implicates for the choice models used for the long trip datasets that where the MNL model assumes 2612 independent observations, the ML evaluates *just* 291 respondents with 9 partly correlated choices. Furthermore, Where MNL uses fixed parameters values, ML allows for taste heterogeneity across respondents. The taste heterogeneity is captured by making parameters stochastic by estimating parameters of a random distribution (e.g. normal, triangular) from which the parameters are drawn.

The panel structure of ML models causes one problem however. The taste heterogeneity is mathematically captured in the probability function by taking integrals over the density of the parameters. And since the unit of observation becomes the sequence of choices made by one individual in a panel structure, the maximum likelihood function does not have a closed form (see equation 3.7). Therefore the choice probabilities for the alternatives need to be simulated, more specifically the parameter values. This is done by making draws from the joint density. We use Quasi-random 'Halton' draws to reduce the number of draws needed. Halton draws efficiently cover the search space, which in turns saves computational power to estimate the mixed logit models. The number of draws is determined by doubling the number of draws until convergence (in terms of consistency of the parameter values and model fit) is reached. In this experiment, the parameters for Covid Risk (CR) and Travel Costs (TC) are made random. Travel Time (TT) is kept fixed because no substantial taste variation across the population was found (i.e. standard error is not significant).

$$L(P) = \prod_{t=1}^{T} P_{n,i}^{t} = \prod_{t=1}^{T} \left(\frac{e^{V_{n,i}}}{\sum_{i=1}^{I} e^{V_{n,i}}} \right) \tag{3.6}$$

$$L(P) = \iint\limits_{\beta_{CR}\,\beta_{TC}} \left(\prod_{t=1}^{T} \left(P_{n,i}^{t} | \beta_{CR}, \beta_{TC} \right) \cdot f(\beta_{CR}, \beta_{TC}) \right) d\beta_{CR} d\beta_{TC} \tag{3.7}$$

For alternative $i \in I$ {trip 1, trip 2, opt-out}; choice situation $t \in T${1,2,3,...,9}; individual $n \in N$

A second issue with the ML model is that by taking draws from a distribution instead of using a fixed value, a share of the draws will take on an unexpected sign (if the distribution is unbounded). In this study, this is a problem since for all main parameters a negative parameter sign is expected. It is unlikely that individuals have a positive taste for either costs, travel time or a higher perceived infection risk.

To check if this concern is justified when a normal distribution in our dataset is used, we estimate the proportion of incorrect signs. For illustration, this is visualized by plotting the normal distributions with parameters mean and standard deviation (S.D.) (see Figure 3.11 and Figure 3.10). This is done for the ML models with and without interaction terms for the parameters CR and TC. It turns out the issue with incorrect signs is only prevalent for the variable CR. In all models, less than 0,3% of the data will attain a positive value for TC, which is considered to be negligible. For CR however, a considerable proportion of the draws takes on a positive sign . This varies between 6% for an ML model with only main effects based on the long trip datasets and 12% for a model with interaction effects (see Figure 3.11).

One solution is to use another distribution which is restricted by zero, such as the lognormal distribution. We nevertheless decided to use a normal distribution due to the fact that in some of the estimated models the S.D. exhibited very unexpected behaviour when a lognormal distribution was used. In addition, the share of wrong signs is considered to be low enough that it can be taken for granted.

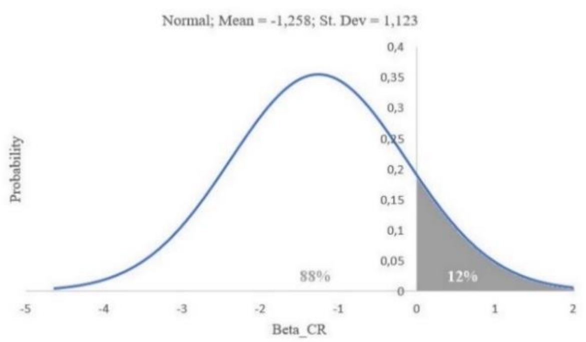


Figure 3.11. Distribution of CR in ML for long trips

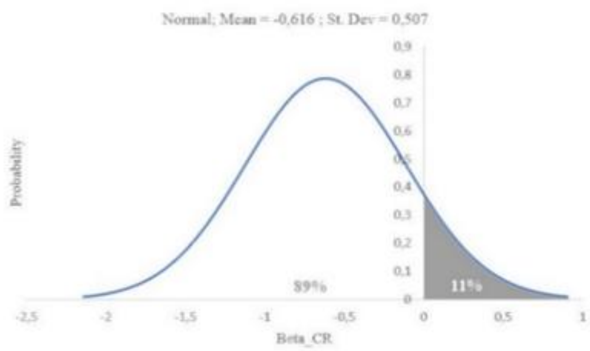


Figure 3.10. Distribution of CR in ML for short trips

Coding

For the categorical background variables used in the choice experiment, coding schemes are used. The variables already discussed for the linear regression can be found in Table 3.8. The ones newly introduced for the choice experiment can be found in Table 3.9.

Table 3.9. Coding schemes choice experiment

Attribute	**Level**	**Effects coding**	
Trip length		length	
	Short (< 30 min.)	-1	
	Long (≥ 30 min.)	1	
		high frequency	
Trip frequency	< 1 day a week	-1	
during pandemic	≥ 1 day a week	1	
Opt-out		re-mode (RM)	home (HO)
	cancel activity	-1	-1
	other mode	1	0
	home activity	0	1
Covid-19 risk		CR1	CR2
	low	-1	-1
	neither low, nor high	1	0
	high	0	1
Trip purpose		education	leisure
	work	-1	-1
	education	1	0
	leisure & other	0	1
Car access		car	
	No car available	1	
	Car available	-1	

4. RESULTS

The data gathered from the survey are processed and analysed in this chapter. General observations are discussed in the first subsection. In subsection 4.2., the results from the linear regression are discussed after the expected outcomes are summed up. Similarly, in section 4.3, everything related to the choice experiment is examined. Lastly, the results from the rating and choice experiment are combined in subsection 4.4. to exhibit practical applications.

4.1. General observations

In this subsection, some general observations, prior to any statistical analyses or choice modelling, are made. We investigate the hypothesis that people without access to a car are more like to cancel the intended activity, in particular when this activity is leisure-related. The travel pattern changes during the pandemic with respect to the situation before the pandemic are also examined.

4.1.1. Modal shift

The first observation is related to the proportion of respondents choosing to opt out relative to having access to a car. From Figure 4.1 it can be seen that using the car is the most popular opt-out alternative. However, because 24% of the respondents do not have direct access to a car, switching modes to car is not a viable alternative for almost a fourth of the respondents in the dataset. Our analysis also shows that many of the non-car owners (48%) cancel the activity instead, which is a considerable difference with travellers who do have access to car (9%). The share of partaking the intended activity at home (home activity) stays roughly the same.

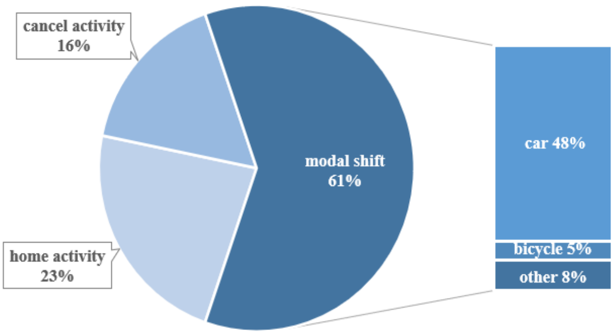


Figure 4.1. Shares of opting out scenarios.

4.1.2. Train usage

With regards to the decreased train usage, from our data we find that 27,2% of the responses did not take the train at all since the start of the pandemic while they did so at least once each two months in the pre-covid era. More than half of the train avoiders (52%) normally took the train for leisure purposes, which is slightly more than the sample proportion of leisure travellers (39,7%). This might be indicative of the fact that travellers with leisure purposes are more likely to leave the train as opposed to other travellers. This is in line what was expected since the national government called for public transport to be used only for essential purposes. Moreover, leisure activities are in general expected to be cancelled more easily than other activities. Because the travel frequency was observed in a rather crude manner (as an average trip frequency over a large time-span with a changing covid-19 context), it is difficult to compare this with train demand reduction which was observed in real-life. But for reference, we computed the average travel reduction over the 8 months we asked the respondents to evaluate (April-November 2020), with tap-in data from OV-Monitor Translink (2021). We calculated an average observed train travel (tap-in) reduction of 60,1% for this period. The added value of our data is that it gives more insight into why and who is part of this reduction.

4.2. Linear regression analysis

In this section, the results from the rating experiment together with the observed individual background variables are reported and analysed. Firstly, a short recap of the attributes and their expected effects on perceived risk is given. The results are then presented according to the estimation procedure as discussed in 3.7.1.

4.2.1. Expectations

With regards to the main attributes it is expected that the trip conditions are all correlated with the perceived risk rating. The risk increasing conditions (crowding and infection rate) will positively influence the risk rating and policy conditions (mask use and cleansing) are expected to have a negative impact. There is however much uncertainty surrounding the explanatory power of mask obligation and extra cleansing given that these measures are criticized in the media. The effect of transfers is even less clear, since it is difficult to predict if people perceive the dangers associated with changing trains (due to increased number of traveller interactions) as higher.

The national lockdown levels can be interpreted in two different ways. Stricter interventions could be interpreted in a way that the chances of getting infected are decreasing. On the other hand, one might argue that stricter lockdown levels indicate that the situation is more critical and thereby infection risk higher. It might also be that people refer to the specific time periods which were given in the survey. For instance, they have an image of how the situation was in April (intelligent lockdown) and compare this with the situation in December (moderate lockdown), when the survey was carried out. Since there was a lower measure adherence in the second infection wave (December) compared to the first (April), people might interpret the moderate lockdown as less risky than the intelligent lockdown.

A non-linear relation between perceived risk and the degree of crowding is furthermore expected as an additional group of people in a quiet train is probably less worse than that same group in an already crowded train. The same effect could be apparent for infection rate.

4.2.2 Results

In this subsection, all results from the linear regression are reported and discussed. An overview of the results is shown in Table 4.1. All main effects are given in the first column of Table 4.1. The second columns presents the statistically significant (p <0,05) main effects resulting from the backward elimination procedure as described in subsection 3.7.1. The results from a model with significant interaction effects are depicted in the last column. For the sake of overview, all estimated but non-significant interaction terms are left out this table. These can be found in Appendix G: Linear regression. The meaning of the variable names for the main attributes can be found in subsection 3.2.1. and for the backgrounds in 3.2.2. In the following paragraphs, we elaborate on the significant main effects first (without interactions) and separately explain how the interaction terms are interpreted afterwards. This is done because it makes the interpretation of the relations more easy.

Table 4.1. Linear regression results

	N=408	**All Main Effects**				**Sign. Main Effects**				**Sign. Main + Interactions**			
	parameter	*Unstan Coeff.*	*Stand. Coeff.*	*t-ratio*	*p-value*	*Unstand. Coeff.*	*Stand. Coeff.*	*t-ratio*	*p-value*	*Unstand. Coeff.*	*Stand. Coeff.*	*t-ratio*	*p-value*
	Constant	2,882		15,159	<0,001	2,883		25,454	<0,001	3,072		20,910	<0,001
risk factors (main attr.)	ob_crowding [oc]	0,113	0,332	15,475	<0,001	0,117	0,346	19,749	<0,001	0,059	0,175	3,292	0,001
	transfer [tf]	-0,022	-0,019	-1,023	0,307								
	mask [ma]	-0,210	-0,183	-9,408	<0,001	-0,216	-0,189	-10,906	<0,001	-0,214	-0,187	-10,882	<0,001
	cleansing [cl]	-0,136	-0,119	-5,840	<0,001	-0,144	-0,126	-7,192	<0,001	-0,143	-0,125	-7,198	<0,001
	infectrate [ir]	0,007	0,245	12,419	<0,001	0,007	0,243	14,146	<0,001	0,010	0,370	7,079	<0,001
	social distancing [ld1]	0,004	0,003	0,098	0,922								
	moderate lockdow [ld2]	-0,236	-0,146	-5,875	0,000	-0,185	-0,114	-6,151	<0,001	-0,343	-0,212	-4,511	<0,001
	intelligent lockdown [ld3]	0,062	0,038	1,428	0,153								
indiv. characteristics (backgr. attr.)	health attide [ha]	0,016	0,009	0,484	0,628								
	health anxiety [hx]	0,107	0,060	3,214	0,001	0,123	0,069	3,967	<0,001	0,121	0,068	3,937	<0,001
	prosociality [so]	-0,001	0,000	-0,022	0,982								
	perc_control [pc]	0,114	0,087	4,815	<0,001	0,115	0,088	5,053	<0,001	0,154	0,117	5,663	<0,001
	personal efficacy [pe]	-0,178	-0,131	-6,733	<0,001	-0,167	-0,124	-6,790	<0,001	-0,169	-0,124	-6,876	<0,001
	risk_for_loved_ones [rl]	-0,168	-0,134	-7,092	<0,001	-0,165	-0,132	-7,336	<0,001	-0,257	-0,205	-6,831	<0,001
	gov_trust [go]	0,027	0,024	1,304	0,192								
	media_regular [me1]	-0,089	-0,038	-0,980	0,327								
	media_deliberate [me2]	-0,058	-0,025	-0,632	0,527								
	experience [ex]	0,078	0,063	3,599	<0,001	0,074	0,060	3,551	<0,001				
	sex	0,047	0,021	1,224	0,221								
	age	0,002	0,023	0,931	0,352								
	high education [edu_high]	0,020	0,017	0,973	0,331								
	employed [wo1]	-0,049	-0,021	-0,776	0,438								
	student [wo2]	-0,141	-0,048	-1,713	0,087	-0,137	-0,047	-2,814	0,005	-0,139	-0,047	-2,864	0,004
	retired [wo3]	0,002	0,000	0,016	0,987								
	education [tp1]	0,006	0,004	0,171	0,864								
	leisure [tp2]	-0,012	-0,005	-0,270	0,787								
interactions	pc.infectrate									-0,001	-0,137	-2,570	0,010
	rl.ob_crowding									0,019	0,178	3,072	0,002
	go.moderate lockdown									0,058	0,105	2,261	0,024
	ex.ob_crowding									0,016	0,081	4,735	<0,001
	R^2	0,347				0,344				0,352			
	adj. R^2	0,340				0,341				0,348			

Risk factors

When applying a model with only risk factors (or main attributes), 4 out of 8 predictor variables (including dummy variables for lockdown) appear to be statistically significant on a 95% confidence level. In total, the risk factors explain 27,6% of the variance of the risk rating. To check which of the variables contributes most to explaining the risk rating we look at standardized coefficients given that the unstandardized coefficients are dependent on the variable's unit. The standardized coefficients are obtained by subtracting the mean from the variable and dividing by its standard deviation. The relative impacts of each of the attribute values can be seen from Table 4.2. These are calculated by a multiplication of the unstandardized coefficient and the attribute level. Please note that the rating impacts are based on main effects only and don't include any non-linearities.

Table 4.2. Risk factor rating impacts for a model without interactions

Parameter	Stand. Coeff.	Unstand. Coeff.	Attr. level	Rating impact
Ob_crowding	0,346	0,117	1	0,117
			4	0,468
			6	0,702
			10	1,170
Infection rate	0,243	0,007	0,2	0,001
			6	0,042
			10	0,070
			100	0,700
Mask	-0,189	-0,216	-1	0,216
			1	-0,21
Cleansing	-0,126	-0,144	-1	0,144
			1	-0,144
Moderate lockdown	-0,114	-0,185	1	-0,185
			-1	0,185

- **On-board crowding** is found to be the parameter with the highest relation with perceived infection risk, with a standardized coefficient of 0,332 in the final model (0,346 without interactions). As expected, higher crowding levels in the train result in a higher perceived risk. The relation is assumed to be linear given that the quadratic component for crowding is non-significant.

- **Infection rate:** The second most important determinant for the risk rating is the national infection rate**.** This attribute has also a positive impact on perceived risk. This effect however, is found to be non-linear when estimated separately. The quadratic component is then small but statistically significant. Due to the small parameter size (-0,001), the quadratic component has only a considerable impact on the rating for the very high infection rate. Infection rate is also captured as a categorical variable with dummy coding. From Figure 4.2 can be seen that very high infection rates do not proportionally increase the rating, while realistic infection rates exhibit a near-linear relation with the rating. This relation is not what was expected, but potentially shows that the highest infection rate value of 10% was not properly perceived by respondents.

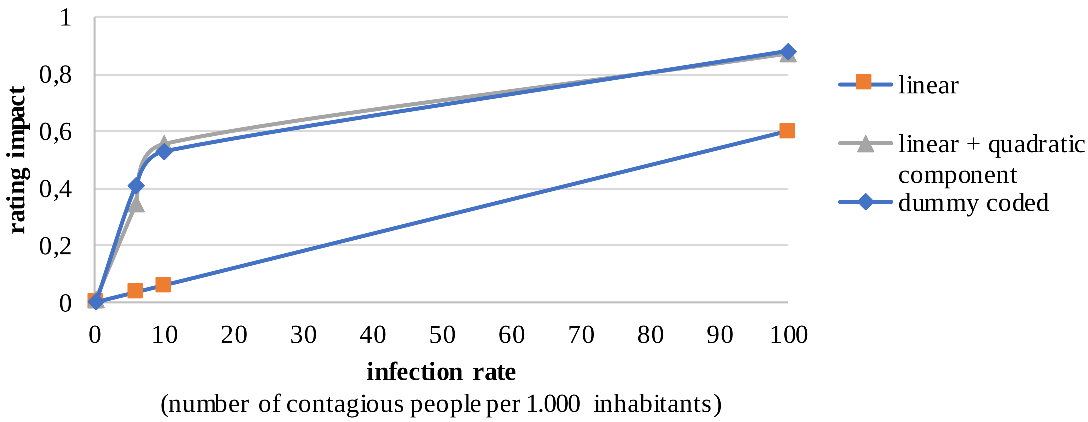


Figure 4.2. Infection rate rating contribution

- **Mask use and cleansing:** The policy measure attributes both have negative significant parameters around the same order of magnitude. This means that obliging to wear a face mask in trains decreases the perceived probability of getting infected, which is in line with intuition. Also the fact that extra cleansing of contact surfaces decreases the risk perception, albeit slightly less, is according to our expectations.

- **Lockdown status** Most interesting is the lockdown status. As explained, this attribute is divided into three different dummy variables. Of these dummies, only the moderate lockdown (level 3 out of 4) is statistically significant in all models and has a negative sign. A 'moderate' lockdown -as was experienced in October/November is apparently decreasing the believed risk of getting infected compared to the reference level, which is no measures taken. Similar to 'social distancing' (level 2 out of 4) no effect is discerned for the intelligent lockdown (highest level) in the regression model with only main effects. The intelligent lockdown has however a significant positive impact in some of the intermediate steps when interaction terms are taken into account. This confirms the contradictory (or ambiguous) effects governmental interventions could have on people's perception (as explained in subsection 3.2.1.).

- **Transfer** Lastly, the need to transfer in a trip does not appear to have an effect on the rating score as with a p-value of 0,307 the parameter is not statistically significant in our model.

Individual characteristics

Of the 18 estimated background parameters, only 6 are found to have a statistically significant effect. With an adjusted R squared of 0,344, the model fit improves compared to a model with only main attributes. The individual characteristics explain roughly 6,5% of the risk score. In order of relative explanatory power (based on standardized coefficients from Table 4.1) the relevant predictors are: risk for loved ones, personal efficacy, perceived control, health anxiety, experience with the virus and being a student. The rating impacts of the individual attribute levels are shown in Table 4.3. Interpretation of the effects needs to be done carefully though. Due to different formulations and coding of the Likert-scale statements the sign is not representative for the relation. Also, the magnitude of the rating impacts can be off from the standardized coefficients caused by differences in the standard deviations. An example is given below. All signs are in line with the expectations.

Table 4.3. Background characteristics rating impact

Parameter	Stand. Coeff.	Unstand. Coeff.	Attr. Level	Rating impact
Risk for loved ones[a]	-0,132	-0,165	1	-0,165
			3	-0,495
			5	-0,825
Pers. efficacy[a]	-0,124	-0,167	1	-0,167
			3	-0,501
			5	-0,835
Perc. control[a]	-0,088	0,115	1	0,115
			3	0,345
			5	0,575
Health anxiety[a]	0,069	0,123	1	0,123
			3	0,369
			5	0,615
Experience	0,060	0,074	-1	-0,074
			1	0,074
Student	-0,047	-0,137	-1	0,137
			1	-0,137

[a]*Attribute levels 2 and 4 are not depicted for sake of overview*

- **Risk for loved ones:** With regards to risk for loved ones (rl) the result can be interpreted in the following way. Travellers who are afraid to pass the virus on to a (vulnerable) family member or friend report a higher risk. The fact that the standardized parameter is (in absolute numbers) almost twice as large as health anxiety confirms that being afraid for others is more important than being afraid for ones own health in covid risk assessment.

- **Perceived control:** The idea that preventing an infection is not in your own sphere of influence also increases the perceived risk. This is line with institution, given the fact that higher levels of perceived control usually go hand in hand with lower perceived risks (Nordgren et al., 2007). It strikes however that this attribute is considerably less predictive than the 'risk for loved ones' indicator.

- **Health anxiety:** Worrying about your own health is impacting the risk rating to a similar extent as perceived control. Health anxiety is statistically significant, in contrast with health attitude (p=0,628), confirming that being anxious is more important than how vulnerable you think you are.

- **Personal efficacy:** The effect of personal efficacy is less straight-forward. Believing that personal preventive actions are not effective decreases the risk perception levels. This is opposite to the relation with perceived control and therefore remarkable. A potential explanation may be found in the fact that people who think that actions such as wearing face masks or frequently washing your hands are not important, also believe that the chance of getting infected is in general fairly low.

- **Experience:** More than half of the respondents (68,7%) knows someone personally who has been infected with the coronavirus. The effect of knowing someone who has experienced the covid disease is also impacting the rating positively, albeit smaller than the preceding characteristics. The 'experienced' travellers are potentially more aware of the risk. It makes sense that you assess a risk as lower when you don't see the risk.

- **Student:** Lastly, the only sociodemographic with a significant effect is the dummy variable student (which is part of the work status) attribute. Students, apparently, rate the infection rate overall lower than others. Also, from Table 4.3. it can be seen that the attribute student has a higher rating impact than experience, despite having a lower standardized coefficient. This can be attributed to a larger S.D. for experience. In other words, there is relatively much uncertainty with the attribute student.

No relation with age was found, which was expected, but also confirmed by some covid studies to not correlate (see subsection 2.2.1.). We did not find any relation with media consumption and the risk rating. Also the personal health conditions (health attitude), prosociality and governmental trust are not good predictors for the risk rating in our sample.

Interactions

In the last column of Table 4.1 and in Table 4.4, the significant interaction terms are reported. After removal of all non-significant parameters using the aforementioned procedure (backwards elimination, main effects having priority) the final model contains 4 interaction terms. The interactions add just 0,8% additional explained variance of risk perception. Yet, it is interesting to interpret the different significant interactions. Those are discussed below. The interactions can be interpreted as that the impact of an attribute varies for different individuals and is mathematically captured as an additional effect besides the main effect of the risk factor, as is illustrated in equation 4.1.

$$Rating\ impact_{crowding} = \overbrace{(\underbrace{0{,}059}_{\textbf{Main effect}} + \underbrace{0{,}019 * rl}_{\textbf{Interaction effect}})}^{\textbf{Total effect}} * ob\_crowding \tag{4.1}$$

Table 4.4. Interaction terms

Main effect	Background effect	Interaction effect
On-board crowding [oc] 0,059	Risk for loved ones [rl] -0,257	oc.rl 0,019
	Experience [ex] -	oc.ex 0,016
Infection rate [ir] 0,010	Perceived control [pc] 0,154	ir.pc -0,001
Moderate lockdown [ld2] -0,343	Governmental trust [go] -	ld2.go 0,058

- **On-board crowding * Risk for loved ones [oc.rl]:** Risk for loved ones (rl) forms an interaction with on-board crowding. In general, someone who is afraid to infect others thinks crowdedness is more important when evaluating the infection risk as opposed to someone who is less afraid for loved ones. The additional effect of risk for loved ones is illustrated in equation 4.1 as the interaction term. Higher levels of ‘rl’ result in an higher net effect of crowding on perceived risk.
- **On-board crowding * Experience [oc.ex]:** From Table 4.1 you can see that the main effect for covid experience is removed from the model compared to a model with only main effects (second column). This is due to statistical non-significance when an interaction term with crowding is included. The interaction term with on-board crowding takes over enough of the explanatory power from the main effect to make it non-significant. Apparently, the effect of knowing someone who has experienced covid-19 has the most effect on the valuation of crowding. The relation exists in such a way that knowing someone who suffered from covid-19 makes one more sensitive towards crowding with respect to risk perception.

- **Infection rate * Perceived control [ir.pc]:** This interaction effect is explained as follows. Thinking you are able to prevent an infection has an additional effect of the infection rate on risk perception. In other words, the idea of not having control diminishes the importance of infection rate. Reversely, this also tells us that when one thinks he or she can prevent an infection, he or she is more concerned about the infection rate when evaluating the infection risk.
- **Moderate lockdown * Governmental trust [ld2.go]:** This interaction term is interesting because governmental trust does not have a significant main effect on risk, but is appearing in an interaction with on-board crowding. The governmental trust indicator in itself is thus not a good predictor for risk perception, but is determinative for the effect of the moderate lockdown level on the risk score. In fact, trusting the government in their crisis management capabilities increases the positive effect a moderate lockdown has on risk perception. In other words, the public opinion of actions taken by the government to prevent virus spreading is indeed correlated with the governmental interventions in our experiment, at least for one of the lockdown levels.

No interactions effects were found between media consumption and both mask usage and cleansing. The hypothesis that the 'doing own research' was an indicator for more critical viewpoints can thus not be confirmed.

Risk components

Lastly, we estimate how the higher order covid-19 risk perception components relate to the other independent variables and the dependent rating variable. We do this in a separate model because it is expected that these perception variables are (highly) correlated with the rating. It would therefore explain much of the variance at the cost of other variables which we are more interested in. In Appendix G: Linear regression, an overview of the risk component models can be found. The main take-away is that inclusion of the risk perception components eats away explanatory power from especially the background variables, indicating multicollinearity. The main attributes are barely affected by the extra higher order variables, which is also what was expected. The general attitudinal risk component (c-19 attitude) explains most of the risk rating overall and the affective risk (measure for worry) correlates most with the psychometric variables. In the model with only a cognitive risk (likelihood estimate) perception element, the background parameters stay relatively similar to the model without risk components. This result makes sense since the dependent variable (the risk rating) is measuring risk in the same dimension as the cognitive risk attribute, but on a different scale.

Key findings

- On-board crowding is most important for the perceived trip risk, followed by the national infection rate; having to transfer is not found important.
- Sociodemographics are barely correlated with risk perception.
- Students have lower risk perceptions compared to other groups.

4.3. Discrete choice modelling

The second part of the experiment is the discrete choice model. We firstly elaborate on the expected outcomes. The results are presented and analysed afterwards.

4.3.1. Expectations

As already mentioned above, the main trip attributes are all expected to have a negative parameter sign. Opting out is more difficult to predict due to its relation with the alternative specific parameters for opting out. In itself, not performing a trip will have attain a negative utility, but the different opting out scenarios could change the ASC for opting out. After all, cancelling the activity will most probably have a negative sign, but a private mode could be preferred above taking the train during the pandemic by many people. It is also expected that CR will play a significant role in choosing between train trips. The extent to which is does, is the main goal of the section.

It is also expected that one or more of the trip purposes influence the trade-offs. For example, people taking trips executed for leisure activities might in general be more risk-averse and therefore have a higher absolute parameter for covid risk. The same line of reasoning can be applied to travel frequency during the pandemic. The interaction effect between travel time and covid risk is also expected to be significant, given the infection probability is already proven to be linear with the exposure time when sitting in a PT vehicle with confirmed covid-19 cases (Hu et al., 2020). With regards to sociodemographics, the expectations are given in subsection 3.2.2. Among these expectations are that age is correlated with attaching a higher value to covid risk, together with being women as was found by Brown et al., (2020); Dryhurst et al. (2020) and in general risk evaluations by Weber et al. (2002). Work status and education level are related to each other. These characteristics are expected to be most important for the opt-out scenarios and might also influence the trade-offs between the trip attributes. It has to do with trip urgency and having alternatives available. Students might not have other transport options available and are therefore less likely to opt-out, however home education is likely to diminish the need for travelling by train.

4.3.2. Results

The results of the most relevant discrete choice models are depicted in Table 4.5. The results will be discussed according to both the short trips and long trips, and all models that are estimated. The most important differences between the datasets and the estimation methods will be discussed first. Afterwards, the main attributes and interaction terms are analysed sequentially.

Table 4.5. Choice modelling results

	LONG TRIPS (N=291)	**MNL final**			**ML final (400 draws)**		
	Parameter	*Estimate*	*Rob. t-ratio*	*p-value*	*Estimate*	*Rob. t-ratio*	*p-value*
main attribute	Travel Costs (TC)	-0,175	-8,638	<0,001	-0,399	-11,044	<0,001
	Travel Time (TT)	-0,027	-7,316	<0,001	-0,054	-9,209	<0,001
	Covid Risk (CR)	-0,588	-6,985	<0,001	-1,258	-5,250	<0,001
	Covid Risk Sq. (CRsq)						
	Opt-out (OPT)	-5,289	-12,586	<0,001	-11,538	-13,788	<0,001
stand. dev.	Std. Dev. TC				0,067	3,775	<0,001
	Std. Dev. CR				1,123	8,413	<0,001
background interactions	student * TC	0,063	2,336	0,020	0,080	2,365	0,018
	student * TT	-0,026	-3,025	0,002	-0,029	-3,140	0,002
	freq. * TT	0,009	4,201	<0,001			
	age * CR	-0,005	-2,400	0,016	-0,015	-2,794	0,005
	edu * CR	-0,083	-2,865	0,004	-0,224	-2,471	0,013
	empl. * CR						
	student * CR						
	retired * CR						
	freq. * CR				0,273	2,821	0,005
	R^2	0,1956			0,3805		
	Adj. R^2	0,1925			0,3766		
	LL 0	-2869,575			-2869,575		
	LL final	-2.308,257			-1777,753		

	SHORT TRIPS (N=117)	**MNL final**			**ML final (800 draws)**		
	Parameter	*Estimate*	*Rob. t-ratio*	*p-value*	*Estimate*	*Rob. t-ratio*	*p-value*
main attribute	Travel Costs (TC)	-0,224	-4,526	<0,001	-0,501	-6,922	
	Travel Time (TT)	-0,051	-5,246	<0,001	-0,104	-7,543	
	Covid Risk (CR)				-0,616	-2,809	0,005
	Covid Risk Sq. (CRsq)	-0,112	-11,725	<0,001			
	Opt-out (OPT)	-3,323	-7,360	<0,001	-7,703	-9,410	0,000
stand. dev.	Std. Dev. TC				0,163	3,529	0,000
	Std. Dev. CR				0,507	5,690	0,000
background interactions	student * TC						
	student * TT						
	freq. * TT						
	age * CR						
	edu * CR				0,158	2,333	0,020
	empl. * CR				-0,457	-1,971	0,049
	student * CR				-0,646	-2,504	0,012
	retired * CR	-0,156	-2,196	0,028	-0,768	-3,103	0,002
	freq. * CR						
	R^2	0,1315			0,238		
	Adj. R^2	0,1271			0,229		
	LL 0	-1148,050			-1148,050		
	LL final	-997,105			-875,218		

First observations

When comparing the model statistics of the ML model with the MNL model in Table 4.5, a large increase in model fit is observed, especially for the long trip dataset, implying that the ML model is statistical superior to the MNL. Together with the fact that the estimated standard deviations for CR and TC are statistically significant, we can reasonably state that the conclusions inferred from the ML results are most valuable. The differences will be explained in the following subsections. Referring to the forced option datasets, we decided to disregard the models without opting out. This is because it was apparent that opting out was not problematically often chosen (see 4.1.2.) and the opting out parameter was statistically significant. Also when comparing the long trips and short trip datasets quite some dissimilarities can be observed. Although the specific differences will be discussed later on, it strikes that the model fit is higher for the long trip. This can be attributed to the fact that more significant interaction effects are found for this dataset.

Choice attributes

All main attribute parameter values have the expected negative sign, including the ASC for opting out (OPT in Table 4.5). All main attributes are statistically significant on a 95% confidence interval. A quick calculation reveals that for both datasets covid risk is the most dominant factor when choosing between the trips. The results are shown in Table 4.6 and are based on a multiplication of the estimate in the final models with the corresponding attribute range. It is clear that CR has the largest impact on the utility on both datasets. This shows that the perceived risk of attaining the virus is an important denominator in choosing train trips. Please note that comparing these values across the models is not possible.

Table 4.6. Relative importance of the estimated parameters

Parameter	**Relative importance MNL**		**Relative importance ML**	
	Long trips	*Short trips*	*Long trips*	*Short trips*
TC	-1,05	-0,67	-2,39	-1,50
TT	-0,54	-0,71	-1,08	-1,46
CR	-2,35	-2,80	-5,03	-2,46

Value of Risk

Comparing the ratios between the attributes does give more insight in the trade-offs people make than the relative contributions as calculated above. The value of time (VOT) is a commonly used metric in transportation science to provide tangible insights in how negatively travel time is valued, expressed in monetary units. We can apply the same logic for a value of risk (VOR). Both travel time and covid risk are compared towards travel costs by dividing it by the costs (TC) effect (main and interactions) to arrive at a willingness to pay (WTP) for travel time savings (VOT) and a willingness to pay for reduced infection risk (VOR) respectively. More theoretically, in equation 4.2, the VOT is calculated by taking the ratio of the marginal utility of travel time and travel costs. The same procedure is performed for the VOR (equation 4.3). The VOT is multiplied by 60 to arrive at a more conventional unit (euro per hour). The formula becomes somewhat more complex when including interaction terms with the background variables, as is shown for in equation 4.4 (VOR for long trips). The VOT and VOR results (with interaction effects) are given in Table 4.7.

$$VOT = \frac{\frac{\partial V}{\partial TT}}{\frac{\partial V}{\partial TC}} * 60 = \frac{\beta_{TT}}{\beta_{TC}} * 60 \tag{4.2}$$

$$VOR = \frac{\frac{\partial V}{\partial CR}}{\frac{\partial V}{\partial TC}} = \frac{\beta_{CR}}{\beta_{TC}} \tag{4.3}$$

$$VOR_{long\ trip} = \frac{\beta_{CR}+\beta_{age.CR}*age+\beta_{edu.CR}*edu+\beta_{freq.CR}*freq}{\beta_{TC}+\beta_{wo2.TC}*student} \tag{4.4}$$

edu= education level; freq= trip frequency during pandemic; wo2= student

Table 4.7. value of time & value of risk

	MNL		ML	
	long trips	*short trips*	*long trips*	*short trips*
VOT (€ / hr)	9,28	13,52	8,17	12,50
VOR (€ / risk level)	4,41	2,29	4,64	2,17

With an average (weighted over the short trip and long trip ML models) VOT of 9,41 euro per hour, our estimates are fairly close to what Bates (2013) reported in an extensive study related the value of travel time savings in the Netherlands. Their study found an average willingness to pay of 9,25 euro per hour for Dutch train travellers. An interesting finding is that the VOT is higher in the short dataset compared to the long dataset. The interpretation is that travel time is more important for shorter train trips than for longer train trips. A potential explanation can be that the differences in travel costs are perceived less important in the short dataset because the fares are always relatively low (compared to the long trips), causing no real trade-offs are made between the choice tasks.

For the VOR we see the opposite effect. A higher VOR for the long trip dataset is found, indicating risk is valued more heavily in long trips. Due to interactions, the value of risk differs among respondents. For an average respondent of 39 year old ,who is not a student and usually travels longer than 30 minutes, the willingness to pay for one point of risk reduction is 4,64 euros. For the same individual usually travelling shorter than 30 minutes, the value of risk is less than half (2,17 euros). This is in line with the hypothesis that travel time has a positive impact on covid risk perception. Interestingly, this effect was not found using this study's initial approach which involved measuring a direct relation between travel time and covid risk. The interaction term between CR and TT is statistically significant in none of the estimated models. One can conclude that risk evaluation is not affected by the travel times within the datasets, but on a higher level, between the datasets, it is.

As explained in 3.7.2. a linearity check for CR is performed. There are differences in the shape of the relation between perceived risk and their utility contribution, as can be seen in Figure 4.3. For the long trip dataset the quadratic component of CR (CRsq) is not statistically significant, however for the short dataset it is. The quadratic parameter has a negative value, indicating that the impact of covid risk is higher for high risk levels compared to lower risk levels. A categorical variable (effect coded) in which low risk is the reference level is also estimated. For the long dataset only the high risk estimation is significant, indicating again a linear relation. For the short dataset, both the medium risk and high risk dummy are significant.

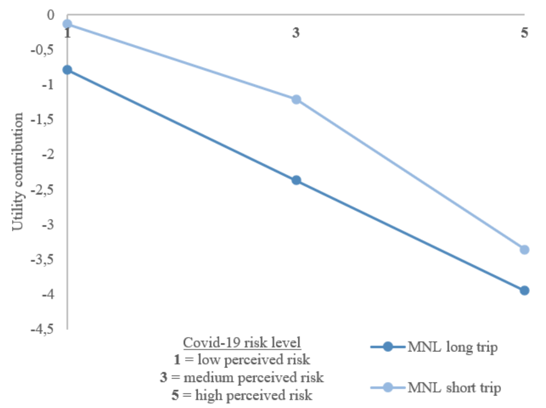


Figure 4.3. Covid Risk utility contributions.

Individual characteristics

As explained, the background variables (individual characteristics) are merely captured as interaction effects with the choice attributes. When examining the interactions, there are several background variables for which significant relations are found. What stands out the most when comparing the different models is that the short trip model reports fewer and different significant interaction terms than the long trip model. This might have something to do with the size difference of the two samples, although 117 responses is still considered fairly high. The dissimilarities between the two dataset could also show that the found effects are relatively unreliable and merely resemble certain peculiarities in the dataset. Despite these differences, these significant interaction effects will be discussed as estimated by the ML model (since this model has a higher model fit) for both datasets.

The most important observation is that none of the trip purpose indicators are found to have a correlation with any of the travel attributes in either of the datasets. We can therefore not confirm the hypothesis that trip purpose is associated with how people trade-off risk. For the long trip models we find that being student is correlated with both TC and TT in the long trip model and with only CR in the short trip model. The long trip model shows that students are less cost-sensitive, which is not in line with intuition given that they usually have a smaller budget. Considering travel time, the effect of being student is opposite. The fact that most Dutch students have a free public transport card could play a role (despite they were asked to imagine they had to pay full fare) in the trade-offs they make. Interestingly enough, travelling for education purposes does not influence any of the parameters, while most respondents who indicated themselves as students (18,6% of sample) also filled in education as their main travel purpose (77,0%). This could also be a result of multicollinearity between being student and travelling for education purposes.

The significant interaction terms between the work statuses and CR in the short tip model are not as outstanding as the parameter sizes would suspect. All work status variables have in fact a significant interaction effect with risk of roughly the same size, revealing that the reference category (unemployed) is the outlier. In Figure 4.4 can be seen that not having a job is affecting the weight attached to CR considerably less than the other work statuses. It is however not possible to conclude that unemployed people are less sensitive to perceived risk. This is mainly due to the small number of unemployed respondents in the short trip dataset (N=16). This observation explains why interaction terms between work status and CR were only found in the short dataset and not for the long trips. We cannot conclude there are differences found in risk valuation between people with different work statuses.

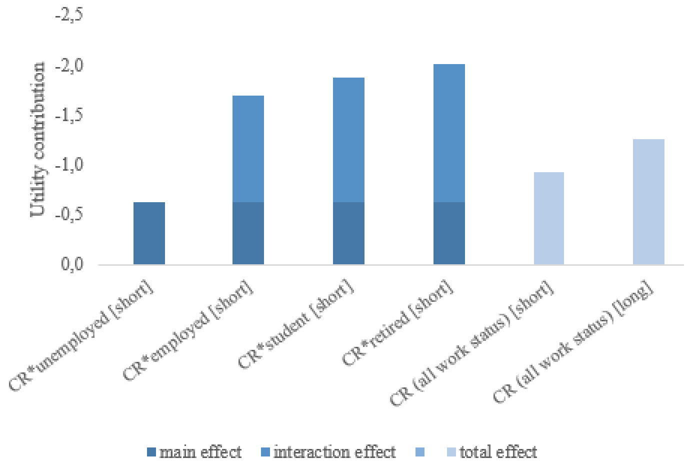


Figure 4.4. Utility contribution of CR for different work status categories

Education level is the only background effect appearing in both datasets with a meaningful impact. The direction of the relation is inconsistent though. Where for long trips, higher educated people weight risk more heavily, in the short dataset higher educated people attach less weight to risk. The background variable with the highest absolute impact on the utility is age, however only for the long trips. Higher age corresponds with a higher disutility for CR, being in line what was expected, but is contrary to what Gerhold et al. (2020) found in their covid-19 risk perception study. The last significant relation found in our choice model is the trip frequency with CR. It exists in such a way that people who travel more than once a week during the pandemic have a lower negative taste for infection risk compared to less frequent travellers.

With regards to the different opt-out scenarios it is possible to check whether people who have access to a car are more likely to opt out in general. With a t-value of 1,49 (p-value: 0,459) this relation is not found in the long trip dataset. It appears that having access to a car a does not significantly impact the chance of choosing to not make one of the train trips.

Key findings

- Infection risk is the most important attribute in choosing between train trips.
- Infection risk is more important in longer trips, although no significant interaction was found between travel time and covid risk attributes.

4.4. Model combination

Now that both parts of the experiment are estimated it is possible to combine the results. In the rating experiment, covid-19 risk perception was the dependent variable which was fed into the discrete choice model as one of the independent variables. Together with the other attributes, risk determined the trip alternatives' utility. In this subsection, the results from both experiments are used to exhibit two practical applications. Firstly, the probability of opting out is calculated for different trip conditions. This gives an indication about the reduced travel demand caused by the pandemic under different circumstances (scenarios). Secondly, the appropriateness of obliging all passengers to wear masks and cleansing contact surfaces is reviewed by calculating the willingness to pay for these preventive policy actions using the value of risk (in euros).

A willingness to pay value for cleansing can help governments or operators in justifying this measure if they consider increasing cleansing regimes.. The value of (on-board) crowding is also quantified using this approach. This is done to provide insights in the increased impact of crowding on the passenger's travel experience during the covid-19 pandemic. In general, the monetization of crowding, mask use and cleansing can be used as inputs for appraisal methods such as cost-benefit analyses. These effects then serve as subjective benefits, additional to the benefits related to the objective transmission reduction caused by these measures/changes and can consequently be compared to the costs.

4.4.1.Train demand scenario analysis

A combination of both model estimates can be used to draw conclusions about the probability of opting out (or making the train trip) under different circumstances. The probability of opting out is an indicator for the ridership reduction in comparison with pre-pandemic conditions. The probability of making a train trip is calculated for several scenarios with a MNL choice probability function using equation 4.5. The utility for opting out (V_{optout}) stems from the choice model (equation 3.3) and remains constant for all scenarios. The utility for the train trip (V_{train}) is based on the outcomes of the choice experiment and rating experiment (equation 3.2). The trip attributes travel time and travel costs are systematically varied and the value for covid risk is based on relevant risk factors, relevant individual characteristics (dependent on the scenario) and their regression coefficients. All trip attributes are then multiplied with the weights estimated in the choice experiments.

In the scenario analyses we aim to variate the risk factors to see what is the impact on the choice probabilities. It is important to note that only a part of the risk factors is controllable, most notably the policy measures. Crowding is only partially in the sphere of influence of the operators and the infection rate is not all. Also the background variables are non-controllable.

$$P_{train} = \frac{e^{V_{train}}}{e^{V_{train}}+e^{V_{optout}}} \tag{4.5}$$

Scenario 1: Off-peak trip in October 2020

For the first scenario analysis, the starting point is a hypothetical off-peak train trip taking place during the covid-19 pandemic. The seat occupancy is set to 30% and the prevalent infection rate is 0,6% of the population. This should resemble a context in which the infection numbers are not extremely high, but high enough to justify governmental lockdown measures to limit virus spreading (as it was in October 2020). The obligatory use of face masks and the cleansing regime are then varied. For the relevant individual sociodemographic characteristics, an 'average respondent' is used. This means that the individual is 39 years old, scores average (rounded to integers) on all psychometrics and has a paid job. A characteristic is considered relevant when it contributes to the perceived risk rating (either as main effect or interaction effect) or influences one of the attribute tastes. The relevant characteristics are depicted in Table 4.8.

Table 4.8. Relevant characteristics of an average respondent

individual characteristic	Value
Age	39
Health anxiety [hx]	2
Perceived control [pc]	3
Perceived efficacy [pe]	2
Risk for loved ones [rl]	3
Governmental trust [go]	3
Experience with the virus [ex]	yes
Work status [wo]	employed

The risk rating (CR) can now be predicted with equation 4.6. The only components varying in this equation are the mask (ma) and cleansing (cl) values. These are either '-1' (for measure not imposed) or '+1' for measure imposed. The predicted risk ratings under different policy scenarios are shown in Table 4.9.

$$CR = C + (\beta_{oc} + \beta_{rl.oc} * \ rl) * oc + \left(\beta_{ir} - \beta_{pc.ir} * pc\right) * ir + \beta_{hx} * hx + \beta_{pc} * pc + \beta_{pe} * p + \beta_{rl} * rl + \beta_{ma} * ma + \beta_{cl} * cl$$

$$= 3{,}072 + (0{,}059 + 0{,}019 * 3) * 3 + (0{,}010 - 0{,}001 * 3) * 6 + 0{,}121 * 2 + 0{,}154 * 3 - 0{,}169 * 2 - 0{,}257 * 2 - 0{,}214 * ma - 0{,}143 * cl \qquad (4.6)$$

oc=on-board crowding, ir=infection rate, ma=mask, cl=cleansing, other see table 4.7

Table 4.9. Risk ratings (CR) under different policy scenarios

	Extra cleansing	No cleansing
Mask obligation	2,70	2,99
No mask obligation	3,13	3,41

Based on the predicted ratings from Table 4.9, the probability of making the trip is calculated. Because two different choice models were estimated, the utility for a trip longer than 30 minutes is calculated based on other variables (equation 4.7) than trips shorter than 30 minutes (equation 4.8). Note that some significant variables (e.g. travel frequency and education level) are not included in the equations since the mean effect of a (binary) effect coded variable can be captured by setting the values to 0.

$$V_{TT=45,\ TC=9,\ average resp.} = \beta_{TC} * TC + \beta_{TT} * TT + \left(\beta_{CR} + \beta_{age.CR} * age\right) * CRb$$

$$= -0{,}399 \ * \ 9 - 0{,}054 \ * 45 + (-1{,}258 - 0{,}015 * 39) * CR \qquad (4.7)$$

$$V_{TT=17,\ TC=4.5,\ average\ resp.} = \beta_{TC} * TC + \beta_{TT} * TT + \left(\beta_{CR} + \beta_{empl.CR} * empl\right) * CR$$

$$= -0{,}501 \ * \ 4{,}5 - 0{,}104 \ * 17 + (-0{,}616 - 0{,}457 * 1) * CR \qquad (4.8)$$

After calculating the utilities (and applying equation 4.5), the marginal probability increase for a long trip taking 45 minutes and costing 9 euros, caused by mask obligation is then found to be 18,8%. Extra cleansing increase the boarding probability with 12,3%. These results reflect the differences in the regression analysis, where the obligation of masks was found to be more predictive for the perceived risk than extra cleansing. We can observe from Table 4.10 that the impact of both preventive measures on the likelihood of boarding are lower for shorter trips than for longer trips. Generally speaking, over all travel time-cost combinations, we can conclude that the average increase in probability of taking the train instead of opting out is 11,4% as a consequence of face mask obligation. 7,2% can be attributed to extra cleansing of contact surfaces. These figures are calculated by taking the average increase in boarding probability of all time-cost combinations. The increases range from 2,7% to 19,3% for mask use and 1,6% to 13,1% for extra cleansing for long trips, as can be seen in Table 4.11.

Table 4.10. Probability of taking the train under scenario 1 for an average respondent

	Mask & cleansing	**Only mask**	**Only cleansing**	**None**	**Marginal impact of both measures**
TT: 45 min TC: 9 euros	63,2 %	50,3 %	43,8 %	31,5 %	31,7%
TT: 17 min TC: 4,5 euros	68,6 %	61,7 %	58,03 %	50,4 %	17,8%

Table 4.11. Increase in probability of taking the train due to policy measures (long trips only)

TT [min]	**TC [euros]**	**Difference due to mask**	**Difference due to cleansing**	**Difference due to mask**	**Difference due to cleansing**
		Scenario 1		***Scenario 2***	
35	9	19,3%	13,1%	18,2%	11,8%
35	12	15,2%	9,5%	10,1%	6,2%
35	15	7,0%	4,2%	3,9%	2,3%
45	9	18,8%	12,3%	14,9%	9,3%
45	12	11,2%	6,9%	6,8%	4,0%
45	15	4,4%	2,6%	2,4%	1,4%
55	9	16,0%	10,1%	11,0%	6,7%
55	12	7,6%	4,6%	4,3%	2,5%
55	15	2,7%	1,6%	1,4%	0,8%
Average		**11,4%**	**7,2%**	**8,1%**	**5,0%**

Scenario 2: Peak-hour train trip in March 2020

We also estimate a second scenario with higher infection rates (1% contagious people) and higher crowding levels (60% seating occupancy) (see Table 4.11). This resembles a train trip in a context with infection rates as observed in the first infection wave (March 2020) and a relatively crowded train. The marginal demand increase as a consequence of mandated mask use ranges from 1,4% to 18,2% and for extra cleansing from 0,8% to 11,8%. It is obvious that the overall probability of opting out increases with higher infection rates and crowding levels, but compared to the previous scenario, it appears that the marginal impact of both safety measures decrease under more risky circumstances. However it may seem counterinitiative (as safety measures should be more important as the threat increases), we could explain this with the notion that the effect of higher infection rates and higher crowding levels are overshadowing the impact of the safety measures on perceived risk. In other words, the measures do little to improve the perceived risk. The results for short trips are not further discussed, but show similar relations.

Scenario 3: Varying crowding and infection rates
Lastly, we vary the crowding level and infection rate while fixing the policy measures. We take a trip length of 45 minutes and trip costs of 9 euros and assume a scenario in which mask use is obliged and no extra cleansing regime is applied (resembling real-life from June 2020 onwards). In Figure 4.5, we plotted the boarding probability as a function of the crowding levels for different infection rates. We observe that the realistic infection rates only have a limited impact on the boarding probabilities. The unrealistic infection rate of 10% contagious people is reducing the probability roughly half compared to the other rates.

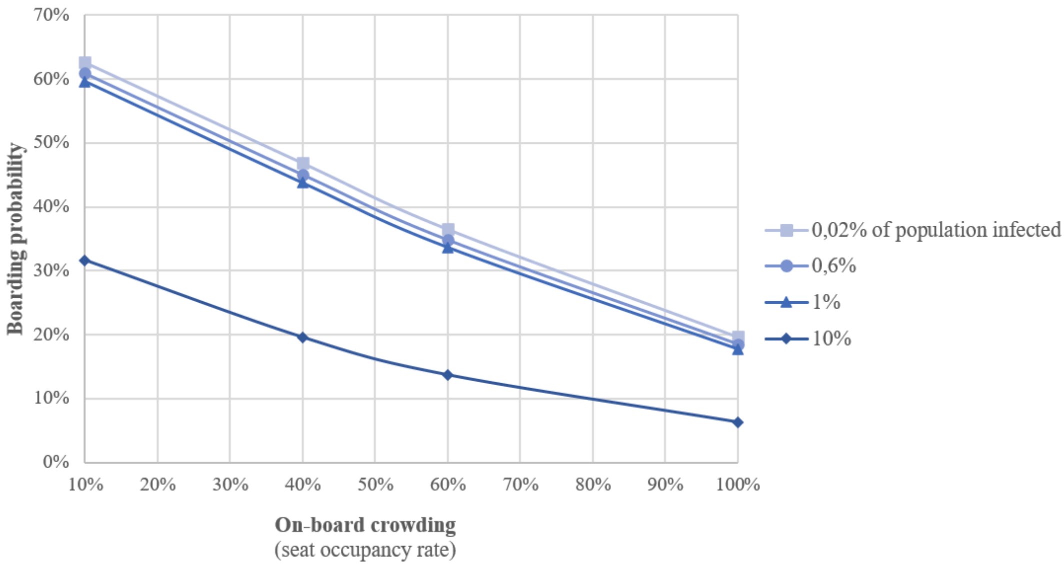


Figure 4.5. Boarding probabilities for different crowding and infection rate levels

4.4.2. Willingness to pay for risk reducing factors
The willingness to pay (WTP) for a reduction of the perceived risk level was already obtained from the choice model in 4.3.2 and was named the value of risk (VOR). In this subsection, we link the VOR with estimates from the rating experiment to find the WTP to change risk-inducing factors. This extends the knowledge of the perceived importance of these factors with how much traveller's are willing to pay to reduce the infection risk by changing a risk factor. These values could be used as inputs in for example cost-benefit analyses. We evaluate the WTP to oblige everyone to wear a mask and the WTP for extra cleansing, but first calculate the value of crowding. We note again that the risk-inducing factors are only partly controllable by the operators.

Value of crowding
We know that travelling in crowded conditions incurs additional costs compared to less crowded conditions in non-pandemic situations (e.g. Wardman & Whelan, 2011). The willingness to reduce crowding levels is expected to increase during the covid-19 pandemic given that distancing people is a key element in curbing the corona pandemic. On-board crowding was already found to be the most important predictor for the risk score in this study. We make this concrete by computing a value of crowding (VOC). The VOC is in fact the WTP for a 10% reduction in seating occupancy.

The VOC is calculated by a multiplication of the average VOR (from the choice experiment) with the linear regression coefficient of crowding (equation 4.9). Because crowding interacts with both 'risk for loved ones' and 'virus experience', these interaction terms are also included. For these individual characteristics, we assume again an average respondent (Table 4.12). Because crowding is measured on an interval ratio, we are able to capture different increments. One level increment stands for 10% difference in seating capacity.

$$VOC_{long\,trip} = \ (\beta_{oc} * \beta_{rl.oc} * rl + \beta_{ex.co} * ex) * oc * VOR \ = € \ 0{,}88 \tag{4.9}$$

Table 4.12. Elements from $VOC_{long\ trip}$ equation

Element	Name	Value
β_{oc}	on-board crowding	0,117
$\beta_{rl.oc}$	risk for loved ones * on-board crowding	0,019
$\beta_{ex.co}$	experience * on-board crowding	0,016
oc	on-board crowding	3
rl	risk for loved ones	3
ex	experience	1
VOR	value of risk	4,64

We calculated an average VOC of 0,88 euros for trips longer than 30 minutes and 0,41 euros for shorter trips. Considering that in the survey, the seat occupancy rate of 30% was described as ‘easy to find a spot to sit alone’ and 60% was defined as ‘not able to sit alone, it is possible to interpret these findings as following. An average traveller is willing to spend around € 2,65 (0,88 euros multiplied with 3 increments; equation 4.10) extra on a long journey (>30 minutes) to easily be able to sit alone instead of sitting next to someone else. Taking into account that travel costs were varied between 9 and 15 euros in our long trip experiment, this yields on average a WTP of 22% of the ticket price.

$$WTP_{crowding\,reduction\,from\,60\%\,to\,30\%} = (6-3) * VOC = 3 * 0{,}88 = € \ 2{,}65 \tag{4.10}$$

An alternative, but in real-life existent option to travel in a more quiet environment is to travel first-class. Such an upgrade would have an average fee of around 8 euros for our average 45 minutes trip. This indicates that people are not likely to pay for a first-class upgrade in corona times to reduce the infection risk. However, it is important to keep in mind that first-class comes with other benefits too (e.g. wider seats).

When we compare our estimates with other findings related to value of crowding in non-pandemic conditions, it is possible to draw conclusions regarding the impact of the covid pandemic on crowding valuation. Drawing conclusions about our VOC is however complex because crowding valuations are among other things dependent on how crowding is measured, on wages, the prevalent crowding levels in real-life and the type of public transport (e.g. train or metro). In order to be able to make sensible comparisons, The VOC is converted into a time multiplier, which is according to Wardman & Whelan (2011) inherently more transferable than monetary units. This makes comparisons across countries and contexts possible. Using a similar approach as the WTP for crowding reduction, a willingness to pay in terms of additional travel time is computed. A time penalty of 6,52 minutes is then found for a 10% increase in seating occupancy. Translating this to a penalty for a seating occupancy increase from 30% (not able to sit alone) to 60% (able to sit alone), a time multiplier of 1,43 is found (based on a 45 minute trip). Comparing this with a Dutch urban Public transportation study from Yap et al. (2018) who found a time multiplier of 1,16 for frequent and 1,31 for non-frequent travellers when all seats are occupied, it is slightly higher. Also the meta-analysis of Wardman & Whelan (2011) which comprises 84 different studies, report a lower multiplier of 1,19. Although our time multiplier is calculated in a different manner than other studies did, making direct comparisons impossible, it gives an indication that our study found a considerable higher willingness to reduce crowding. Most probably caused by the pandemic.

Willingness to pay for policy measures

Another WTP application is the willingness to pay for risk-reducing policy measures. Similarly to the VOC it is calculated by taking the average VOR and multiply it with the regression coefficient for masks (equation 4.11) and cleansing respectively. Since no interactions are involved with mask and cleansing the equations are simpler. The results are shown in Table 4.13.

$$WTP_{mask\ obligation} = \beta_{ma} * ma * VOR \tag{4.11}$$

It turns out that the willingness to pay to oblige everyone to wear a mask, for a 39 (average) traveller who usually travels longer than 30 minutes, is around 2 euros. The interaction effects in the choice models cause that the value of risk is different across people, which in turn causes the WTP to vary across people. A younger traveller will have a lower willingness to pay for obliged mask use. Being a student has an increasing effect on the weight attached to risk, causing a 20 year old student to have higher WTP of 2,10 euro, compared to a non-student of similar age (1,68 euro). This find finding is interesting, given that students generally have a smaller budget and that they were found to be less risk aware in the rating experiment. The effect of having a higher educational degree is around half a euro and is thereby similar to the effect of being student. People who attain a diploma from higher vocational education or university, are on average willing to pay 48 cents more for masks compared to lower educated people. The fact that higher educated individuals are willing to pay more can be caused by the fact they have higher salaries. Another explanation is that these people tend to understand the urgency of wearing mask better.

Table 4.13. Willingness to pay [euro per trip]

	Long trips average resp.[a] [bandwidth]	**Short trips** average resp.[a] [bandwidth]
mask	1,99 [1,11-3,95]	0,92 [0,39-1,32]
cleansing	1,33 [0,74-2,64]	0,61 [0,26-0,88]

[a]Values for an average respondent: age 39, employed, non-student, average frequency, average education level

In concrete terms it is now possible to say that an average respondent is willing to spend around 2 euros extra on a ticket to ensure everyone wears a mask on a journey that is at least 30 minutes long. This value varies on a bandwidth from 1,11 to 3,95, mostly depending on age, but also on education level, being student and the travel frequency. As can be seen in Table 4.13, respondents usually making short trips, report slightly less than half of that WTP value, compared to long trips. This reflects the lower value of risk discussed earlier. Similar to the WTP for mask obligation, the WTP for extra cleansing is calculated, which is roughly two thirds of that for masks (see Table 4.13).

It is important to note that a traveller is not able to pay a fee such that every traveller has to wear a face mask in real-life situations. The WTP values are just theoretical and only give an indication for how important these measures are for the safety perception of train users. This can be used as an input for the societal benefits of a cost-benefit analysis regarding safety measures.

Key findings

- Mask use and cleansing affect the train demand more when the objective infection risk is lower.
- The willingness to pay for mask use in long (>30 min.) trips for an average traveller is around €2 and for cleansing €1,33. For short (<30 min.) trips these values are half.
- The willingness to pay for 10% crowding reduction is €0,88 in long (>30 min.) trips.

5. CONLUSIONS & RECOMMENDATIONS

In this chapter, the conclusions are formulated. We firstly restate the main objectives of this study and discuss how the results from this study can help answer the research questions. Afterwards, the main contributions are summed up after which the limitations are discussed. Lastly, some avenues for future research are explored.

5.1. Objective & key findings

The covid-19 pandemic in 2020 has severely affected travel demand and travel experience of public transport systems. Firstly, as mass transit is a potential source for large-scale virus spreading, the use of public transport was massively discouraged by the national government. Secondly, fear of becoming infected with the virus could also play an important role in avoiding crowded trains. In order to transport people as safely as possible, preventive actions such as wearing face masks were imposed, despite the lack of scientific prove.

This study attempted to gain insights in how preventive measures affect the travel experience and how other potential risk factors are perceived in Dutch trains. Another objective of this study was to investigate the role of covid-19 infection risk in public transport travel behaviour while taken into account how risk is perceived. To reach these goals the following research questions were put forward:

1. To what extent influence trip conditions the perceived risk of an infection with the coronavirus?
2. To what extent is the perceived risk of an infection with the coronavirus influenced by individual characteristics?
3. How are travel time and travel costs traded off against the perceived risk of a covid-19 infection?
4. How much of the decreased demand for train use in the Netherlands can be attributed to fear of getting infected with the coronavirus?

To answer the questions, a stated preference survey was set up in which 408 respondents took part. With a rating experiment we identified which risk factors and individual characteristics contribute most to the perceived risk of getting infected with the virus. The importance of potentially contracting an infection in choosing between travel options was captured in a stated choice experiment. Both models were combined with an approach based on the Hierarchical Information Integration theory.

5.1.1. Trip conditions

Regarding the trip conditions varied in this study, on-board crowding was found to have the greatest impact on perceived risk. The impact of crowding on the perceived risk is higher for people who are afraid for others (rather than being afraid for themselves) and know someone who've experienced the illness. By translating crowding into a monetary value it was possible to conclude that travellers are willing to spend roughly 2,65 euros to reduce the seat occupancy from 60% to 30%, which could be compared to a difference between sitting next to a stranger and being able so sit alone.

Besides crowding, the infection rate has a significant impact on the traveller's risk ratings. The importance of this context condition is relatively equally perceived by travellers, but is higher for people who think that they can easily prevent an infection as opposed to people who think it is out of their control. This can be linked to that infection rate is out of the direct sphere of influence from the government, the operator and the traveller. Obligatory face mask use within train vehicles and extra cleansing of contact surfaces also have a significant impact on the perceived risk, indicating that these measures are perceived as effective by traveller, despite the efficacy debates. The willingness to pay for everyone to wear a mask to reduce the risk of an infection varies heavily between 0,39 and 3,95 euros (averaging at 2 euros), depending mostly on the length of the journey and some other individual-specific factors. Similar, albeit slightly lower values are found for extra cleansing.

These findings can help in justifying to take these measures, when an argument is tried to make in favour of these measures, irrespective of the factual contribution these measures have on limiting virus spreading among people. This is especially true for extra cleansing because this is not extensively done in Dutch trains. It is however important to note that is unknown if the benefits outweigh the (societal and economical) costs of these measures and that the usefulness and necessity of cleansing is not substantially scientifically proven. A cost-benefit analysis could reveal this.

Furthermore, it was possible to formulate some conclusions regarding the national lockdown levels. As expected, the impact of the lockdown measures on the risk perception was at least partially depending on the level of trust someone has in the government. Besides that, it appears that some form of governmental intervention results in people believing that the likelihood of getting contaminated decreases. This while a strict (intelligent) lockdown provokes higher risk levels, possibly due to higher awareness or due to the fact that people associate harsh government interventions with the first corona wave when fear was generally higher. Lastly, having to transfer does not lead to a higher believed chance of getting infected, despite the additional human interactions that travellers will encounter.

5.1.2. Individual differences

Besides assessment differences for crowding and infection rates, the general risk of getting infected with the coronavirus is not perceived equally across all train travellers. Especially students, who make up for a substantial proportion of the total train users (±30% in peak hours (Vos, 2011)), perceive the probability of getting infected as lower than the rest of the population. This population group might therefore be more likely to travel during the pandemic for non-urgent reasons (e.g. leisure), despite governmental calls to only use the train for urgent purposes. This is further exacerbated by the fact that many students have no alternative travel options available. No other significant differences across the individual sociodemographic characteristics were found. While there are several covid-related studies reporting that female are more risk averse towards covid-19 ((Brown et al., 2020; Dryhurst et al., 2020; Shelat et al., 2020), we could not confirm this. There are however some psychometrics characteristics which are predictive for how safe a train trip is valued by someone. Being afraid to carry on the virus to relatives or friends was found to be most important. Protecting others can thus be an important motivation to avoid taking the train. This indicator is especially important for how crowding is valued.

5.1.3. Trading of infection risk

The covid-19 infection risk plays a notable role in choosing between different train options. Although in real-life it is often not possible to choose between train alternatives with different underlying risk factors, our analysis gives valuable information concerning the extent to which travellers consider the risk of attaining the virus as important. Risk is roughly 4 times more important than travel time and 2 to 3 times more than travel costs in choosing between train alternatives. Risk is considered to be more important in trips that are longer than 30 minutes as opposed to shorter train trips. The value of risk in short (<30 minutes) was found to be less than half (2,17 euro) compared to the value of risk in long trips (4,64 euros). The difference seems to be attributable to travel time, though a positive correlation between travel time and the weight attached to infection risk could not be proved. It seemed reasonable to hypothesize that the marginal valuation of risk would be proportional to the time spent in the train, but we are not able to conclude this.

The hypothesis that risk would be traded off differently for different trip purposes could also not be confirmed by this study. Except for the fact that people who travelled more frequently during the pandemic and younger people appear to care less about the virus risk when choosing train trips, no substantial conclusions can be drawn for other individual travel and sociodemographic characters. Interestingly, age is not correlated with lower or higher risk perception in general, but it is correlated with the weight attached to it.

5.1.4. Travel demand

The survey results revealed that more than a quarter of the respondents who travelled regularly (at least six times a year) before the pandemic did not take the train once since the virus outbreak. The reduction indicates that a part of the population is not using the train at all during the pandemic, either due to a decreased number of activities, governmental advise to stay at home or due to fear. We know that most of these non-travellers (52%) usually take the train to perform a leisure-related activity.

By combining the two experiments we were able to estimate the proportion of people opting out under varying circumstances. In our sample we found that in general, for an off-peak trip (30% seat occupancy) with infection rates as they were in October 2020 (600 in 100.000 contagious people), 4 to 19% extra travel demand is expected due to the obligation of wearing face masks (within trains) as an effect of people feeling more safe. The extra travel demand expected accounted to extra cleansing of contact surfaces within trains is between 2,5% and 13%. The use of face masks and extra cleansing therefore appear to have an effect on the safety level. This effect was monetized with an average willingness to pay of 2 euros for obliging everyone to wear mask and 0,80 euros for extra cleansing in long trips. Since we found that crowding is most important in evaluating the infection risk and is also partly within in control of the operator the willingness to pay for crowding reduction was also estimated. The most important finding was that travellers are on average willing to spend 88 eurocents to reduce the occupancy rate by 10%. This boils down to roughly 2,65 euros or 22% of the ticket fare to be easily able to sit alone. Crowding was already known to induce an additional costs element, but comparing these values with literature it can be concluded that the pandemic brings about an increased crowding penalty.

5.2. Recommendations

The results from this study are helpful in making insightful how different trip conditions are perceived by travellers. Most existing literature related to covid-19 (related and non-related to public transport systems) searches for objective relations with certain risk factors (e.g. crowding or mask use). And since there is still no widespread scientific consensus concerning much of these risk factors (particularly for face mask use and cleansing) this study is especially useful. Public transport operators find themselves in an awkward dilemma having an incentive to transport more people to maintain revenue at a respectable level, but also limiting the number of passengers to reduce the infection risks. Our contributions can help in making thoughtful choices in how to get people back into public transport in a responsible manner while also reducing stress encountered by travellers. More specifically, the monetization of risk reducing factors can be used as perceived benefits for appraisal methods such as societal cost-benefits analyses. The most important recommendations are stated below:

- On-board crowding is perceived as the most dominant factor for attaining the coronavirus in a train trip. It is therefore key to reduce crowding levels. There is however no easy solution to limit crowding levels given that obvious solutions such as increasing capacity or spreading peak demand are not easily implemented. Systems that make more insightful how crowded the trains are could help. Given that these systems are already in operation by NS (NS Treinwijzer), but not extensively used, better communication could be done to promote this feature. A more far-reaching solution could be to sell time-slot-specific train tickets. An important point to make is that a higher value of risk calls for higher capacity (to reduce crowding), but on the other hand also reduces the ridership levels, which increases vacant capacity.

- With regards to the safety measures which could be implemented in PT systems it is reported that obligatory mask use and cleansing do have a significant impact on the perceived safety of a train trip. When operators want to nudge people back into the train (if coronavirus allows for it), they might want to consider doing extra cleansing. Most importantly, they also will have to clearly communicate this to their passengers, given that disinfecting contact points is not directly visible.

5.3. Limitations & avenues for future research

When interpreting the reported findings it is important to acknowledge that this study contains some limitations. First of all, during the time-span in which this study was performed, the knowledge related to covid-19 was rapidly evolving. During the initial set-up and literature research there was still much unknown about the coronavirus, causing that some figures or used insights are already outdated when this paper is finished. A vivid example of changed insights which affected this study is that the estimates for the number of contagious people during the first wave in the Netherlands were changed by the Dutch National Institute of Health and Environment, after the survey was already constructed. Also, new far-reaching lockdown measures were imposed just after data collection, the effects of which we could not incorporate. Insights regarding the efficacy of mask use also changed over time.

Secondly, stated preference surveys always have a downside that the observed choices do not exactly resemble actual behaviour. In this study, the consequence of an opt-out option could be underestimated by respondents, especially given that the question what people would do when opting out was only posed after all choice situations were answered. The proportion of opt-out options could therefore be (slightly) overestimated compared to real-life. It is difficult to conclude something definitive about the possibility to generalize this study's results. This is because risk aversion could be different across different countries. Also, the fact that public transport systems and their users vary heavily makes generalization harder.

Thirdly, although it was tried to incorporate the most relevant risk factors, only a few trip conditions were included in the rating experiment. This was mainly based on the author's own intuition and could have been more extensively done by doing interviews or other sorts of qualitative research.

Since crowding is the most important risk factors, it would be a logical step to investigate the effect of different crowding levels more closely. It is for example known that standing attains a much higher negative utility than sitting in a crowded train. This effect was also expected for the increased perceived risk induced by crowding. However, the effect of crowding in our experiment was best described as a linear effect, which is suspicious. Being in a train which is at crush capacity is possibly perceived as so unsafe that many people would not board. But since crowding was only defined as a proportion of seats occupied, this effect could not be measured. Future research could more extensively study the effect of crowding levels and perceived infection risk. Potentially also by including an extra policy condition in which only seats near the window are available, as this was also a measure imposed for a brief period of time in the Netherlands. Furthermore, a more in-depth comparison analysis with crowding penalties in non-pandemic situations could be performed to retrieve the additional effect of covid-19 on crowding.

This study tried to capture the effects of different trip purposes, but could not find any significant relations. Future studies could extend the analysis on the activities PT users are intending to perform. It is for example interesting to know if people who have an essential job trade-off the risks differently, as opposed to people who travel for a different purpose since a relation between essential work and the experienced exposure risk is already shown by Brown et al. (2020).

The rating tasks in the rating experiment were about evaluating the cognitive risk. In order to get a more complete picture of risk, the affective risk and personal impact assessment could also be evaluated as dependent variables in future studies. Another improvement related to the rating experiment is to estimate a ordinal logistic linear regression, as the equal-interval assumption for a Likert-scale rating is more than questionable. Lastly, as an extension to this study, we recommend to use another choice modelling technique for a future study. A latent class model can be used to cluster individuals into separate risk behaviour classes, based on their background attributes. This might give valuable insights in how different groups of people are changing their train travel behaviour during the pandemic.

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APPENDIX

A. Scientific paper

Impacts of COVID-19 Risk Perceptions on Train Travel Decisions: A Hierarchical Information Integration Analysis – T.W. van de Wiel

Abstract

The number of passengers using public transport has decreased drastically as a consequence of the global coronavirus pandemic in 2020. This study aimed to retrieve the importance of the perceived risk of getting infected with the coronavirus in choosing to go by train in the Netherlands. With a Hierarchical Information Integration approach it was possible to retrieve the perceived importance of different risk factors on the likelihood to get infected and evaluate this with respect to the taste for travel time and travel costs. After collecting 408 responses, a multiple linear regression revealed that on-board crowdedness was perceived as the most important risk factor. With discrete choice modelling we were able to calculate that an average traveller is willing to pay around 0,88 euros to reduce the seating occupancy with 10%. Furthermore, we were able to conclude that both the obligation to use face masks and extra cleansing of contact surfaces negatively influence the perceived risk and thereby increase the chances of going by train. Since extra cleansing is not extensively done yet in Dutch trains, it could, together with reducing crowding levels, be the key to nudge people back into the train.

Keywords: COVID-19, Risk perception, Public transport, Hierarchical Information Integration theory, Stated Choice Experiments

1. Introduction

Travel behaviour has been drastically impacted by the coronavirus (COVID-19) outbreak in 2020. Public transport (PT) systems were hit particularly hard as the very nature of mass transit is not compatible with the measures needed to stop spreading of the virus. It seems eminent that PT ridership is to be limited to mitigate the public health crisis, however it could bring about negative effects on the long and short run. Among these are a lack of accessibility for certain (vulnerable) societal groups and increase of cars in the modal share leading to higher congestion levels when the virus is no longer an immediate threat. While numerous studies were started concerning the transferable pathways of the coronavirus (e.g. Hu et al., 2020), the associated risk perceptions in PT systems are not studied specifically. The differences in perception are thereby especially interesting to review in order to gain insights in who and why certain travellers are avoiding trains. Furthermore, the importance of risk-inducing factors, such as crowding and risk-reducing factors such as wearing face masks are relevant to know for operators, in order to take appropriate actions to limit virus spreading.

A wide spectrum of literature exists on fear-related effects on travel behaviour (e.g. Baucum et al., 2018; Molin et al., 2017), also caused by (previous) epidemics specifically (Fenichel et al., 2013; Liu et al., 2011; Wen et al., 2005). The coronavirus is not the first virus that has impacted people's daily routines. The closest related epidemics are the first SARS outbreak in 2003 and the more deadly Middle East Respiratory Syndrome (MERS) virus in 2012. The scale of the covid-19 outbreak is however much bigger and has, unlike SARS and MERS, turned into a global pandemic. Moreover, it is suspected that covid-19 spreads more easily than the previously mentioned diseases due to milder symptoms which results in people still taking part in daily-life activities whilst contagious (Petrosillo et al., 2020).

In this study, we aimed to explore the role of risk aversion towards getting infected with the novel coronavirus in public transport travel behaviour. Secondly, it is about gaining knowledge about what people believe increases the infection risk in a public transport trip and about the personal characteristics that can explain the differences in risk perception among individuals. To meet the stated objectives the following research questions have been put forward:

(1) To what extent influence trip conditions the perceived risk of an infection with the coronavirus?
(2) To what extent is the perceived risk of an infection with the coronavirus influenced by individual characteristics?
(3) How are travel time and travel costs traded off against the perceived risk of an infection with the coronavirus?
(4) How much of the decreased demand for train use in the Netherlands can be attributed to fear of getting infected with the coronavirus?

In this paper, the results of a stated preference survey with two different experiments are discussed. This study focussed on train trips in the Netherlands, assuming covid-19 causes an immediate threat to society and vaccines are not distributed yet.

This paper is organized as follows. The methodology is introduced with corresponding theory, the identification of all relevant characteristics, and estimation procedures. Afterwards the results of the regression analysis and choice experiment are subsequently reported. These results are then combined to exhibit two application with regards to a train demand scenario analysis and the computation of the willingness to pay for risk-reducing measures.

2. Methodology

2.1. A Hierarchical Information Integration approach

In this paper, a stated choice experiment based on the Hierarchical Information Integration (HII) theory developed by (Louviere, 1984) is constructed to answer the research questions. The experimental setup is a combination of a rating experiment in which believed infection likelihood of train trips are rated based on varying risk factors and a (classical) choice experiment in which respondents choose between train trips with varying trip characteristics. By means of a multiple linear regression, the relative importance of the risk factors (or trip conditions) (RQ1) and the differences between individuals are retrieved (RQ2). Discrete choice modelling is applied to estimate trade-off information between perceived risk and trip costs and trip time (RQ3). Lastly, the results of both experiments are combined to gain trade-off knowledge about the underlying risk factors and to calculate how the change of boarding probability is related to the specific risk factors (RQ4).

In the rating experiment, we directly measure the importance of a priori identified risk factors on the perceived risk of getting infected with the virus. We call this cognitive risk since respondents are asked to rate the believed likelihood of getting infected in the proposed train trip. Respondents are asked to rate the likelihood on a scale from 1 to 5, where 1 is 'very unlikely', 3 is 'neither likely nor likely' and 5 'very likely' to get infected. The stated choice experiment is constructed in such a way that respondents are confronted with choice tasks including two train alternatives and one opt-out alternative. The opt-out alternative differs for people, based on what they indicate doing if they would not make the intended train trip. The options include: (1) changing transport mode, (2) partaking the intended activity from home or (3) cancel the activity.

2.2. The selection of the attributes

The attributes for the rating experiment are called the risk factors and are directly measured by the rating tasks. The choice attributes are the train trip attributes. Lastly, there are some individual characteristics that may influence both the perceived risk rating and the weights attached to risk in the choice experiment.

2.2.1 Risk factors

The identification of risk factors was based on literature published on the transmission pathways of the coronavirus and other viruses in general. On-board crowdedness is the first risk factor and is selected because more passengers in the train inherently causes a higher probability of interacting with a covid-19 infected traveller. On top, the distance between passengers will decrease with higher crowding which on its turn increases the transmission risk (Krishnakumari & Cats, 2020). We operationalized crowding as the seat occupancy rate and varied this between 10 and 100%. Secondly, we identified transferring trains as a potential risk factor as one meets most other passengers during boarding and alighting.

The third and fourth factors are policy measures meant to reduce the transmission risk. The first of which is the obligatory use of face masks within train vehicles. Although it is scientifically debated (Greenhalgh et al., 2020), it is clear that the purpose is twofold: preventing virus particles to be emitted from an infectious travellers and preventing to receive it by fellow travellers (Abboah-Offei et al., 2021). This measure was also imposed in the Netherlands as of June 2020 for all PT systems. The other policy measure is extra cleansing of contact surfaces. The efficacy of cleansing is even more questionable, however we know that the virus can persist on inanimate surfaces for a long period (Guo et al., 2020), and that disinfecting easily inactivates the virus (Kampf et al., 2020). Cleansing is not extensively done in the Dutch trains, while extra cleansing could thus be important.

Infection rate is a contextual risk factors and stands for the estimated number of contagious people nationwide. It is obvious that the likelihood of getting infected is proportional to higher infection rates. The number of contagious people was reported in the experiment per 100.000 inhabitants and was varied between rates that were observed during the corona-mild summer months July/August 2020 (200/100.000), during the first infection wave in March 2020 (1.600/100.000) and just before the pilot survey was caried out at the start of the second infection wave in October 2020 (1.000/100.000). The highest infection rate level was an extreme value of 10.000 out of 100.000, incorporated to see if extreme levels overshadow the other risk factors.

The last identified risk factor is the national lockdown status. This stands for the governmental measures imposed to limit virus spreading across the population. The attribute levels were 'no measures imposed', 'only social distancing', 'moderate lockdown' as was experienced in October/November 220 and 'intelligent lockdown' as was set for the first wave from March to June 2020.

2.2.2. Trip attributes

The choice attributes for the choice experiment are the perceived covid-19 infection risk (CR), stemming from the risk factors identified in the rating experiment, the trip travel time (TT) and trip costs (TC). All attributes were varied in three different levels. The attribute levels are discussed later on in this paper. TT and TC differed for people usually travelling longer or shorter than 30 minutes to ensure familiarity with the given choice alternatives.

2.2.3. Individual characteristics

The individual characteristics which might be able to explain differences in perceived risk are based on a short review on already published literature about covid-19 risk perceptions and the author's own ideas. We distinguish between, psychometric, sociodemographic and travel attributes. The second category is only relevant for the linear regression, while the latter is only used for the choice modelling.

Dryhurst et al. (2020) published a paper in which they tried to explain differences in risk perceptions regarding covid-19 for people all around the world. One of the best psychometric predictors was how individualistic someone is (prosociality), other important predictors were the believed personal efficacy of preventive actions (e.g. wearing face masks and washing hands regularly), governmental trust and direct experience with the virus. We extend these psychometric indicators with being afraid to pass on the virus to loved ones, health anxiety, perceived health status and media consumption after reviewing the results of a tailor-made covid-19 questionnaire from Mertens et al. (2020). Lastly, the perceived control over the virus is also included as it known that lower levels of individual control are usually correlated with higher risk valuations (Weinstein, 1984).

With regards to sociodemographic predictors, a similar selection is done. There is scientific consensus that the severity of a covid-19 disease is increasing with age (e.g. Dong et al., 2020). Shelat et al. (2020) showed that older people are also overrepresented in crowd-averse travellers in hypothetical train trips during the covid-19 pandemic. However, there exist studies that suggest that older people perceived the (cognitive) risk of getting corona as less than younger people do (Gerhold et al., 2020). Another important predictor could be sex. Women are often found to be more risk averse than men (Weber et al., 2002). This is also confirmed for covid-19 in several studies (Brown et al., 2020; Dryhurst et al., 2020; Shelat et al., 2020).

Education level could also play a role in risk perception as this might be a proxy for how aware people are. Lastly, work status: going to school or commuting for a job can determine the need for using public transport services. Activities related to work usually attain a higher priority and are less likely to be cancelled during lockdown measures (Kim et al., 2017), which also might influence risk perception.

Besides individual characteristics some individual-specific travel attributes are included. These include the mostly used trip purpose, the train travel frequency (before and during the pandemic), car availability (and ownership) and the respondents' usual trip length.

2.3. Rating experiment

In the rating experiment, respondents evaluate train alternatives with variations of the preceding identified risk factors, in terms of the likelihood of getting infected on a scale from 1 (very low risk) to 5 (very high risk). We assumed an equal interval-scale for the ratings, allowing for a linear regression. With a multiple linear regression analysis, we inferred the relative importance of each of these risk factors. The regression also included the individual characteristics, so that we can identify which groups of travellers are perceiving risk differently. Also interaction effects are estimated, but only between to be expected interactions (psychometrics and some risk factors). A schematic of the rating experiment as part of the linear regression is visualized in figure 1.

The evaluation tasks are sequentially constructed with an orthogonal design. An orthogonal design with three 4-level and three 2-level attributes results in a total of 12 unique profiles. To limit the respondent load, the choice situations are split up into two separate blocks. Respondents are randomly assigned to one of the blocks and only need to rate 6 train trips in total.

We used effect coding for all dummy and categorical variables. The regression was performed in a stepwise manner; backward elimination. Variables not statistically significant on a 95% confidence interval were removed one by one, starting with the one with the highest p-value.

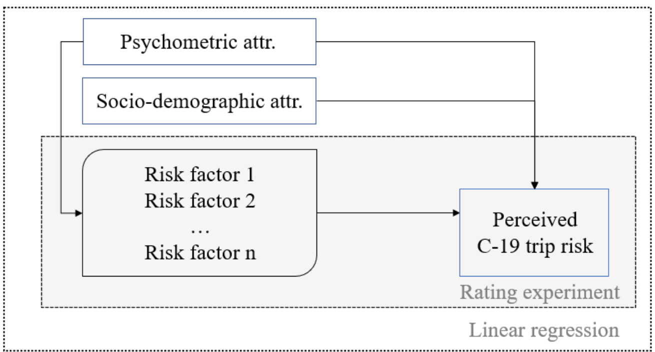

Figure 1. Schematic linear regression analysis

2.4. Stated choice experiment

As explained above, the stated choice experiment was constructed in such a way that respondents had to choose between two train alternatives and an option to not perform any of the proposed trips. The inclusion of an opt-out alternative let's us investigate the potential ridership reduction as a function of the risk factors. A downside of the opt-out alternative is that it could be seen as an 'easy option' for respondents, thereby introducing response bias. Hence, the choice between the train alternative and opting out is presented in a sequential manner. This means that a respondent always needs to evaluate the train alternatives and only after this is done, is allowed to choose to opt out.

The experimental design was constructed with a D-efficient method to minimize standard errors of the estimated parameters and prevent strictly dominant alternatives. The design was fed with prior information obtained from a pilot survey. Two different designs were created to accommodate for one experiment in which only short trips (< 30 minutes) and one in which only long trips (> 30 minute) are shown. We made sure that all cost-time trip combination are existent in real-life. The attribute levels are shown in table 1. People perceive 7 minutes additional travel time on 45 minute as worse than the same amount of additional time on a 17 minute trip. We wanted to make sure that respondents were not indifferent for changes in either costs or time. Hence, the attribute range for the long trips is slightly wider. The perceived risk levels are congruent to the risk ratings and should thereby resemble the underlying risk factors. The levels are 1, 3 and 5.

After construction of the experimental designs, the choice tasks were made up. We obtained 9 choice tasks with 2 profiles for each of the trip length experiments, which were randomly placed in the survey.

To estimate preference we firstly used a Multinomial Logit (MNL) model from the observed choices to observe the first trends. Afterwards, we estimated a Mixed Logit (ML) to account for the panel effect. We also incorporate random taste variation for the estimated model parameters. We included both sociodemographic and travel background effects as interaction effects in the model. For some of the background attributes effect coding was used. The travel frequency (during pandemic) was divided into a high and low frequency category, where '-1' stands for travelling less than once a week and '+1' for one or more times a week. Similar coding is applied for having access to a car (+1) or not (-1). The trip purposes are aggregated into three purposes: work/business, education and leisure.

Table 1. Trip attribute levels

Choice attribute	**# levels**	**levels (long trips[a] / short trips[b])**	**Unit**
Travel Time (TT)	3	10 / 17 / 24 (short trips) 35 / 45 / 55 (long trips)	minutes
Travel Costs (TC)	3	3,0 / 4,5 / 6,0 (short trips) 9,0 / 12,0 / 15,0 (long trips)	euros
Covid-19 Risk (CR)	3	(1) very low / (3) medium / (5) very high (long & short trips)	score

[a]for resp. usually taking train trips with TT < 30 minutes.
[b]for resp. usually taking train trips with TT > 30 minutes.

2.4. Data collection

The conducted survey consisted of three main parts: the rating tasks, the choice tasks and observation of the background characteristics. In total, 18 rating tasks were constructed, but divided into two separate blocks which were randomly assigned to the respondents. The choice experiment consisted of 9 choice tasks which were different for respondents attributed to long trip questions and short trip questions.

After a pilot survey (N=48) was caried out, we updated the D-efficient experimental designs for the choice experiments with prior information and distributed the questionnaire via an online panel

(PanelClix). The target population consisted of frequent and occasional train users in the Netherlands. The latter category was defined as people who use the train at least 6 times a year before the start of the pandemic (March 2020). In the end, we received 408 valid responses.

3. Results

3.1. Risk factor rating impact

After performing a multiple regression analysis, we identified 4 (out of 8) statistically significant on a 95% confidence interval predictor variables for the risk rating. The relative impact of each of the risk factors per attribute level can be seen in table 2. On-board crowding is found to be the most important trip condition, followed by the national infection rate. The policy measures for obligatory mask use and extra cleansing (albeit to a lesser extent) also significantly impacted the risk rating. Lastly, from the individual lockdown levels, only the moderate lockdown (level 3) appeared to be of influence for the perceived covid-19 risk. Our interaction results show that trusting the government in their crisis management capabilities increases the positive effect a moderate lockdown has on risk perception. With a p-value of 0,307 we did not find a meaningful impact of having to transfer.

Table 2. Risk factor rating impacts

Parameter	Stand. Coeff.	Unstand. Coeff.	Attr. level	Rating impact
On-board crowding	0,346	0,117	1	0,117
			4	0,468
			6	0,702
			10	1,170
Infection rate	0,243	0,007	0,2	0,001
			6	0,042
			10	0,070
			100	0,700
Mask	-0,189	-0,216	-1	0,216
			1	-0,216
Cleansing	-0,126	-0,144	-1	0,144
			1	-0,144
Moderate lockdown	-0,114	-0,185	1	-0,185
			-1	0,185

With regards to the individual characteristics, we reported the perceived anxiety to infect loved ones as the most important background variable. The results also show us that this attribute is affecting the importance of crowding. In general, someone who is afraid to infect others thinks crowdedness is more important when evaluating the infection risk as opposed to someone who is less afraid to infect acquaintances. Risk for loved ones is more predictive than being anxious about your own health or the perceived control over preventing an infection. The believed efficacy of personal preventive actions is also closely related to the risk score, however the relation is less intuitive than expected. Believing that actions such as wearing face masks do not contribute much in preventing virus spreading decreases the perceived risk. A potential explanation may be found in the fact that some people in general perceive the risk as fairly low. Higher levels of perceived control also diminishes the importance of infection rate on the perceived infection likelihood.

Knowing someone who has experienced the covid disease also increases the risk perception. This has the most impact on how important one thinks crowding is. Lastly, the only sociodemographic background with a statistically significant effect is being student. Students, apparently, rate the infection rate overall lower compared to non-students.

3.2. Value of Covid-19 Risk

The ML model parameters estimated from the observed choices in the stated choice experiment let us calculate the value of the perceived covid-19 infection risk. First of all, we found that risk was considerably more important than travel time (roughly 4 times) and travel costs (2 to 3 times) by comparing the tastes for the attributes. Comparing the weight of risk towards costs is more insightful and gives us a willingness to pay (WTP) for risk reduction. We calculated the value of risk (VOR) by taking the ratio of the marginal utility of CR and TC. We found that that the WTP for one scale-point of risk reduction is around 4,64 euros for long trips and 2,17 euros for short trips. Although the difference seems to indicate that risk is valued higher in longer trips, the estimated interaction between travel time and perceived risk could not support this.

With regards to different trip purposes, none of these were found to have a statistically significant relation with CR. The hypothesis that trip purpose is associated with how people trade-off risk can therefore not be confirmed. None of the estimated backgrounds appeared statistically significant in both the long and short trips datasets except for the education level. Because the direction is opposite in both datasets a clear conclusion can however not be drawn.

For the long trips we found that students are less cost-sensitive and more time-sensitive, being opposite of what was expected. These student effects are however quite limited. Older people are found to be more risk-averse than younger people. Travellers who travelled more than once a week during the pandemic attain significantly less value to risk. This might explain why they travel more in the first place. In the short trip dataset, we could not attribute any taste variations to the observed background variables.

3.3 Demand scenario analysis

Now that both the linear regression and choice modelling are performed it is possible to gain insights about how important the individual risk factors are in choosing to take the train. The probability of opting out is calculated for several scenarios with a MNL choice probability function. The utilities for the train trip is derived form the estimated model parameters from the ML model. The parameter for CR is varied by changing the underlying risk factors.

In the first scenario analysis, the infection rate and crowding levels remained constant, while the policy measures (mask use and cleansing) were systematically varied. An off-peak trip in October 2020 was assumed in which the seating occupancy is set to 30% and the infection rate to 600 contagious people out of 100.000 inhabitants. For an average respondent (39 years old, scoring the sample average on the psychometrics and has a paid) and a long trip the average marginal boarding probability increase due to obligatory mask use is 11,4% and 7,2% for extra cleansing.

For a second scenario, a relatively crowded train (60% occupancy rate) in March 2020 (1.000 contagious per 100.000 inhabitants), the increased boarding probabilities are 8,1% for mask use and 5,0% for extra cleansing. This shows that in a ‘more dangerous’ context, the use of face masks and extra cleansing is off less importance. However it may seem counterinitiative (as safety measures should be more important as the threat increases), we could explain this with the notion that the impact of higher infection rates and higher crowding levels are overshadowing the impact of the safety measures on perceived risk. In other words, the measures do little to improve the perceived risk.

Lastly we also reviewed a situation in which the policy measures remained constant, resembling the prevalent situation in the Netherlands and vary the crowding levels and infection rates. This meant that wearing face masks is obliged and no extra cleansing is done. The travel time was set to 45 minutes and travel costs to 9 euros. We observed that realistic infection rates only have a limited impact on the boarding probability (figure 2). The extreme infection rate in which 10% of the population is contagious shows that the chance of boarding is close to half compared to the other rates.

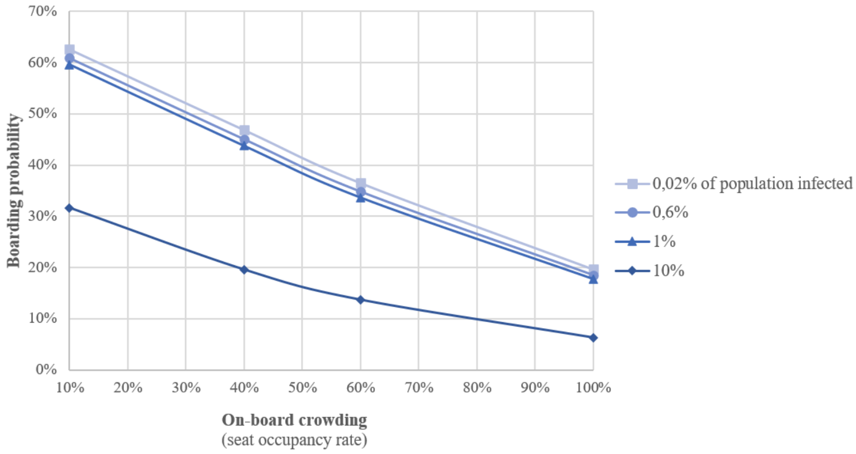

Figure 2 . Boarding probabilities for different crowding and infection rate levels

3.4. Willingness to pay for risk factor reducing

The second application of the model combination was to induce trade-off information between risk factors and travel costs. As crowding was the most important risk factor and is partly in the sphere of influence of the operator we calculated the WTP for crowding reductions (or value of crowding). The value of crowding (VOC) is a 10% reduction in seating occupancy and is obtained by multiplying the average VOR with the linear regression coefficient of crowding. We report for long trips a VOR of 0,88 euros and less than half (0,41 euros) for short trips.

There exist many studies concerning the valuation of crowding in PT. The covid-19 pandemic is likely to cause an additional crowding penalty to the already existent crowding penalty. According to Wardman & Whelan (2011) a time multiplier is inherently more transferable than monetary units. Therefore, we computed a time multiplier which is 1,43 based on 45 minute trip.

Comparing this with a Dutch urban public transportation study from Yap et al. (2018) who found a time multiplier of 1,16 for frequent and 1,31 for non-frequent travellers when all seats are occupied, it is slightly higher. Also the meta-analysis of Wardman & Whelan (2011) which comprises 84 different studies, report a lower multiplier of 1,19. Although our time multiplier is calculated in a different manner than other studies did, making direct comparisons impossible, it gives an indication that our study found a considerable higher willingness to reduce crowding, most probably caused by the pandemic.

Obliging everyone to wear a mask and extra cleansing was monetized using a similar approach as for crowding. The average willingness to pay for masks is 1,99 euros in long trips and 0,92 in short trips. The exact amount varies heavily and mostly depends on age, but also on education level, and the travel frequency during the pandemic. Students are also willing to pay slightly more. The average traveller is willingness to spend 1,33 euros extra for extra cleansing on a long trip and 0,61 euros on a short trip (see table 3).

Table 3.. Willingness to pay for policy measures[euro per trip]

	Long trips **average resp.[a] [bandwidth]**	**Short trips** **average resp.[a] [bandwidth]**
mask	1,99 [1,11-3,95]	0,92 [0,39-1,32]
cleansing	1,33 [0,74-2,64]	0,61 [0,26-0,88]

[a]Values for an average respondent: age 39, employed, non-student, average frequency, average education level

4. Conclusions

This paper described the results from a survey carried out on risk perception concerning the covid-19 infection likelihood in Dutch trains during the coronavirus pandemic. The study attempted to gain insights in how preventive measures affect the travel experience and how other potential preselected risk factors are perceived in Dutch trains. Another objective was to investigate the role of the infection risk in public transport travel behaviour while taken into account how risk is perceived. 408 respondents took part in the survey, who answered questions in the form of rating experiment to infer the importance of the risk factors and a choice experiment in which the they were asked to choose between different train alternatives with varying costs, travel times and infection risk levels. Both models were combined with an approach based on the Hierarchical Information Integration theory.

The results from the rating experiment revealed that on-board crowding is perceived as most determinative for the likelihood of getting infected with the virus. Being afraid for loved ones increases the importance of crowding. We were able to monetize this effect and calculated that an average traveller is roughly willing to spend 2,65 euros to be easily able to sit alone. Also infection rate was found to be important, especially for people who think they can easily prevent an infection. Obligatory face mask use within train vehicles and extra cleansing of contact surfaces also have a significant impact on the perceived risk, indicating that these measures are perceived as effective by traveller, despite the societal debates. The willingness to pay for everyone to wear a mask to reduce the risk of an infection averages at around 2 euro and 1,33 euros for extra cleansing in long trips. Short trips are almost half of that. Furthermore, it was possible to formulate some conclusions regarding the national lockdown levels. As expected, the impact of the lockdown measures on the risk perception was at least partially depending on the level of trust someone has in the government. Besides that, it appeared that some form of governmental intervention results in people believing that the likelihood of getting contaminated decreases. Lastly, having to transfer does not lead to a higher believed chance of getting infected, despite the additional human interactions that travellers will encounter.

The covid-19 infection risk plays a notable role in choosing between different train options. The value of risk was calculated and was for trips shorter than 30 minutes half (2,17) of the VOR in long trip (4,64 euros). It seemed therefore reasonable to hypothesize that the marginal valuation of risk would be proportional to the time spent in the train, but we were not able to conclude this in general. Also no statistical significant differences across different trip purposes were observed. Except for the fact that people who travelled more frequently during the pandemic and younger people appear to care less about the virus risk when choosing train trips, no substantial conclusions can be drawn for other individual travel and sociodemographic characters. Interestingly, age is not correlated with lower or higher risk perception in general, but it is correlated with the weight attached to it.

By combining the two experiments we were able to estimate the proportion of people opting out under varying circumstances. In our sample we found that in general, with higher infection rates and higher crowding levels, the marginal impact of both mask use and cleansing is decreasing. Still, the use of face masks and extra cleansing have a significant effect on the safety level and also appear to have to have an impact on people's choices to take the train.

5. Recommendations and discussion

Public transport operators find themselves in an awkward dilemma having an incentive to transport more people to maintain revenue at a respectable level, but also limiting the number of passengers to reduce the infection risks. Our contributions can help in making thoughtful choices in how to get people back into public transport in a responsible manner while also reducing stress encountered by travellers. The monetized risk factors can be used in societal cost benefit analyses as perceived benefits. With regards to societal contributions we formulated two recommendations:

(1) Crowding is the most important risk factors for travellers. It is (partly) in control of the operator, however it is very difficult to reduce. It is therefore important to make crowding insightful for travellers upfront to boarding the trains.
(2) When operators want to nudge people back into the train (if coronavirus allows for it), they might want to consider doing extra cleansing. Most importantly, they also will have to clearly communicate this to their passengers, given that disinfecting contact points is not directly visible.

This study was performed while the covid-19 pandemic was going on and evolving in a rapid pace. Knowledge concerning the transmission pathways and about the infection rates changed along the time-span of the study. Furthermore, risk perceptions in the population are also likely to be changed as the pandemic preceded and people got more used to living with the virus. This all caused that the results of this study should be interpreted with the right assumptions.

For future research, we recommend to include other risk dimensions than the perceived likelihood. The affective risk (worry) was covered in this study, but not as a dependent variable. Lastly, as an extension to this study, we recommend to use another choice modelling technique for a future study. A latent class model can be used to cluster individuals into separate risk behaviour classes, based on their background attributes. This might give valuable insights in how different groups of people are changing their train travel behaviour in the pandemic.

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B. Ngene syntax

I. Rating experiment (orthogonal, sequential)

```
design
;alts = alt1, alt2
;rows = 12
;orth= seq
;block= 2
;model:
U(alt1)=oc*ob_crowding[1,2,3,4]+tf*transfer[0,1]+ma*mask[0,1]+cl*cleansing[
0,1]+ir*infectrate[1,2,3,4]+lo*lockdown[0,1,2,3]
$
```

II. Choice experiment (d-efficient, final design, long trips)

```
design
;alts = alt1*,alt2*,alt3
;rows = 9
;eff= (mnl,d)
;model:
U(alt1)=b1[-0.2197]*costs[9,12,15]+b2[-0.0312]*time[35,45,55]+b3[-
1.2346]*c19_risk[1,3,5]+b4[0.0087]*time*c19_risk/
U(alt2)=b1*costs+b2*time+b3*c19_risk+b4*time*c19_risk/
U(alt3)=b0[-6.4301]
$
```

III. Choice experiment (d-efficient, final design, short trips)

```
design
;alts = alt1*,alt2*,alt3
;rows = 9
;eff= (mnl,d)
;model:
U(alt1)=b1[-0.7424]*costs[3,4.5,6]+b2[-0.1359]*time[10,17,24]+b3[-
1.3354]*c19_risk[1,3,5]/
U(alt2)=b1*costs+b2*time+b3*c19_risk/
U(alt3)=b0[-10.6646]
$
```

C. Experimental designs

Experimental design: risk perception (rating experiment)

Table C.1. Experimental design: rating experiment

Case	ob_crowding	transfer	mask	cleansing	infectrate	lockdown	Block
2	4	0	0	1	6	0	1
5	3	1	1	0	100	0	1
6	1	0	1	1	10	1	1
7	1	1	0	0	6	3	1
9	2	1	1	1	2	2	1
10	4	0	0	0	10	3	1
1	2	0	1	0	6	1	2
3	3	1	0	1	2	1	2
4	2	1	0	0	10	0	2
8	3	0	1	0	2	2	2
11	1	0	0	1	100	2	2
12	4	1	1	1	100	3	2

Ob_crowding = on-board crowding level

Transfer= number of transfers

Mask = on-board face mask obligation

Cleansing = number of extra cleansing rounds

Infectrate = number of contagious people per 1.000 inhabitants

Lockdown = level of national lockdown measures

Experimental design: trip choice (choice experiment)

Alt1 = choice alternative 1

Alt2 = choice alternative 2

….costs = travel costs of …

….time = travel time of …

….c19_risk = Perceived covid-19 infection risk of …

Table C.2. Experimental design: choice experiment (short trips)

Choice situation	alt1.costs	alt1.time	alt1.c19_risk	alt2.costs	alt2.time	alt2.c19_risk
A	6	24	1	3	10	5
B	4.5	10	3	4.5	24	1
C	4.5	17	5	3	24	5
D	6	17	1	4.5	17	3
E	6	10	3	3	24	3
F	3	10	3	6	17	1
G	3	17	5	4.5	10	3
H	4.5	24	5	6	17	5
I	3	24	1	6	10	1

Table C.3. Experimental design: choice experiment (long trips)

Choice situation	alt1.costs	alt1.time	alt1.c19_risk	alt2.costs	alt2.time	alt2.c19_risk
A	9	55	5	12	45	5
B	9	35	3	15	55	1
C	12	45	5	15	35	5
D	12	35	3	12	55	1
E	15	45	5	12	55	5
F	15	45	1	9	45	3
G	12	55	1	9	35	3
H	9	55	3	15	35	1
I	15	35	1	9	45	3

D. Apollo syntax

```
#### DEFINE MODEL AND LIKELIHOOD FUNCTION


apollo_probabilities=function(apollo_beta, apollo_inputs,
functionality="estimate"){


  ### Attach inputs and detach after function exit
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))


  ### Create list of probabilities P
  P = list()


  ### List of utilities: these must use the same names as in mnl_settings,
order is irrelevant
  V = list()
  V[['A']]  = TCA * BETA_TC + TTA * BETA_TT + CRA * BETA_CR + CRAsq *
BETA_CRsq + TCA * (BETA_TC_wo2 * wo2 + BETA_TC_fr * fr_du) + TTA *
(BETA_TT_age * Age + BETA_TT_wo2 * wo2 + BETA_TT_fr * fr_du) + CRA *
(BETA_CR_age * Age + BETA_CR_edu * Edu + BETA_CR_wo1 * wo1 + BETA_CR_wo2 *
wo2 + BETA_CR_wo3 * wo3)
  V[['B']]  = TCB * BETA_TC + TTB * BETA_TT + CRB * BETA_CR + CRBsq *
BETA_CRsq + TCB * (BETA_TC_wo2 * wo2 + BETA_TC_fr * fr_du) + TTB *
(BETA_TT_age * Age + BETA_TT_wo2 * wo2 + BETA_TT_fr * fr_du) + CRB *
(BETA_CR_age * Age + BETA_CR_edu * Edu + BETA_CR_wo1 * wo1 + BETA_CR_wo2 *
wo2 + BETA_CR_wo3 * wo3)
  V[['C']]  = T1 * BETA_RM + T2  * BETA_HO + BETA_OPTOUT
```

E. Survey questions

Table E.1. Survey questions, translated into English

Label	Attribute/ element	Question(s)	Scale
consent	-	4 x consent [a]	-
travel	travel frequency before	How often did you use the following transport modes, before the coronavirus outbreak in the Netherlands (before March 2020) - train[b] - car - bus/tram/metro - bicycle	ordinal
	travel frequency during	How often did you use the following transport modes, during the coronavirus pandemic in the Netherlands? -train - car - bus/tram/metro - bicycle	ordinal
	trip purpose	What was your most frequently used purpose to travel by train before the coronavirus outbreak?	nominal
	trip length	What is the travel time of your most frequently performed train trip? *(<30 min.; 30-120 min.; >120 min.)*	ordinal
	car availability	Do you have a (private) car available?	ordinal
	cancel work	Do you have the opportunity to work from home?	binary
	cancel education	Did you follow any form of home education due to the pandemic?	ordinal
	cancel leisure	How severely would you rate a cancellation of your most performed activity for which you used the train?	Likert
rating experiment	RE (6x)	Please indicate on a 5-point scale how you estimate the coronavirus infection risk for the next train journey, based on the travel conditions below.	Likert
choice experiment	CE (9x)	Choose the train journey you prefer, based on price, travel time and your risk assessment with regard to the corona virus.	binary
	CE* (9x)	If given the choice, would you choose to perform the train journey just selected?	binary
	opt-out	If you decide not to take the train ride, what would you do instead?	nominal
psychometric	health attitude	Overall, I would rate my health condition as *(very good – somewhat good– neutral – somewhat bad- very bad)*	Likert (1-5)
	health anxiety	This questions consists of a group of four statements. Please read each group of statements carefully and then select the one which best describes your feelings, over the past six months. *(I never worry about my health –…– I (almost) always worry about my health)*	ordinal (1-4)
	prosociality	To what extent do you think it's important to do things for the benefit of others and society even if they have some costs to you personally?	Likert

	perceived control	Overall, I believe that I can control or avoid becoming infected by the coronavirus (e.g.,by limiting social contact, washing hands, wearing a face mask, etc.)	Likert
	personal efficacy	The actions that I personally take to prevent the spread of the coronavirus (e.g. by limiting the number of social contacts, washing hands, wearing a face mask, etc.) are effective.	Likert
	risk for loved ones	Overall, I believe that people that I care about (e.g., grandparents) are at risk of becoming infected and seriously ill due to the coronavirus outbreak	Likert
	governmental trust	I trust the government in effectively handling the outbreak	Likert
	C-19 affective risk	I am afraid of getting ill from the coronavirus	Likert
	C-19 risk attitude	The coronavirus is a serious threat for humans and society	Likert
	C-19 cognitive risk	How high do you estimate the probability of getting infected with the coranavirus	Likert
	media experience	Did you search for information regarding the coronavirus? (only via regular media or did own research)	ordinal (1-3)
	experience	Do you know someone who attained the coronavirus? Now or in the past?	binary
socio-demographic	sex	What is your gender?	binary
	age	What was your year of birth?	interval
	education	What is your highest level of education?	ordinal
	work status	Which is of the following statements regarding your daily activities is most applicable to you?	nominal

[a]consent statements are depicted in Appendix I
[b]respondents are screened out if they travelled less than 6 times a year

Table E.2. Likert-scale answer options.

Psychometric attribute	Answer options
Covid-19 statements • prosociality • perceived control • pers. efficacy • risk for loved ones • gov. trust Covid-19 risk components • C-19 affective • C-19 cognitive • C-19 attitude	1 completely agree 2 agree 3 not agree nor disagree 4 disagree 5 completely disagree
• health attitude	health 1 very good 2 good 3 not good, nor bad 4 bad 5 very bad
• health anxiety	worried 1 never 2 sometimes 3 often 4 always

F. Final Survey

Beste deelnemer,

Hartelijk bedankt voor uw deelname aan dit onderzoek.
De uitbraak van het coronavirus heeft ingrijpende veranderingen teweeg gebracht. Er wordt veel minder gereisd en het openbaar vervoer is daarbij in het bijzonder hard geraakt.

In deze enquête worden vragen gesteld over het reizen met de trein gedurende de coronapandemie. Voor dit onderzoek zijn we geïnteresseerd in uw beweegredenen om wel of niet de trein te gebruiken en hoe u het besmettingsgevaar inschat tijdens een treinrit.

Het invullen van de enquête duurt ongeveer 15 minuten. De enquête bestaat uit 4 verschillende delen over uw reisgedrag, risicoperceptie in de trein, reisvoorkeuren en persoonlijke achtergrondkenmerken.

Uw antwoorden zullen vertrouwelijk behandeld worden en enkel gebruikt worden voor dit onderzoek. De enquête wordt uitgevoerd als onderdeel van een masterscriptie aan de Technische Universiteit Delft.

Voor vragen en/of opmerkingen kunt u contact opnemen via:
t.w.vandewiel@student.tudelft.nl
Thijs van de Wiel

Voordat we beginnen, wordt u gevraagd om akkoord te gaan met de volgende voorwaarden.

	Akkoord	Niet akkoord
Ik geef vrijwillig toestemming om deel te nemen aan deze enquête	○	○
Ik begrijp dat ik het invullen van deze enquête te allen tijden kan afbreken	○	○
Ik begrijp dat de informatie die ik verstrek zal worden gebruikt voor onderzoeksdoeleinden en dat de bevindingen mogelijk worden verspreid door middel van wetenschappelijke publicaties	○	○

U moet akkoord gaan met de voorwaarden om deel te kunnen nemen aan deze enquête.

Ga terug om alsnog akkoord te gaan of u wordt naar het einde van deze enquête geleid.

Deel 1: Reisgedrag

Hoe vaak maakte u gebruik van de volgende transportmiddelen, voordat het coronavirus uitbrak in Nederland (maart 2020)?

	Vrijwel elke dag	5-6 dagen per week	3-4 dagen per week	1-2 dagen per week	1-3 dagen per maand	6-11 dagen per jaar	1-5 dagen per jaar	minder dan 1 dag per jaar
Trein	○	○	○	○	○	○	○	○
Auto (als bestuurder)	○	○	○	○	○	○	○	○
Bus, tram en/of metro	○	○	○	○	○	○	○	○
Fiets	○	○	○	○	○	○	○	○

Hoe vaak maakte u gebruik van de volgende transportmiddelen, gedurende de coronapandemie?

	Vrijwel elke dag	5-6 dagen per week	3-4 dagen per week	1-2 dagen per week	1-3 dagen per maand	minder dan 1 dag per maand	Nooit
Trein	○	○	○	○	○	○	○
Auto (als bestuurder)	○	○	○	○	○	○	○
Bus, tram en/of metro	○	○	○	○	○	○	○
Fiets	○	○	○	○	○	○	○

Wat was voor de corona-uitbraak voor u de belangrijkste reden om met de trein te reizen?

- ○ Woon-werkverkeer
- ○ Zakenreis/dienstreis
- ○ School of studie
- ○ Bezoek aan familie/vrienden/bekenden
- ○ Winkelen
- ○ Vakantie of uitstapje
- ○ Sport en/of hobby

U heeft aangegeven meestal de trein te nemen met als doel:
"${*selected trip purpose*}".

Geef een indicatie van hoe lang uw meest gemaakte treinreis met dit reisdoel duurt.
Neem hierbij enkel de reistijd in de trein en eventueel overstappen in ogenschouw.
We vragen naar een enkele reis. Dus alleen heen- of terugreis.

- ○ Korter dan 30 minuten
- ○ Langer dan 30 minuten, maar niet langer dan 120 minuten
- ○ Langer dan 120 minuten

Had u voor de uitbraak van het coronavirus (maart 2020) een abonnementsvorm of kortingskaart die u bij het reizen met de trein kon gebruiken?

- ☐ NS Voordeelurenkaart
- ☐ Dal voordeel
- ☐ Altijd voordeel
- ☐ Dal vrij
- ☐ Weekend vrij
- ☐ Altijd vrij
- ☐ NS Voordeelurenkaart voor 60-plussers
- ☐ NS jaarkaart
- ☐ NS Jaartrajectkaart of NS Maandtrajectkaart
- ☐ NS Business Card
- ☐ Studentreisproduct (weekend of week)
- ☐ Anders
- ☐ Ik had geen abonnementsvorm of kortingskaart

Heeft u de zojuist geselecteerde abonnementsvorm(en) of kortingskaart(en) ("*selected discount card*}") aangehouden tijdens de pandemie?

- ○ Ja, deze heb ik aangehouden
- ○ Nee, deze heb ik of heeft een ander voor mij stop gezet

Kunt u altijd over een auto beschikken?

- ○ Ja, wanneer ik maar wil
- ○ Nee, dat gaat in overleg met mensen binnen mijn huishouden
- ○ Nee, dat gaat in overleg met mensen buiten mijn huishouden
- nee, (vrijwel) nooit

Geef aan wat het meest voor u van toepassing is wat betreft uw voornaamste dagelijkse bezigheid

- ○ Ik heb een betaalde baan
- ○ Ik heb (tijdelijk) geen betaalde baan
- ○ Ik studeer
- ○ Ik ben gepensioneerd
- ○ Zeg ik liever niet
- ○ Anders

Heeft u de mogelijkheid om thuis te werken?
Dat wil zeggen dat u uw werk thuis kunt uitvoeren omdat u toestemming van uw werkgever heeft en/of omdat u over de benodigde ICT faciliteiten beschikt.

- ○ Ja, ik heb de mogelijkheid om thuis te werken
- ○ Nee, ik heb geen mogelijkheid om thuis te werken

Heeft u thuisonderwijs gevolgd als gevolg van de coronapandemie?

- ◯ Ja
- ◯ Ja, maar niet meer dan voor de coronapandemie
- ◯ Nee

U selecteerde de volgende reden om met de trein te reizen:
"Selected trip purpose}"

Hoe vervelend zou u het vinden om de hierboven genoemde activiteit niet uit te kunnen voeren?

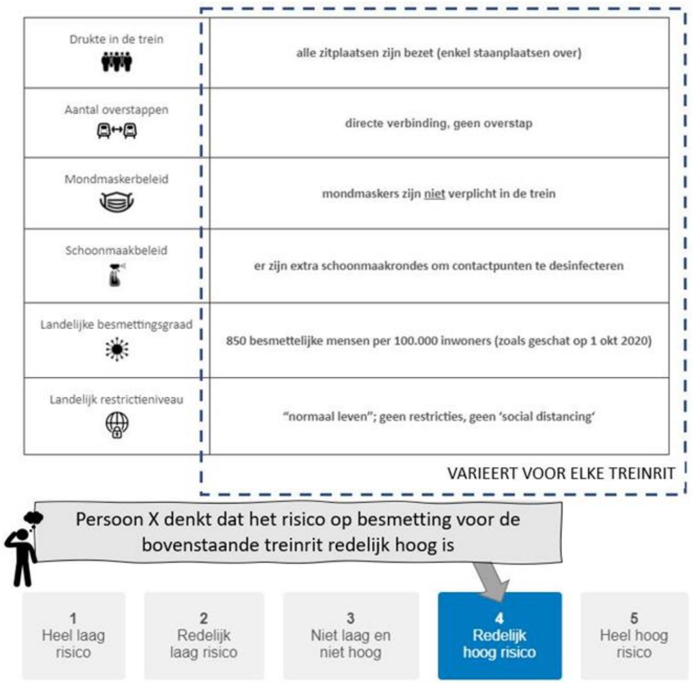
Helemaal niet vervelend	Niet vervelend	Neutraal	Vervelend	Heel erg vervelend
◯	◯	◯	◯	◯

<u>Deel 2: Besmettingsrisico in de trein</u>

Stelt u zich in dit deel van de enquête voor dat u de trein gaat nemen. U maakt deze treinreis voor het door u aangegeven doel: "${q://QID10/ChoiceGroup/SelectedChoices}".
U krijgt 6 verschillende treinritten gepresenteerd, waarna u gevraagd wordt het risico op een coronabesmetting in te schatten. De treinritten variëren op verschillende vlakken, maar betreffen allemaal dezelfde enkele rit tussen twee stations.

Een voorbeeldvraag is hieronder weergegeven:

Geef op een een 5 puntschaal aan hoe u het coronavirus-besmettingsrisico inschat voor de volgende treinreis, gebaseerd op de onderstaande reiscondities.



Mocht u extra uitleg willen over de reisvariaties, dan kunt u deze hieronder terugvinden:

Drukte in de trein:
De drukte is weergegeven als een percentage van het aantal stoelen dat bezet is. Daarnaast is aangegeven of het mogelijk is om alleen (met een lege stoel naast u) te zitten.

Overstappen:
De voorgestelde treinrit bestaat uit een directe reis of bevat één overstap.

Mondmaskers:
Voor een aantal van de voorgestelde treinritten is het verplicht een mondmasker te dragen.

Schoonmaakrondes:
In Nederland worden op dit moment in de treinen geen desinfectierondes uitgevoerd om contactpunten besmettingsvrij te maken. Bij een aantal van de voorgestelde treinritten wordt het interieur van de trein gedesinfecteerd op regelmatige basis. Bij andere ritten is er enkel sprake van reguliere schoonmaakrondes (op elke eindstation).

Landelijke besmettingsgraad:
De landelijke besmettingsgraad is een schatting van het totaal aantal mensen in Nederland dat op het moment van reizen besmet is met het coronavirus. Een tijdsindicatie is gegeven.

Landelijk restrictieniveau:
Het landelijk restrictieniveau zegt iets over de overheidsmaatregelen die worden genomen om verspreiding van het virus tegen te gaan.

Geef op een een 5 puntschaal aan hoe u het coronavirus-besmettingsrisico inschat voor de volgende treinreis, gebaseerd op de onderstaande reiscondities.

Drukte in de trein	alle zitplaatsen zijn bezet (enkel staanplaatsen over)
Aantal overstappen	directe verbinding, geen overstap
Mondmaskerbeleid	mondmaskers zijn niet verplicht in de trein
Schoonmaakbeleid	er zijn extra schoonmaakrondes om contactpunten te desinfecteren
Landelijke besmettingsgraad	600 besmettelijk mensen per 100.000 inwoners (zoals geschat op 24 sept 2020, 2e golf)
Landelijk restrictieniveau	"normaal leven"; geen restricties, geen 'social distancing'

1	2	3	4	5
Heel laag risico	Redelijk laag risico	Niet laag en niet hoog	Redelijk hoog risico	Heel hoog risico
○	○	○	○	○

Geef op een een 5 puntschaal aan hoe u het coronavirus-besmettingsrisico inschat voor de volgende treinreis, gebaseerd op de onderstaande reiscondities.

Drukte in de trein	60% zitplaatsen bezet (enkel zitplaatsen naast anderen vrij)
Aantal overstappen	één overstap in treinreis
Mondmaskerbeleid	mondmaskers zijn verplicht in de trein
Schoonmaakbeleid	er zijn geen extra schoonmaakrondes
Landelijke besmettingsgraad	10.000 besmettelijke mensen per 100.000 inwoners (extreem hoog, niet voorgekomen)
Landelijk restrictieniveau	"normaal leven"; geen restric es, geen 'social distancing'

1	2	3	4	5
Heel laag risico	Redelijk laag risico	Niet laag en niet hoog	Redelijk hoog risico	Heel hoog risico
○	○	○	○	○

Geef op een een 5 puntschaal aan hoe u het coronavirus-besmettingsrisico inschat voor de volgende treinreis, gebaseerd op de onderstaande reiscondities.

Drukte in de trein	10% van de zitplaatsen is bezet (vrije zitplaatskeuze)
Aantal overstappen	**directe verbinding, geen overstap**
Mondmaskerbeleid	mondmaskers zijn verplicht in de trein
Schoonmaakbeleid	er zijn extra schoonmaakrondes om contactpunten te desinfecteren
Landelijke besmettingngsgraad	1.000 besmettelijke mensen per 100.000 inwoners (zoals geschat op 24 maart 2020, 1e golf)
Landelijk restrictieeniveau	enkel dringend advies tot 'social distancing', vaak handenwassen en geen handen schudden

1	2	3	4	5
Heel laag risico	Redelijk laag risico	Niet laag en niet hoog	Redelijk hoog risico	Heel hoog risico
○	○	○	○	○

Drukte in de trein	10% van de zitplaatsen is bezet (vrije zitplaatskeuze)
Aantal overstappen	één overstap in treinreis
Mondmaskerbeleid	mondmaskers zijn niet verplicht in de trein
Schoonmaakbeleid	er zijn geen extra schoonmaakrondes
Landelijke besmettingsgraad	600 besmettelijke mensen per 100.000 inwoners (zoals geschat op 24 sept 2020, 2e golf)
Landelijk restrictieniveau	'intelligente lockdown'; thuiswerken is de norm, horeca & theaters/bioscopen gesloten, max. 3 personen op bezoek

1	2	3	4	5
Heel laag risico	Redelijk laag risico	Niet laag en niet hoog	Redelijk hoog risico	Heel hoog risico
○	○	○	○	○

Geef op een 5 puntschaal aan hoe u het coronavirus-besmettingsrisico inschat voor de volgende treinreis, gebaseerd op de onderstaande reiscondities.

Drukte in de trein	30% van de zitplaatsen is bezet (genoeg stoelen vrij om 'alleen' te zi en)
Aantal overstappen	één overstap in treinreis
Mondmaskerbeleid	mondmaskers zijn verplicht in de trein
Schoonmaakbeleid	er zijn extra schoonmaakrondes om contactpunten te desinfecteren
Landelijke besmettingsgraad	20 besmettelijke mensen per 100.000 inwoners (zoals geschat op 1 juli 2020)
Landelijk restrictieniveau	'gedeeltelijke lockdown'; thuiswerken is de norm, horeca open tot 22:00 , max. 6 personen op bezoek

1	2	3	4	5
Heel laag risico	Redelijk laag risico	Niet laag en niet hoog	Redelijk hoog risico	Heel hoog risico
○	○	○	○	○

Drukte in de trein	alle zitplaatsen zijn bezet (enkel staanplaatsen over)
Aantal overstappen	directe verbinding, geen overstap
Mondmaskerbeleid	mondmaskers zijn niet verplicht in de trein
Schoonmaakbeleid	er zijn extra geen schoonmaakrondes
Landelijke besmettingsgraad	1.000 besmettelijke mensen per 100.000 inwoners (zoals geschat op 24 maart 2020, 1e golf)
Landelijk restrictieniveau	'intelligente lockdown'; thuiswerken is de norm, horeca & theaters/bioscopen zijn gesloten, max. 3 personen op bezoek

1	2	3	4	5
Heel laag risico	Redelijk laag risico	Niet laag en niet hoog	Redelijk hoog risico	Heel hoog risico
○	○	○	○	○

Deel 3: Treinrit keuze-experiment

In dit deel van de enquête wordt u telkens gevraagd om te kiezen tussen twee verschillende treinritten.

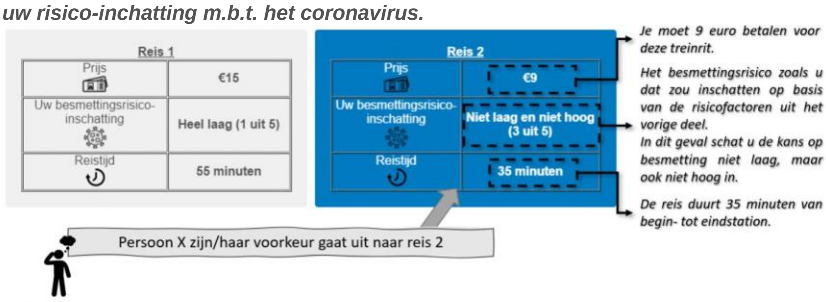
Neem aan dat...

- *iedere treinrit hetzelfde vertrek- en eindstation heeft.*
- *de reis wordt gemaakt gedurende de coronapandemie.*
- *iedere treinrit wordt gemaakt met het volgende reisdoel: "${q://QID10/ChoiceGroup/SelectedChoices}".*
- *alle ritten exclusief eventueel voor- en/of natransport (het reizen van en naar het treinstation) zijn.*
- *eventuele korting door een abonnement voor deze reis niet geldig is. U moet de gegeven prijs betalen.*

De ritten variëren in ritprijs, reistijd en de inschatting met betrekking tot het besmettingsrisico zoals u die zou maken. Deze inschatting is hetzelfde als de risico-inschattingen gemaakt in het vorige deel van de enquête. Dat wil zeggen dat een 'heel laag risico' betekent dat u de kans op besmetting heel laag acht, gegeven de reiscondities.

Een voorbeeldvraag:

Kies de treinreis waar uw voorkeur naar uitgaat, gebaseerd op prijs, reistijd en uw risico-inchatting m.b.t. het coronavirus.



Mocht u extra uitleg willen over de reisvariaties, dan kunt u deze hieronder terugvinden:

Prijs:
Dit is de prijs die u moet betalen voor een enkele treinrit. Dit is gebaseerd op een tarief in de spits <u>zonder</u> kortingskaart.

Uw besmettingsrisico-inschatting:
Deze inschatting geeft aan hoe hoog u het besmettingsrisico van een treinrit zou inschatten. Dit komt overeen met de beoordelingen uit het vorige deel van de enquête en is weergegeven op de volgende manier:

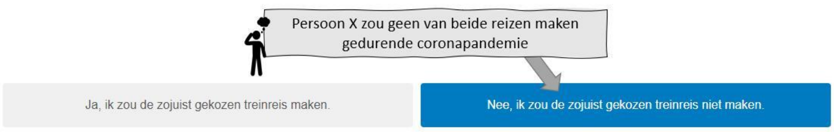
- Heel laag risico (1 uit 5)
- Niet laag en niet hoog risico (3 uit 5)
  Heel hoog risico (5 uit 5)

Reistijd:
De totale reistijd van vertrek- tot eindstation.

Wel reizen of niet reizen:
Nadat u een keuze heeft gemaakt tussen een van de twee treinritten wordt u gevraagd of u nog steeds met de trein zou reizen als dit de enige twee alternatieven zijn.

Als u besluit niet met de trein te reizen, dan reist u met een ander vervoermiddel (bijvoorbeeld auto), kiest u er voor om de activiteit op een andere manier uit te voeren (bijvoorbeeld online) of om de activiteit niet uit te voeren.

Voorbeeldvraag:
Als u de keuze zou krijgen, zou u er dan voor kiezen om de zojuist gekozen treinreis uit te voeren?



1. Kies de treinreis waar uw voorkeur naar uitgaat, gebaseerd op prijs, reistijd en uw risico inschatting m.b.t. het coronavirus.
U maakt deze reis met als reden: "${q://QID10/ChoiceGroup/SelectedChoices}"

Reis 1

Prijs	€9
Uw besmettingsrisico-inschatting	Heel hoog (5 uit 5)
Reistijd	55 minuten

Reis 2

Prijs	€12
Uw besmettingsrisico-inschatting	Heel hoog (5 uit 5)
Reistijd	45 minuten

Als u de keuze zou krijgen, zou u er dan voor kiezen om de zojuist gekozen treinreis uit te voeren?

Ja, ik zou de zojuist gekozen treinreis maken.

Nee, ik zou de zojuist gekozen treinreis niet maken.

2. Kies de treinreis waar uw voorkeur naar uitgaat, gebaseerd op prijs, reistijd en uw risico inschatting m.b.t. het coronavirus.

U maakt deze reis met als reden: "${q://QID10/ChoiceGroup/SelectedChoices}"

Reis 1

Prijs	€9
Uw besmettingsrisico-inschatting	Niet laag en niet hoog (3 uit 5)
Reistijd	35 minuten

Reis 2

Prijs	€15
Uw besmettingsrisico-inschatting	Heel laag (1 uit 5)
Reistijd	55 minuten

Als u de keuze zou krijgen, zou u er dan voor kiezen om de zojuist gekozen treinreis uit te voeren?

Ja, ik zou de zojuist gekozen treinreis maken.

Nee, ik zou de zojuist gekozen treinreis niet maken.

3. Kies de treinreis waar uw voorkeur naar uitgaat, gebaseerd op prijs, reistijd en uw risico inschatting m.b.t. het coronavirus.

U maakt deze reis met als reden: "${q://QID10/ChoiceGroup/SelectedChoices}"

Reis 1

Prijs	€12
Uw besmettingsrisico-inschatting	Heel hoog (5 uit 5)
Reistijd	45 minuten

Reis 2

Prijs	€15
Uw besmettingsrisico-inschatting	Heel hoog (5 uit 5)
Reistijd	35 minuten

Als u de keuze zou krijgen, zou u er dan voor kiezen om de zojuist gekozen treinreis uit te voeren?

Ja, ik zou de zojuist gekozen treinreis maken.

Nee, ik zou de zojuist gekozen treinreis niet maken.

4. Kies de treinreis waar uw voorkeur naar uitgaat, gebaseerd op prijs, reistijd en uw risico inschatting m.b.t. het coronavirus.

U maakt deze reis met als reden: "${q://QID10/ChoiceGroup/SelectedChoices}"

Reis 1

Prijs	€12
Uw besmettingsrisico-inschatting	Niet laag en niet hoog (3 uit 5)
Reistijd	35 minuten

Reis 2

Prijs	€12
Uw besmettingsrisico-inschatting	Heel laag (1 uit 5)
Reistijd	55 minuten

Als u de keuze zou krijgen, zou u er dan voor kiezen om de zojuist gekozen treinreis uit te voeren?

Ja, ik zou de zojuist gekozen treinreis maken.

Nee, ik zou de zojuist gekozen treinreis niet maken.

5. Kies de treinreis waar uw voorkeur naar uitgaat, gebaseerd op prijs, reistijd en uw risico inschatting m.b.t. het coronavirus.

U maakt deze reis met als reden: "${q://QID10/ChoiceGroup/SelectedChoices}"

Reis 1	
Prijs	€15
Uw besmettingsrisico-inschatting	Heel hoog (5 uit 5)
Reistijd	45 minuten

Reis 2	
Prijs	€12
Uw besmettingsrisico-inschatting	Heel hoog (5 uit 5)
Reistijd	55 minuten

Als u de keuze zou krijgen, zou u er dan voor kiezen om de zojuist gekozen treinreis uit te voeren?

Ja, ik zou de zojuist gekozen treinreis maken.

Nee, ik zou de zojuist gekozen treinreis niet maken.

6. Kies de treinreis waar uw voorkeur naar uitgaat, gebaseerd op prijs, reistijd en uw risico inschatting m.b.t. het coronavirus.

U maakt deze reis met als reden: "${q://QID10/ChoiceGroup/SelectedChoices}"

Reis 1	
Prijs	€15
Uw besmettingsrisico-inschatting	Heel laag (1 uit 5)
Reistijd	45 minuten

Reis 2	
Prijs	€9
Uw besmettingsrisico-inschatting	Niet laag en niet hoog (3 uit 5)
Reistijd	45 minuten

Als u de keuze zou krijgen, zou u er dan voor kiezen om de zojuist gekozen treinreis uit te voeren?

Ja, ik zou de zojuist gekozen treinreis maken.

Nee, ik zou de zojuist gekozen treinreis niet maken.

7. Kies de treinreis waar uw voorkeur naar uitgaat, gebaseerd op prijs, reistijd en uw risico inschatting m.b.t. het coronavirus.

U maakt deze reis met als reden: "${q://QID10/ChoiceGroup/SelectedChoices}"

Reis 1	
Prijs	€12
Uw besmettingsrisico-inschatting	Heel laag (1 uit 5)
Reistijd	55 minuten

Reis 2	
Prijs	€9
Uw besmettingsrisico-inschatting	Niet laag en niet hoog (3 uit 5)
Reistijd	35 minuten

Als u de keuze zou krijgen, zou u er dan voor kiezen om de zojuist gekozen treinreis uit te voeren?

Ja, ik zou de zojuist gekozen treinreis maken.

Nee, ik zou de zojuist gekozen treinreis niet maken.

8. Kies de treinreis waar uw voorkeur naar uitgaat, gebaseerd op prijs, reistijd en uw risico inschatting m.b.t. het coronavirus.

U maakt deze reis met als reden: "${q://QID10/ChoiceGroup/SelectedChoices}"

Reis 1

Prijs	**€9**
Uw besmettingsrisico-inschatting	**Niet laag en niet hoog (3 uit 5)**
Reistijd	**55 minuten**

Reis 2

Prijs	**€15**
Uw besmettingsrisico-inschatting	**Heel laag (1 uit 5)**
Reistijd	**35 minuten**

Als u de keuze zou krijgen, zou u er dan voor kiezen om de zojuist gekozen treinreis uit te voeren?

Ja, ik zou de zojuist gekozen treinreis maken.

Nee, ik zou de zojuist gekozen treinreis niet maken.

9. Kies de treinreis waar uw voorkeur naar uitgaat, gebaseerd op prijs, reistijd en uw risico inschatting m.b.t. het coronavirus.

U maakt deze reis met als reden: "${q://QID10/ChoiceGroup/SelectedChoices}"

Reis 1

Prijs	**€15**
Uw besmettingsrisico-inschatting	**Heel laag (1 uit 5)**
Reistijd	**35 minuten**

Reis 2

Prijs	**€9**
Uw besmettingsrisico-inschatting	**Niet laag en niet hoog (3 uit 5)**
Reistijd	**45 minuten**

Als u de keuze zou krijgen, zou u er dan voor kiezen om de zojuist gekozen treinreis uit te voeren?

Ja, ik zou de zojuist gekozen treinreis maken.

Nee, ik zou de zojuist gekozen treinreis niet maken.

Als u besluit de treinrit niet uit te voeren, wat zou u dan doen?

Neem aan dat u wilt reizen met het volgende doel:

"${Selected trip purpose }"

Ik zal ...

- de auto gebruiken zodat ik alsnog de activiteit ({*Selected trip purpose*}) kan uitvoeren.
- de fiets gebruiken zodat ik alsnog de activiteit ({*Selected trip purpose*}) kan uitvoeren.
- een ander vervoersmiddel gebruiken zodat ik alsnog de activiteit({*Selected trip purpose*}) kan uitvoeren.
- vanuit huis werken.
- vanuit huis mijn school of studie volgen en/of mijn studietaken vanuit huis uitvoeren.
- mijn afspraak afzeggen en de activiteit ({*Selected trip purpose*})}) niet uitvoeren.

Deel 4: Achtergrondvragen

Nu volgen enkele achtergrondvragen.

Over het algemeen zou ik mijn algehele gezondheid beoordelen als

- ○ Heel goed
- ○ Goed
- ○ Niet goed, maar ook niet slecht
- ○ Slecht
- ○ Heel slecht

De volgende vraag bestaat uit een set van vier stellingen. Leest u alstublieft iedere stelling zorgvuldig door en kies de stelling die het beste uw gevoelens van de afgelopen zes maanden (tijdens de coronapandemie) beschrijft.

- ○ Ik maak me geen zorgen over mijn gezondheid.
- ○ Ik maak me af en toe zorgen over mijn gezondheid.
- ○ Ik maak me vaak zorgen over mijn gezondheid.
- ○ Ik maak me (bijna) altijd zorgen over mijn gezondheid.

De volgende vragen bestaan uit stellingen. Geef aan in hoeverre u het eens of oneens bent met de volgende stellingen.

Ik denk dat het belangrijk is om dingen te doen in het belang van anderen en/of de samenleving, zelfs als dat mij persoonlijk wat kost (in de vorm van inspanning, moeite of ongemak).

- Helemaal mee eens
- Mee eens
- Niet mee eens, maar ook niet mee oneens
- Mee oneens
- Helemaal mee oneens

Over het algemeen denk ik dat ik een besmetting met het coronavirus kan voorkomen.

- Helemaal mee eens
- Mee eens
- Niet mee eens, maar ook niet mee oneens
- Mee oneens
- Helemaal mee oneens

De acties die ik persoonlijk neem om verspreiding van het coronavirus te voorkomen (bijvoorbeeld door het aantal sociale contacten te beperken, handen te wassen, een gezichtsmasker te dragen, enz.) zijn effectief.

- Helemaal mee eens
- Mee eens
- Niet mee eens, maar ook niet mee oneens
- Mee oneens
- Helemaal mee oneens

Over het algemeen denk ik dat mensen om wie ik geef een groot risico lopen om besmet te raken en ernstig ziek te worden als gevolg van de coronavirusuitbraak.

- Helemaal mee eens
- Mee eens
- Niet mee eens, maar ook niet mee oneens
- Mee oneens
- Helemaal mee oneens

Ik vertrouw de overheid in het effectief omgaan met de uitbraak van het coronavirus.

- Helemaal mee eens
- Mee eens
- Niet mee eens, maar ook niet mee oneens
- Mee oneens
- Helemaal mee oneens

Ik ben bang om ziek te worden van het coronavirus.

- Helemaal mee eens
- Mee eens
- Niet mee eens, maar ook niet mee oneens
- Mee oneens
- Helemaal mee oneens

Het coronavirus is een serieuze bedreiging voor de volksgezondheid en de maatschappij.

- Helemaal mee eens
- Mee eens
- Niet mee eens, maar ook niet mee oneens
- Mee oneens
- Helemaal mee oneens

Hoe waarschijnlijk acht u in het algemeen de kans op een besmetting met het coronavirus?

- Heel erg waarschijnlijk
- Waarschijnlijk
- niet waarschijnlijk, maar ook niet onwaarschijnlijk
- Onwaarschijnlijk
- Heel erg onwaarschijnlijk

Heeft u zelf naar extra informatie over het coronavirus gezocht?

- Ja, ik ben bewust en op eigen initiatief op zoek gegaan naar extra informatie (bijv. via het internet of andere bronnen).
- Nee, ik heb alleen informatie via de reguliere kanalen (TV, krant, etc.) ontvangen.
- Nee, ik vermijd informatie over het coronavirus of de pandemie het liefst.

Kent u iemand in uw omgeving (vrienden of familie) die het coronavirus gehad heeft of nu heeft?

- Ja
- Nee
- Zeg ik liever niet

Wat is uw geslacht?

- Man
- Vrouw
- Anders
- Zeg ik liever niet

Wat is uw geboortejaar?

Wat is uw hoogst voltooide opleiding?
Hiermee wordt bedoeld dat uw diploma behaald is.

- Basis onderwijs (lagere school)
- Voortgezet Onderwijs
- MBO
- Bachelor HBO/WO
- Master HBO/WO, WO doctoraal / post-doctoraal

Anders

Dit is het einde van deze enquête. Bedankt voor uw deelname.
Mocht u nog opmerkingen hebben over de enquête dan kunt u deze hieronder achterlaten. Voor vragen of andere opmerkingen over het onderzoek kunt u ook contact opnemen middels het volgende e-mailadres:
t.w.vandewiel@student.tudelft.nl

Nogmaals hartelijk bedankt voor uw tijd.
Om uw antwoorden in te leveren druk nogmaals op de 'volgende' knop.

G. Linear regression

Table F.1. Linear regression results: intermediate steps

		Main attributes (all)					Main & background (all)					Main & background (final)					Final model				
	parameter	Unstand. Coefficients		Stand. Coe	t	Sig.	Unstand. Coefficients		Stand. Coe	t	Sig.	Unstand. Coefficients		Stand. Coe	t	Sig.	Unstand. Coefficients		Stand. Coe	t	Sig.
		B	Std. Error	Beta			B	Std. Error	Beta			B	Std. Error	Beta			B	Std. Error	Beta		
	Constant	2,611	0,048		53,997	0,000	2,882	0,190		15,159	0,000	2,883	0,113		25,454	0,000	3,072	0,147		20,910	0,000
main attributes	ob_crowding (1-10)	0,112	0,008	0,331	14,774	0,000	0,113	0,007	0,332	15,475	0,000	0,117	0,006	0,346	19,749	0,000	0,059	0,018	0,175	3,292	0,001
	transfer (-1,1)	-0,023	0,023	-0,020	-1,024	0,306	-0,022	0,022	-0,019	-1,023	0,307										
	mask (-1,1)	-0,208	0,023	-0,182	-8,951	0,000	-0,210	0,022	-0,183	-9,408	0,000	-0,216	0,020	-0,189	-10,906	0,000	-0,214	0,020	-0,187	-10,882	0,000
	cleansing (-1,1)	-0,134	0,024	-0,117	-5,513	0,000	-0,136	0,023	-0,119	-5,840	0,000	-0,144	0,020	-0,126	-7,192	0,000	-0,143	0,020	-0,125	-7,198	0,000
	infectrate (0.2-100)	0,007	0,001	0,243	11,834	0,000	0,007	0,001	0,245	12,419	0,000	0,007	0,000	0,243	14,146	0,000	0,010	0,001	0,370	7,079	0,000
	social distancing (-1,1)	-0,001	0,046	-0,001	-0,025	0,980	0,004	0,045	0,003	0,098	0,922										
	moderate lockdown (-1,1)	-0,239	0,042	-0,148	-5,698	0,000	-0,236	0,040	-0,146	-5,875	0,000	-0,185	0,030	-0,114	-6,151	0,000	-0,343	0,076	-0,212	-4,511	0,000
	intelligent lockdown (-1,1)	0,066	0,045	0,041	1,472	0,141	0,062	0,043	0,038	1,428	0,153										
backgrounds	health_att (1-5)						0,016	0,032	0,009	0,484	0,628										
	health_anx (1-5)						0,107	0,033	0,060	3,214	0,001	0,123	0,031	0,069	3,967	0,000	0,121	0,031	0,068	3,937	0,000
	prosociality (1-5)						-0,001	0,027	0,000	-0,022	0,982										
	perc_control (1-5)						0,114	0,024	0,087	4,815	0,000	0,115	0,023	0,088	5,053	0,000	0,154	0,027	0,117	5,663	0,000
	pers_eff (1-5)						-0,178	0,026	-0,131	-6,733	0,000	-0,167	0,025	-0,124	-6,790	0,000	-0,169	0,025	-0,124	-6,876	0,000
	risk_for_loved_ones (1-5)						-0,168	0,024	-0,134	-7,092	0,000	-0,165	0,022	-0,132	-7,336	0,000	-0,257	0,038	-0,205	-6,831	0,000
	gov_trust (1-5)						0,027	0,020	0,024	1,304	0,192										
	media_regular (-1,1)						-0,089	0,091	-0,038	-0,980	0,327										
	media_deliberate (-1,1)						-0,058	0,091	-0,025	-0,632	0,527										
	ex (-1,1)						0,078	0,022	0,063	3,599	0,000	0,074	0,021	0,060	3,551	0,000					
	seks (-1,1)						0,047	0,039	0,021	1,224	0,221										
	age (18-78)						0,002	0,002	0,023	0,931	0,352										
	edu_high (-1,1)						0,020	0,020	0,017	0,973	0,331										
	employed (0,1)						-0,049	0,063	-0,021	-0,776	0,438										
	student (0,1)						-0,141	0,082	-0,048	-1,713	0,087	-0,137	0,049	-0,047	-2,814	0,005	-0,139	0,048	-0,047	-2,864	0,004
	retired (0,1)						0,002	0,111	0,000	0,016	0,987										
	education (-1,1)						0,006	0,034	0,004	0,171	0,864										
	leisure (-1,1)						-0,012	0,043	-0,005	-0,270	0,787										
interactions	pc.infectrate																-0,001	0,001	-0,137	-2,570	0,010
	rl.ob_crowding																0,019	0,006	0,178	3,072	0,002
	go.lockdown_2																0,058	0,026	0,105	2,261	0,024
	ex.crowdin																0,016	0,003	0,081	4,735	0,000
	R^2	0,278					0,347					0,344					0,352				
	adj. R^2	0,276					0,34					0,341					0,348				

Table G.2. Linear regression results: general risk components

	parameter	Main, background & C-19 risk components					Main & background & c-19 aff					Main & background & c-19 att					Main & background & c-19 cogn				
		Unstand. Coefficients		Stand. Coe	t	Sig.	Unstand. Coefficients		Stand. Coeff	t	Sig.	Unstand. Coefficients		Stand. Coefficie	t	Sig.	Unstand. Coefficients		Stand. Coefficie	t	Sig.
		B	Std. Error	Beta			B	Std. Error	Beta			B	Std. Error	Beta			B	Std. Error	Beta		
	Constant	3,286	0,141		23,251	0,000	3,088	0,120		25,709	0,000	3,030	0,113		26,707	0,000	3,162	0,140		22,522	0,000
main attributes	ob_crowding	0,117	0,006	0,346	20,045	0,000	0,117	0,006	0,346	19,848	0,000	0,117	0,006	0,346	20,002	0,000	0,117	0,006	0,345	19,787	0,000
	transfer																				
	mask	-0,216	0,020	-0,188	-11,034	0,000	-0,216	0,020	-0,189	-10,981	0,000	-0,216	0,020	-0,188	-11,006	0,000	-0,216	0,020	-0,188	-10,913	0,000
	cleansing	-0,144	0,020	-0,126	-7,291	0,000	-0,145	0,020	-0,126	-7,250	0,000	-0,144	0,020	-0,126	-7,271	0,000	-0,144	0,020	-0,126	-7,190	0,000
	infectrate	0,007	0,000	0,243	14,335	0,000	0,007	0,000	0,244	14,260	0,000	0,007	0,000	0,243	14,296	0,000	0,007	0,000	0,242	14,143	0,000
	social distancing																				
	moderate lockdown	-0,184	0,030	-0,114	-6,207	0,000	-0,183	0,030	-0,113	-6,120	0,000	-0,185	0,030	-0,114	-6,210	0,000	-0,186	0,030	-0,115	-6,205	0,000
	intelligent lockdown																				
backgrounds	health_att																				
	health_anx	0,049	0,033	0,028	1,487	0,137	0,058	0,033	0,033	1,752	0,080	0,087	0,031	0,049	2,831	0,005	0,108	0,031	0,061	3,482	0,001
	prosociality																				
	perc_control	0,086	0,024	0,065	3,581	0,000	0,101	0,023	0,077	4,440	0,000	0,109	0,022	0,083	4,853	0,000	0,087	0,024	0,066	3,602	0,000
	pers_eff	-0,084	0,026	-0,062	-3,219	0,001	-0,147	0,025	-0,108	-5,907	0,000	-0,092	0,026	-0,068	-3,518	0,000	-0,156	0,025	-0,115	-6,274	0,000
	risk_for_loved_ones	-0,086	0,025	-0,068	-3,502	0,000	-0,123	0,024	-0,098	-5,155	0,000	-0,113	0,023	-0,090	-4,878	0,000	-0,144	0,023	-0,115	-6,159	0,000
	gov_trust																				
	media_regular																				
	media_deliberate																				
	ex_effects	0,054	0,021	0,043	2,571	0,010	0,075	0,021	0,061	3,648	0,000	0,056	0,021	0,045	2,695	0,007	0,064	0,021	0,052	3,048	0,002
	sex																				
	age																				
	edu_high_effect																				
	employed																				
	student	-0,092	0,049	-0,031	-1,879	0,060	-0,090	0,049	-0,031	-1,829	0,067	-0,111	0,048	-0,038	-2,302	0,021	-0,141	0,049	-0,048	-2,897	0,004
	retired																				
	education																				
	leisure																				
C-19 risk comp.	C-19 affective risk	-0,033	0,013	-0,056	-2,548	0,011	-0,061	0,012	-0,103	-4,940	0,000										
	C-19 risk attitude	-0,159	0,025	-0,133	-6,401	0,000						-0,184	0,024	-0,155	-7,777	0,000					
	C-19 cognitive risk	-0,056	0,029	-0,038	-1,937	0,053											-0,096	0,029	-0,065	-3,348	0,001
interactions	pc.infectrate																				
	rl.ob_crowding																				
	go.lockdown_2																				
	ex.crowding																				
	R^2	0,364					0,35					0,361					0,347				
	adj. R^2	0,36					0,347					0,357					0,344				

Table G.3. Linear regression results: all estimated interaction terms

	All parameters					
	parameter	Unstand. B	Std. Error	Stand. Beta	t	Sig.
	Constant	3,073	0,261		11,795	<0,001
main attributes	ob_crowding	0,050	0,034	0,148	1,482	0,139
	transfer	-0,018	0,022	-0,015	-0,820	0,412
	mask	-0,325	0,130	-0,283	-2,487	0,013
	cleansing	-0,061	0,113	-0,053	-0,539	0,590
	infectrate	0,011	0,003	0,400	3,888	<0,001
	social dist. (lockdown_1)	-0,078	0,097	-0,048	-0,807	0,420
	moderate (lockdown_2)	-0,421	0,095	-0,260	-4,445	<0,001
	intelligent (lockdown_3)	0,234	0,098	0,144	2,383	0,017
backgrounds	health_att (ha)	0,047	0,058	0,027	0,806	0,421
	health_anx (hx)	0,046	0,062	0,026	0,747	0,455
	prosociality (so)	0,054	0,047	0,036	1,152	0,249
	perc_control (pc)	0,158	0,028	0,121	5,585	<0,001
	pers_eff (pe)	-0,180	0,026	-0,133	-6,848	<0,001
	risk_for_loved_ones (rl)	-0,282	0,042	-0,225	-6,707	<0,001
	gov_trust (go)	0,026	0,020	0,024	1,287	0,198
	media_regular [me1]	-0,018	0,039	-0,014	-0,447	0,655
	media_deliberate [me2]	-0,140	0,082	-0,047	-1,701	0,089
	experience [ex]	-0,094	0,091	-0,040	-1,042	0,298
	sex	-0,064	0,091	-0,028	-0,707	0,480
	age	0,049	0,038	0,021	1,281	0,200
	high education	0,002	0,002	0,023	0,947	0,343
	employed [wo1]	0,021	0,020	0,018	1,043	0,297
	student [wo2]	-0,049	0,063	-0,020	-0,778	0,437
	retired [wo3]	0,004	0,110	0,001	0,036	0,971
	education [tp1]	0,006	0,034	0,004	0,175	0,861
	leisure [tp2]	-0,011	0,042	-0,004	-0,263	0,793
interactions	ha.mask	-0,048	0,031	-0,087	-1,544	0,123
	hx.mask	-0,013	0,032	-0,022	-0,405	0,686
	so.mask	0,022	0,027	0,040	0,810	0,418
	pc.mask	0,009	0,024	0,021	0,366	0,715
	pe.mask	0,029	0,024	0,058	1,175	0,240
	regular.mask	0,090	0,088	0,048	1,028	0,304
	deliberate.mask	0,108	0,088	0,072	1,236	0,217
	deliberate.cleansing	-0,077	0,087	-0,051	-0,883	0,378
	regular.cleansing	-0,103	0,087	-0,055	-1,184	0,236
	pc.cleansing	0,015	0,022	0,035	0,659	0,510
	hx.cleansing	-0,046	0,033	-0,077	-1,405	0,160
	ha.cleansing	0,028	0,031	0,050	0,884	0,377
	so.ob_crowding	-0,010	0,008	-0,074	-1,380	0,168
	ha.ob_crowding	-0,009	0,009	-0,058	-0,940	0,347
	ha.infectrate	0,000	0,001	0,037	0,620	0,535
	hx.ob_crowding	0,016	0,010	0,102	1,655	0,098
	hx.infectrate	-0,001	0,001	-0,050	-0,877	0,381
	pc.infectrate	-0,002	0,001	-0,155	-2,763	0,006
	rl.ob_crowding	0,023	0,007	0,220	3,509	<0,001
	rl.infectrate	0,000	0,001	-0,005	-0,092	0,927
	go.lockdown_1	0,031	0,031	0,056	0,986	0,324
	go.lockdown_2	0,067	0,031	0,123	2,157	0,031
	go.lockdown_3	-0,063	0,032	-0,115	-1,987	0,047
	ex.ob_crowding	0,017	0,006	0,084	2,710	0,007
	ex.infect	0,000	0,001	0,018	0,790	0,430
	ex.mask	0,031	0,022	0,027	1,430	0,153
	ex.cleansing	-0,003	0,022	-0,003	-0,155	0,877
	R^2	0,363				
	adjusted R^2	0,348				

H. Discrete Choice Models

Table H.1. Results choice modelling: long trips (≥ 30 minutes)

	LONG TRIPS (>= 30 MIN)	**MNL final**			**ML all effects (50 draws)**			**ML final (400 draws)**		
	Parameter	Estimate	Rob.t-ratio	p-value	Estimate	Rob.t-ratio	p-value	Estimate	Rob.t-ratio	p-value
main attributes	Travel Costs (TC)	-0,175	-8,638	<0,001	-0,450	-6,511	<0,001	-0,399	-11,044	<0,001
	Travel Time (TT)	-0,027	-7,316	<0,001	-0,061	-3,422	<0,001	-0,054	-9,209	<0,001
	Covid Risk (CR)	-0,588	-6,985	<0,001	-0,838	-2,494	0,013	-1,258	-5,250	<0,001
	Covid Risk Sq. (CRsq)									
	Remode (RM)									
	Home activity (HO)									
	Opt-out (OPT)	-5,289	-12,586	<0,001	-11,629	-14,135	<0,001	-11,538	-13,788	<0,001
	Interaction TT * CR (base model)	-0,801	-10,409	0,599*						
stand. dev.	Std. Dev. TC				0,063	3,794	<0,001	0,067	3,775	<0,001
	Std. Dev. CR				1,138	8,266	<0,001	1,123	8,413	<0,001
trip purpose	Edu * TC				0,012	0,375	0,708			
	Leisure * TC				-0,021	-0,890	0,373			
	Edu * TT				0,000	0,028	0,977			
	Leisure * TC				0,008	1,237	0,216			
	Edu * CR				0,045	0,334	0,738			
	Leisure * CR				-0,043	-0,346	0,729			
backgroudn interactions	age * TC				0,000	0,060	0,952			
	seks * TC				-0,016	-0,583	0,560			
	edu * TC				-0,007	-0,476	0,634			
	empl. * TC				0,064	1,563	0,118			
	student * TC	0,063	2,336	0,020	0,123	2,033	0,042	0,080	2,365	0,018
	retired * TC				0,115	1,502	0,133			
	freq. * TC				-0,002	-0,152	0,879			
	age * TT				0,000	0,784	0,433			
	sex * TT				0,009	1,186	0,236			
	edu * TT				0,005	1,242	0,214			
	empl. * TT				-0,008	-0,770	0,441			
	student * TT	-0,026	-3,025	0,002	-0,035	-1,944	0,052	-0,029	-3,140	0,002
	retired * TT				-0,011	-0,659	0,510			
	freq. * TT	0,009	4,201	<0,001	0,007	1,749	0,080			
	age * CR	-0,005	-2,400	0,016	-0,019	-2,432	0,015	-0,015	-2,794	0,005
	sex * CR				-0,264	-1,609	0,108			
	edu * CR	-0,083	-2,865	0,004	-0,220	-2,625	0,009	-0,224	-2,471	0,013
	empl. * CR				-0,163	-0,702	0,483			
	student * CR				-0,327	-1,149	0,250			
	retired * CR				0,116	0,271	0,786			
	freq. * CR				0,289	3,459	0,001	0,273	2,821	0,005
	R^2	0,1956			0,3854			0,3805		
	Adj. R^2	0,1925			0,3739			0,3766		
	LL 0				-2869,575			-2869,58		
	LL final	-2.308,257			-1763,654			-1777,75		

N=291

**not in final model*

Table H.2. Results choice modelling: short trips (<30 minutes)

	SHORT TRIPS (<30 MIN)	**MNL Final**			**ML all effects (50 draws)**			**ML final (800 draws)**		
	Parameter	Estimate	Rob.t-ratio	p-value	Estimate	Rob.t-ratio	p-value			
main attributes	Travel Costs (TC)	-0,224	-4,526	<0,001	-0,727	-4,199	<0,001	-0,501	-6,922	
	Travel Time (TT)	-0,051	-5,246	<0,001	-0,033	-0,950	0,342	-0,104	-7,543	
	Covid Risk (CR)				-0,848	-2,760	0,006	-0,616	-2,809	0,005
	Covid Risk Sq. (CRsq)	-0,112	-11,725	<0,001						
	Remode (RM)									
	Home activity (HO)									
	Opt-out (OPT)	-3,323	-7,360	<0,001	-7,598	-8,899	0,000	-7,703	-9,410	0,000
	Interaction TT * CR (base model)	-0,007	-1,057	0,290*						
stan d. dev.	Std. Dev. TC				0,158	3,091	0,002	0,163	3,529	0,000
	Std. Dev. CR				0,509	5,588	0,000	0,507	5,690	0,000
trip purpose	Edu * TC				-0,001	-0,016	0,987			
	Leisure * TC				0,030	0,464	0,643			
	Edu * TT				0,010	0,598	0,550			
	Leisure * TC				-0,010	-0,649	0,516			
	Edu * CR				0,153	1,067	0,286			
	Leisure * CR				-0,109	-1,015	0,310			
backgroudn interactions	age * TC				0,004	1,121	0,262			
	seks * TC				0,007	0,101	0,920			
	edu * TC				-0,025	-0,716	0,474			
	empl. * TC				0,078	0,615	0,538			
	student * TC				0,157	0,977	0,329			
	retired * TC				0,094	0,458	0,647			
	freq. * TC				0,069	1,831	0,067			
	age * TT				-0,001	-1,806	0,071			
	sex* TT				-0,012	-0,718	0,473			
	edu * TT				-0,008	-0,983	0,326			
	empl. * TT				-0,007	-0,255	0,798			
	student * TT				-0,040	-1,253	0,210			
	retired * TT				0,039	0,688	0,491			
	freq. * TT				-0,018	-2,087	0,037			
	age * CR				0,005	0,838	0,402			
	seks * CR				0,030	0,245	0,806			
	edu * CR				0,142	2,245	0,025	0,158	2,333	0,020
	empl. * CR				-0,414	-1,808	0,071	-0,457	-1,971	0,049
	student * CR				-0,654	-2,244	0,025	-0,646	-2,504	0,012
	retired * CR	-0,156	-2,196	0,028	-0,704	-2,195	0,028	-0,768	-3,103	0,002
	freq. * CR				0,088	1,232	0,218			
	R^2	0,1315			0,2493			0,238		
	Adj. R^2	0,1271			0,2206			0,229		
	LL 0	-1148,050			-1148,050			-1148,050		
	LL final	-997,105			-861,833			-875,218		

N=117

**not in final model*

I. Data Management Plan

MSc. TIL- graduation project. The perception of covid- 19 transmission in public transport: understanding travellers' trade-offs and the role of trip conditions in risk perception

A. General TU Delft data management questions

Name of data management support staff consulted during the preparation of this plan

Kees den Heijer, the Data Steward of the faculty of Civil Engineering & Geosciences.

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1. Is TU Delft the lead institution for this project?

- Yes, the only institution involved

2. If you leave TU Delft (or are unavailable), who is going to be responsible for the data resulting from this project?

Chair of graduation committee: Oded Cats (o.cats@tudelft.nl)

3. Where will the data (and code, if applicable) be stored and backed-up during the project lifetime?

- Another storage system - please explain below

  Own PC

4. How much data storage will you require during the project lifetime?

- < 250 GB

5. What data will be shared in a research data repository?

- All data (and code) underlying published articles / reports / theses

6. How much of your data will be shared in a research data repository?

- < 100 GB

7. How will you share your research data (and code)?

- Data will be uploaded to the 4TU.Centre for Research Data

8. Does your research involve human subjects?

- Yes

9. Will you process any personal data? Tick all that apply

- Other types of personal data – please explain below
- Date of birth/age
- Gender

Other type of personal data: Attitudes concerning own health risks

B. TU Delft questions about management of personal research data

1. Please detail what type of personal data you will collect, for what purpose, how you will store and protect that data, and who has access to the data.

Please provide your answer in the table below. Add an extra row for every new type of data processed:

Type of data	How will the data be collected?	Purpose of processing	Storage location	Who will have access to the data
Gender	Through an online survey	To research if gender is correlated with covid-19 risk perception	-	Supervisors, researcher
Age	Through an online survey	To research if age is correlated with covid-19 risk perception	-	Supervisors, researcher
Attitudes concerning own health risks	Through an online survey	To research if health judgement is correlated with covid-19 risk perception	-	Supervisors, researcher
Knowing people having had the coronavirus	Through an online survey	To research if knowing people who have had the coronavirus is correlated with covid-19 risk perception	-	Supervisors, researcher

2. Will you be sharing personal data with individuals/organisations outside of the EEA (European Economic Area)?

- No

3. What is the legal ground for personal data processing?

- Informed consent - please describe the informed consent procedures you will follow

  The respondents are asked to agree with 4 informed consent statements in the beginning of the survey. The following statements are posed:
  - I consent voluntarily to participate in this survey.
  - I understand that I can cancel the completion of this survey at any time.
  - I understand that information I provide will be used for research purposes and the findings may be disseminated through scientific publications.
  - I understand that I will remain completely anonymous and that my answers cannot be traced back to myself.

4. Will the personal data be shared with others after the end of the research project, and if so, how and for what purpose?

no

5. Does the processing of the personal data results in a high risk to the data subjects?

If the processing of the personal data results in a high risk to the data subjects, it is required to perform a Data Protection Impact Assessment (DPIA). In order to determine if there is a high risk for the data subjects, please check if any of the options below that are applicable to the processing of the personal data during your research (check all that apply).
If two or more of the options listed below apply, you will have to [complete the DPIA](). Please get in touch with the privacy team: [privacy-tud@tudelft.nl]() to receive support with DPIA. If only one of the options listed below applies, your project might need a DPIA. Please get in touch with the privacy team: [privacy-tud@tudelft.nl]() to get advice as to whether DPIA is necessary.

If you have any additional comments, please add them in the box below.

None of the above apply

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