The bidirectional relationships between travel behaviour, attitude and risk perception during the COVID-19 pandemic

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Summary

Policy makers have several reasons to want people to change their travel behaviour. Car travel is, compared to most other modes, worse for the climate, accessibility, local economies and people's health. To get people out of their car policy makers generally try to influence people's attitude. This can be done by negatively influencing undesired behaviour (e.g. car use) or by positively influencing the desired behaviour (e.g. riding bicycles). The theory behind this is that by affecting people's attitudes, they will change their (travel) behaviour.

However, from a scientific perspective there are quite some knowledge gaps in this field. Although this relationship from attitude to behaviour is generally assumed, recent studies have suggested that not all these assumptions are correct. A main finding is the notion of the bidirectional relationship between the two. Meaning that attitude not only influences behaviour, but behaviour also does that to attitude. Thus, there is still research to be done in this field.

Additionally, in 2020, the COVID-19 pandemic has had a enormous effect on travel behaviour. Governments worldwide imposed travel restrictions to limit the spread of the coronavirus. In the Netherlands, public transport usage dropped massively. As travel behaviour is so fast changing during this period, it allows for a renewed analysis of the relationship between travel behaviour and attitude. Furthermore, new factors due to the influence of COVID-19 on transportation may be identified.

There are several scientific theories relating to travel behaviour and attitude, such as the Theory of Reasoned Action and the Theory of Planned Behaviour. This is a field that has been researched for quite some time. Reasonably new are findings of reverse causality; the idea that the attitude–behaviour relationship is bidirectional. This has not yet been researched extensively.

Another relevant theory is that of the mobility biographies. In this theory behaviour and attitude are considered rather stable over time, until a 'key event' occurs. Examples are changing jobs or moving houses. It is argued that the COVID-19 pandemic can also be seen as a key event, as it has lead to drastic changes to day-to-day life. Thus, due to the pandemic changes to attitude and behaviour are to be expected.

As COVID-19 plays such large of a role for this study, factors of it are taken into account. Public transport is much more affected in terms of number of trips and travelers than private transport (e.g. personal car). An important aspect here is likely the fear people have of being infected. This perception of risk is considered, as it expected to affect attitude and behaviour. However, the exact effect of risk perception is unknown for now. Another specific factor is the necessity to travel that is present for some people, but not for others. People who cannot work or study from home need to travel, which leads to different attitudes and behaviour than the people who do not have to travel.

To scope this study, it will specifically look at travel done by car and train. This is chosen as especially for longer distances car has the highest mode share, while for shorter distances other modes such as cycling are way more common. Furthermore, long distance trips make up most of the distance traveled in a year. Therefore, from a policy perspective, it makes the most sense to try to influence those.

Research question

These considerations have lead to the research question of this study:

What are the relationships between travel behaviour, attitude and the perception

of risk of getting COVID-19 for traveling by car and train and how is this influenced by people's necessity to travel?

To answer this research question four parts are considered: what scientific knowledge is available on travel behaviour and attitude and perception of risk; what developments regarding those occurred during the pandemic; how large are the bidirectional relationships between them; and what is the influence of the necessity to travel on these three.

Literature

The first part is answered by conducting a literature review. Relevant literature regarding travel behaviour, attitude and its interactions, as well as the effects of COVID-19 have been reviewed. Here it is shown that most literature agrees that travel behaviour is caused by attitudes.

When further reviewing literature on attitude, it is shown that there are multiple ways to influence attitude. These are affective evaluations, cognitive evaluations and behavioural responses. The first two mainly show the classic way of thinking about attitudes; they are evaluations of something or some action. The third one – behavioural responses – suggests that specific behaviour influences attitudes towards that behaviour. Thus, this already suggests that behaviour has an influence on attitude and not only the other way around. More recent literature delves further into this reverse causality, suggesting that the reverse effect (behaviour on attitude) is as strong or even stronger than attitude on behaviour.

Furthermore, the theory of mobility biographies and its key events or triggers is further analysed. Based on the definitions of those in literature, COVID-19 can be considered a trigger for attitude and behaviour change. Therefore, it is expected that this will also be seen in the results.

Next, the perception of risk is discussed, however little scientific knowledge exists regarding the relation between risk perception and travel behaviour or attitude. A study has shown that there are differences between travelers who have to travel and those who do not. Suggesting that taking this necessity to travel into account will give different results.

Based on the scientific literature that has been analysed, a conceptual model has been made which serves as the basis for the rest of this study. The conceptual model is shown in Figure 1. It assumes that there are causal relations between all three predictors (travel behaviour, attitude and perception of risk) at two moments in time. Furthermore, the necessity to travel is assumed to have a moderating effect on these relations.

Hypotheses

Hypotheses are made based on this conceptual model. The autoregressive effects (effects between the same predictor) are expected to be the highest, as they are the basis for each parameter. Between attitude and behaviour the cross-lagged effects are expected to be significant. Previous research has shown that the relationship behaviour–attitude is stronger than vice versa, thus that is likely also the case here.

Risk perception is expected to have significant effects from and to attitude, as both can be seen people's personal evaluations. This would especially be the case for train travel, where risk perception is expected to play a much larger role. The question exists whether risk perception and travel behaviour have direct effects between them. This is expected to be the case, as risk perception could overrule attitude, and thus directly influencing travel

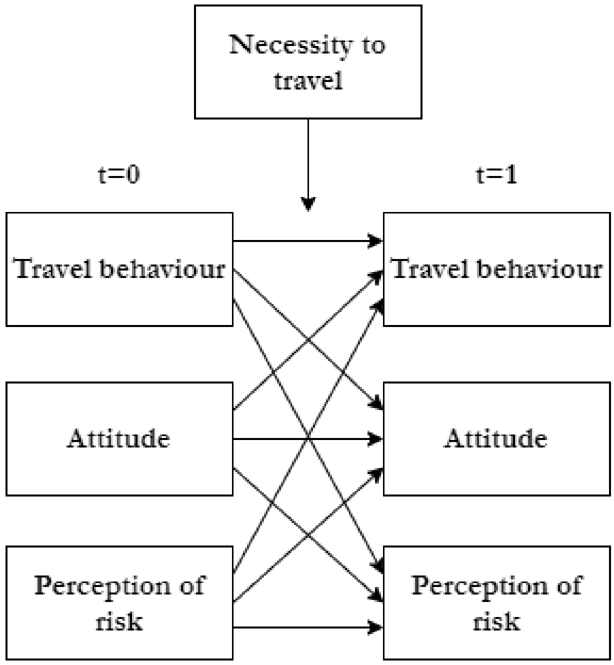

Figure 1: Conceptual model.

behaviour. In the other direction travel behaviour could influence risk perception as traveling more or less likely influences this perception.

For the necessity to travel we expect more rigid relations, thus the effects are less significant. Furthermore, the perception risk is considered to be less relevant for people who have to travel.

Research design

The research is conducted by using data collected by the NS Panel. The specific research is a panel survey that was conducted in April, June, September and December 2020 to gain more insight into corona and traveling by train. It contains questions relating to travel behaviour and attitude, for both car and train, and risk perception. This dataset is weighted to be representative for the train traveling population of the Netherlands.

The data allows for statistical analysis of the development of travel behaviour, attitude and risk perception during the pandemic. Furthermore, because the questions are asked at four moments in time, causality between the three predictors can be analysed. We are interested in this causality as it gives insight in which direction effects take place. To do so, a cross-lagged panel model is set up. The results from this model will show how attitude, behaviour and risk perception influence each other and in which direction.

Before doing so, the data is prepared for this study. Only respondents who answered in all four waves are selected. Based on different questions the three predictors and necessity to travel are operationalised.

Based on the conceptual model, this operationalisation and the scientific knowledge about the cross-lagged panel model, the structural model for the analysis of the bidirectional relationships is generated. It considers the bidirectional effect between all three predictors from one moment in time to the next. Additionally, error terms and correlations are put in place for proper working of the model.

Results

Developments during the pandemic

The results of the developments during the pandemic show that the dataset corresponds rather good with the observed public transport usage. Furthermore, a clear trend between travel behaviour and the severity of the pandemic is shown.

When comparing car and train travel, it becomes very clear that train travel has been affected way more than car travel. Both do follow approximately the trend as the severity of the pandemic. However, car travel actually increases above the reported behaviour of before the pandemic. This suggests that people have changed from other mode of transport to cars. For attitude a similar trend is shown, train attitudes are clearly more affected than car attitudes.

Risk perception follows a bit of a different trend, the results suggest that risk perception is mostly affected by the direction of the severity of the pandemic (i.e. increasing of decreasing), rather than the absolute severity of the pandemic. This is an interesting result, but with the limited data points available (four in 2020) it cannot be fully proven.

Bidirectional relationships

The results from the cross-lagged panel model on the bidirectional relationships between the three predictors are largely as expected. The autoregressive effects are the largest and there are significant relationships between behaviour and attitude. The stronger behaviour-attitude relation as suggested in literature has not been found here.

The effects of risk perception are rather small. For car travel they are very close to zero, and some of them not statistically significant. In the train travel model they are a bit more significant, but still have a way smaller effect than attitude and behaviour on each other. These effects are negative, thus risk perception negatively influences attitude and behaviour, and vice versa.

Adjustments to the base model are made. One of those is constraining the regressions between waves. This means that the estimates from a certain predictor to another for all four waves are considered the same value. However, a chi-squared test shows that this model does not perform better. Therefore, this model is rejected.

Necessity to travel

Another consideration mentioned before is the inclusion of the necessity to travel: there is a group which needs to travel and a group which does not.

For car travel it is hard to draw conclusions from the model considering groups. This is because due to the small groups sizes a lot of the results are not statistically significant. The train travel results are more interesting. However, the results are not very consistent. Mainly, the people who are not forced to travel have larger effects from their perception of risk, as was expected.

A chi-squared test shows that there are significant differences in the estimates between the two groups. Furthermore, the model fit indices show slightly better results when considering groups. Still, these values are below the cut-off values for a good model fit.

As final analysis, the bidirectional relations between the two modes are analysed. The results here show that there is a consistent negative relation between car and train travel behaviour and attitudes.

The main results are that there are significant bidirectional relationships between travel behaviour and attitude. However, there is no clear stronger direction in this relationship. Risk perception has little influence on car travel, but does have some on train travel.

More specifically, the relationship behaviour–risk perception for car travel seems to almost not exist. For train travel a clear negative effect is shown here. Attitude–risk perception does have some interesting results. While for train travel this effect is negative as expected, for car the opposite is true. Car travel attitudes have a positive effect on risk perception.

Discussion and conclusion

It is important to note some of the limitations of this study. The analysis of the developments during the pandemic takes large steps as there are only four moments of measurement. Therefore, it is hard to draw meaningful conclusions about the developments. Furthermore, the models did not reach the goodness-of-fit cut-off values, thus it is likely that the model is incomplete. Improving the model fit can help in acquiring more statistically significant results, which could lead to more meaningful conclusions. A way to improve the model is by adapting the cross-lagged panel model to incorporate within-person effects.

Concluding, there are some interesting results which allow for future research and which give policy makers more insight into the relations that exist here. The results show that behaviour can indeed be influenced by attitude, but this is not a one on one effect. Thus, the effectiveness of this method is not great. Therefore, it is recommended to also use different means as policy-maker. One opportunity here is to use behaviour as a way to change behaviour. The results show that experiencing a certain behaviour changes people's attitude towards that behaviour. Therefore, if policy-makers would somehow temporarily change people's behaviour, they are also more likely to do so on the long term.

For the NS the results show that people are generally expected to return to the train, although this might take some time. However, these are not hard conclusions and it is recommended to look into the future developments and see if other factors can be identified to better predict future behaviour.

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1 Introduction

From a policy perspective, there are numerous reasons to try to get people out of cars and instead get them to walk, cycle or use public transport. To reach the climate policy targets for emissions, personal car use needs to decrease (Miotti, Supran, Kim, & Trancik, 2016). In order to keep city centres accessible, traffic congestion due to large numbers of private cars must be reduced (Aftabuzzaman, Currie, & Sarvi, 2010). Less traffic congestion in city centres is also considered to be beneficial to the local economy (Sweet, 2011). Studies have found that a switch from car to bicycle has a positive impact on someone's health (Rojas-Rueda, De Nazelle, Tainio, & Nieuwenhuijsen, 2011). A relationship between hours spent in a car and obesity rates has also been established (Frank, Andresen, & Schmid, 2004).

Therefore, the questions rises how to discourage the use of personal vehicles. It is widely accepted that attitude towards a certain behaviour is a large factor in determining behaviour (Gärling, Gillholm, & Gärling, 1998). Thus, by negatively shifting people's attitude of car use or positively influencing attitudes of other transport modes, people's transport behaviour can be changed. Such shifts in attitude could be established by governmental campaigns, e.g. promoting certain behaviour or creating more awareness (Rezai, Hosseinpour, Shamsudin, AbdLatif, & Sharifuddin, 2015). Setting up campaigns to shift attitude might be preferable to policies that directly influence behaviour, as politics are involved and harder measures often lead to heavier political repercussions (Gavin, 2009).

However, it was found that the travel behaviour people have also influences their attitudes towards different modes of transport. A recent study found that a larger effect of behaviour on attitude than vice versa (Kroesen, Handy, & Chorus, 2017). That would mean that the travel behaviour people have, has a large impact on their attitude towards that behaviour. This questions the effectiveness of focusing on shifting attitudes as a policy; *"these results have important implications for travel behavior researchers"* (Kroesen et al., 2017, p. 200). Besides researchers, this is also important for policy makers, as it questions current approaches to travel behaviour change practices. If the effect from attitude to behaviour is less prominent than assumed, then changing behaviour via people's attitude will be significantly less effective.

The current COVID-19 pandemic has huge effects on passenger transport. A decrease of up to fifty percent for road transport and up to ninety percent for public transport has been observed by Statistics Netherlands (2021a). Clearly, travel behaviour has been drastically altered during the pandemic. This could be explained by implemented travel restrictions – especially regarding public transport – or by a fear of getting the coronavirus when traveling.

As the pandemic has caused day-to-day life to change significantly, the relationship between travel attitude and behaviour might be very different from what was found earlier (e.g. by Kroesen et al. (2017)). This makes it interesting to take another look into the relationship between travel attitude and behaviour and take the influences from the pandemic into consideration.

1.1 Knowledge gap

The idea that attitude does not only influence behaviour but also the other way around is not new. That behaviour also affects attitude has been considered for quite some time (e.g. Dobson, Dunbar, Smith, Reibstein, and Lovelock (1978)). However, most travel behaviour researchers kept holding on to the notion of attitude causing behaviour, and not vice versa (Chorus & Kroesen, 2014).

Using theories from social psychology, Van Wee et al. (2019) proposed a conceptual model explaining changes in attitudes caused by behaviour, i.e. reverse causality – the notion that causality does not only go from attitude to behaviour, but also reversed. This has already been proven by Kroesen et al. (2017); they noticed a bidirectional relation between travel attitude and behaviour.

Kroesen et al. (2017) note that their findings could be combined with the mobility biographies approach. In this approach travel behaviour is considered relatively stable due to constant factors and habits. Key life events can cause behavioural changes however, as people are then forced to rethink their travel behaviour (Kroesen et al., 2017; Lanzendorf, 2010; Scheiner, 2007).

This is in line with the findings of Van Wee et al. (2019), who identified two processes which cause changes to travel attitudes. The first is exposure to new experiences, which can be categorised at a personal level, social level or environmental context. This kind of triggers can be defined as *"external initiators of internal processes"* (Van Wee et al., 2019, p. 3). Second is the process that *"people change attitudes to reduce a mismatch between behaviour and attitudes"* (Van Wee et al., 2019, p. 7).

Examples of key events are residential or workplace relocation and the birth of children (Scheiner, 2007). And while the COVID-19 pandemic is unalike those examples, it could be considered a key life event. As noted before, travel behaviour has certainly been changed vastly due to the coronavirus (Statistics Netherlands, 2021a). Therefore, it allows for the opportunity to further delve into the relationship between travel attitude and travel behaviour.

During the COVID-19 pandemic, a multitude of travel attitude and behaviour factors are present. The fear of infection can play a big role on travel attitudes; likely drastically altering the attitude towards shared travel modes. At the same time, governmental travel restrictions have drastically altered travel behaviour by putting up hard barriers. As this is such a topical issue, little research has been published about the relationship between travel attitude and behaviour during the pandemic.

Furthermore, it is unknown what will become of the currently changed behaviours. People may fall back to their habits as they were before the pandemic, but attitudes and behaviour might also be changed for longer. This is relevant to know for a smooth transportation system when the pandemic has been halted.

A study that has been conducted which specifically includes the pandemic shows signals of structural changes due to the current circumstances (De Haas, Faber, & Hamersma, 2020). This is a sign of that the pandemic can be considered a key life event. Although both travel attitude and behaviour are taken into account, the relationship between the two remains under-explored.

To what degree different factors are evaluated in determining attitudes varies from person to person. However, it has been shown before that the risk perception of a certain mode has a significant role (Elias & Shiftan, 2012). While this usually considers things like road safety conditions, during the pandemic it can be translated to the (perceived) risk of infection. This is considered a main reason for initial attitude changes. The fact that public transport trips experienced a significantly steeper reduction compared to other (non-shared) modes, agrees with this. However, the exact effect has not been researched yet.

Another effect that COVID-19 has on travel is that it has changed who travel. As mentioned, there were many government imposed travel restrictions, especially for public transport. Furthermore, there were restrictions and recommendations on working and studying from home. However, not everyone is able to work or study from home. Therefore, there are groups that still needed to travel, while others could drastically limit their trips while still attending their job or school. This (lack of) necessity to travel is a factor that normally is not present, thus has not been researched much. This makes it interesting to also take this factor up in this study, and see what differences exist between those groups of people.

1.2 Research questions

Given the knowledge gap, we are interested in further identifying the travel attitude and travel behaviour relationship. The first objective is to see if the findings of Kroesen et al. (2017) – a bidirectional relationship between travel behaviour and attitude – can also be observed in this study during the corona pandemic.

The current pandemic has led to (travel) restrictions and influences the perception of risk from travelling by certain modes. These can be seen as triggers to travel attitude change. As especially the attitudes of using shared modes (i.e. public transport) have been affected, the focus will be on public transport.

Public transport will be compared to car travel. Before the pandemic (2019), Dutch citizens traveled the most distance by car (Statistics Netherlands, 2021b). As mentioned before, there are numerous reasons for policy makers to be interested in changing travel behaviour away from personal vehicles (e.g. environmental and economic reasons). Commuting to and from work takes up the largest fraction of travel motives. Compared to other motives, traveling by car is much more common for commuting. The largest 'competitor' for car travel to and from work is travel by train (Statistics Netherlands, 2021b).

A study in the Netherlands has also shown that travelling by train is a valid alternative to using the car for a large number of travelers, especially for destinations within (larger) cities (Van Exel & Rietveld, 2009).

The largest difference between car and train travel is of course that a car is private while the train is public. This is extremely relevant during the corona pandemic, in which people were instructed to socially distance. Thus, there are clear benefits to both modes, the car is more private (and thus safer) but the train is more sustainable. For these reasons the focus of this study is on travel using cars and trains.

Based on this, the following research question is proposed:

> *What are the relationships between travel behaviour, attitude and the perception of risk of getting COVID-19 for traveling by car and train and how is this influenced by people's necessity to travel?*

To support answering the main research question, additional sub-questions are proposed:

1. What scientific knowledge already exists regarding travel attitude, behaviour and risk perception and its relations, and what can be learnt from this?
2. How did travel behaviour by car and train, attitude and risk perception develop during the COVID-19 pandemic, and what caused these developments?
3. How large are the bidirectional relationships between travel behaviour, attitude and perception of risk for train and car during the COVID-19 pandemic?
4. What is the influence of the necessity to travel on the bidirectional relationships?

1.3 Definitions

To further clarify the research question and its sub-questions, some definitions are presented first.

Travel attitude is described as the *"evaluative response to some object which disposes a person to behave in a certain way toward it."* (Gärling et al., 1998, p. 130). In other words, it is the degree of (dis)like people have towards a certain thing – in this case: travel modes.

Travel behaviour is the outcome of the decision-making process when travelling, *"regarding travel mode choice, route choice, departure time choice, destination choice, and so on"* (Li, Zou, & Li, 2019, p. 113). In this study the focus will mainly be on travel mode choice, specifically car versus train.

Perception of risk is the degree of risk people feel doing something. This is different from the actual risk which is attached to it (Slovic, 1987). In this case, the perception of risk of getting infected with COVID-19 while travelling by train is considered. Related to the perception of risk is the perceived crowdedness in the train, as a larger number of people in the same space increases the risk of infection. This perception is therefore also included.

In the literature review (Chapter 2), these notions will be reviewed in more detail.

1.4 Research structure

To answer the sub-questions and ultimately the main research question, as stated in Section 1.2, the following structure will be used.

First, a literature review of the presented notions will be conducted. This will give insight into the current existing body of knowledge regarding these notions, and more specifically their relationships. This literature review can be found in Chapter 2. It will answer sub-question 1 and provide the conceptual basis for the rest of this study.

Next, to give insight into the development of travel behaviour, attitude and risk perception, statistical analyses will be conducted on survey responses from a panel. This will show the effects of the pandemic on these three variables and give an initial answer to what caused these developments. Thus, this part will mainly answer sub-question 2. In Chapter 3 the design and methodology of this part will be elaborated upon. The results will be published in Chapter 4.

To answer the third sub-question, a cross-lagged panel model will be set up using survey data from a four-wave panel. The four-wave panel allows to accurately measure the interactions between the different factors, including any bidirectional relationships. The workings of the cross-lagged panel model will also be elaborated upon in Chapter 3, specifically Section 3.3. Some adjustments to the cross-lagged panel model will be made (seeSection 3.6), which will among other things allow for considering a specific subset of the respondents. This allows answering sub-question 4, as only respondents with or without the necessity to travel can be taken into account. The results of these analyses will also be published in Chapter 4.

With the answers to the the sub-questions it will also be possible to give an answer to the main research question. This will be discussed in Chapter 5, together with important remarks about this study.

Finally, the conclusion of this study will be presented in Chapter 6. There, recommendations for policy-making and future research will also be discussed.

2 Literature review

In this chapter the literature review into the relationship between travel attitude and mode choice, as well as the potential relationship with COVID-19, is presented. The aim of the literature review is to get a better understanding of the current body of knowledge in this field and thereby lay the conceptual basis for this study. By doing so, this study can build upon this existing knowledge and provide further scientific insight. The conceptual model will be used to build the structural model of the cross-lagged panel model.

First, studies analysing relevant factors in travel mode choice are reviewed. This is presented in Section 2.1. Next, the role of attitudes is reviewed and presented in Section 2.2. In extension to that, how attitudes can change is discusses in Section 2.3. Knowledge of risk perception in pandemics and its potential link to attitudes is reviewed. This is presented in Section 2.4. Finally, reverse causality between attitude and behaviour is reviewed in Section 2.5. This leads to the conceptual model considered in this study, which is shown in Section 2.6.

2.1 Travel behaviour

First and foremost we are interested in the effect of the COVID-19 pandemic on travel behaviour. Thus, it is important to properly review what influences people's travel behaviour.

The theory of reasoned behaviour (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975) states that the root of a certain behaviour is the intention to that specific behaviour. This 'behavioural intention' is based on the likelihood that the behaviour leads to a specific outcome. The likelihood is determined by salient information and beliefs. Thus, besides available information, an individual's beliefs play a role in evaluating (the intention to) certain behaviour. According to the theory of reasoned behaviour, these beliefs can be split into behavioural and normative ones. Behavioural beliefs create the individual's attitude towards certain behaviour (attitudes are discussed more in depth in Section 2.2). Normative beliefs can be seen as the *"perceived social pressure to perform (or not to perform) a given behavior"* (Fishbein & Ajzen, 2009, p. 130). The conceptual model of the theory of reasoned action is shown in Figure 2 (A) (Madden et al., 1992).

Fishbein and Ajzen (1975) note that all other variables only affect behavioural intentions through attitude or subjective norm. However, while showing prove for the theory of reasoned action, the original model is limited to situations in which the individual has complete and volitional control over its behaviour. Therefore, Ajzen (1991) has extended the theory of reasoned action to a new theory; the theory of planned behaviour. In this extension, perceived behavioural control has been added to the model. By perceived behavioural control is meant how much influence feel they have themselves over their behaviour. An example of low (perceived) behavioural control could be that someone feels traveling by car is their only option, as there is no public transport available for their trip. The inclusion of the perceived behavioural control is shown in the conceptual model of the theory of planned behaviour: Figure 2 (B) (Madden et al., 1992).

The perceived behavioural control influences behaviour directly and indirectly via the intention to the behaviour. As low (perceived) behavioural control limits the ability to select a certain behaviour, this directly influences behaviour. Similarly to attitudes and subjective norms, the belief of (not) owning the required resources for specific behaviour, impacts the intention to the behaviour. Studies have shown that, when applicable, the inclusion of perceived behavioural control improves the prediction of behavioural intentions (Madden et al.,

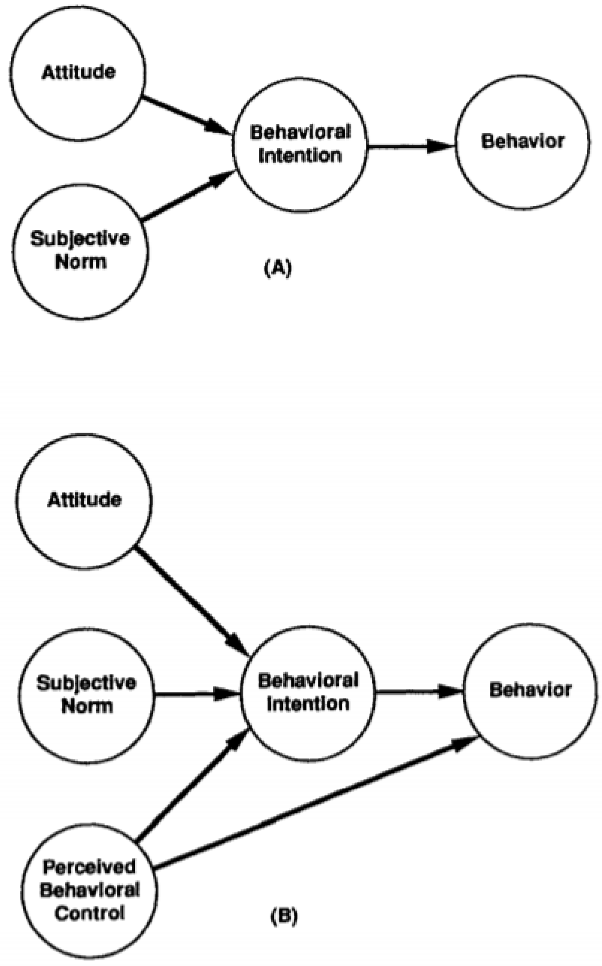

Figure 2: The theory of reasoned action (A) and the theory of planned behaviour (B) (Madden et al., 1992).

1992).

Thus, (travel) behaviour is determined by the intention to that behaviour. In turn, this intention is based on attitudes and subjective norms. Additionally, the perceived behavioural control plays a role. However, it has been shown that attitudes and subjective norms can overlap significantly. Therefore, attitudes are generally used as the broad term for both personal and social beliefs (Park, 2000). It can be concluded that *"travel behaviour is guided by attitudes"* (Van Wee et al., 2019, p. 1).

2.2 Attitude

Given the findings that attitude is an important factor in determining travel behaviour, the literature review is directed towards (travel) attitudes.

The concept of attitude finds its origin in social psychology. While there are many definitions of attitude suggested, an often used broad one is that *"attitude is a psychological tendency that is expressed by evaluating a particular entity with some degree of favour or disfavour"* (Eagly & Chaiken, 1993, p. 1). Here, the evaluation can be defined as affective evaluations, cognitive evaluations or behavioural responses (Bohte, Maat, & Van Wee, 2009).

Affective evaluations refer to the simple like or dislike of something or doing something (e.g. 'I like taking the train'). Cognitive evaluations consist of the (subjective) probability that something exists or is true, this can also be a relationship (e.g. 'taking the train is environmentally friendly'). Given this probability, cognitive attitudes can be seen as beliefs. Lastly, behavioural responses are actual (observable) actions performed related to the entity in question (Bohte et al., 2009; Eagly & Chaiken, 1993).

Attitudes can be related to objects (e.g. trains) or behaviour (e.g. traveling by train). Furthermore, attitudes may regard one specific object (e.g. one's (personal) bike) or an object in general (e.g. trains in general). Finally, attitudes can concern something in general but can also be very specified (i.e. in terms of action, target, context and time) (Ajzen & Fishbein, 1977; Bohte et al., 2009; Eagly & Chaiken, 1993).

In the theory of planned behaviour (Ajzen, 1991) it is suggested that beliefs link certain behaviour to its outcomes or consequences. *"Since the attributes that come to be linked to the behavior are already valued positively or negatively, we automatically and simultaneously acquire an attitude toward the behavior"* (Ajzen, 1991, p. 191). The strength of a certain belief – thus the subjective probability of an outcome – and the weight given to that outcome contribute to the value of the attitude (Ajzen, 1991).

Therefore, the value of an attitude can be estimated by analysing observed beliefs and weights. However, this considers only attitudes based on beliefs, i.e. cognitive evaluations. Affective evaluations and behavioural responses should be considered separately.

2.3 Attitude change

A large limitation in the theory of reasoned action and the theory of planned behaviour is that attitudes are assumed to be constant. Van Wee et al. (2019) have developed a model for attitude changes, which is conceptually shown in Figure 3.

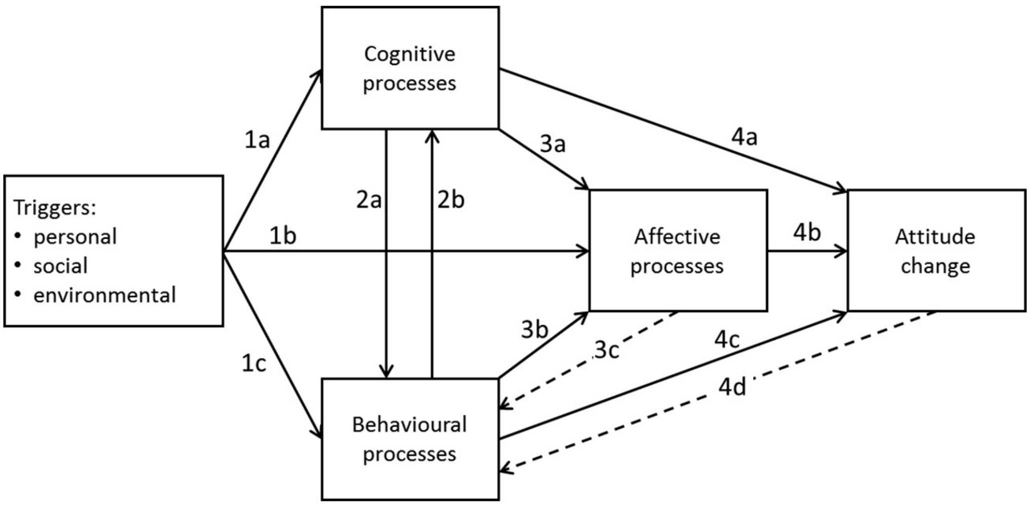

Figure 3: Model for attitude change by Van Wee et al. (2019).

The processes that lead to attitude changes, according to Van Wee et al. (2019), are the same as Eagly and Chaiken (1993) defined and are mentioned above; cognitive, affective and behavioural processes (arrows 4a, 4b and 4c in Figure 3). When considering attitude change, cognitive processes refer to the individual learning something which was unknown before, and therefore change their attitude. Affective processes are triggered when the individual 'feels' something, which causes their attitude to change. Behavioural processes regard the individual doing something, which leads to a change in attitude. These three clusters are not independent and the same 'triggers' can influence them. (Van Wee et al., 2019).

These so-called triggers can be categorised as personal, social or environmental and can cause change in the three processes (arrow 1a, 1b and 1c in Figure 3). The individual's own knowledge (i.e. information and experiences) can be seen as the personal level. On the social level are influences from the individual's social network (e.g. family, friends and colleagues). The environmental level consists of all other triggers. Notable ones in this context are changes in the transport system and societal changes (Van Wee et al., 2019). The social level and societal changes subcategory also fit the description of subjective norms, which again shows the thin line between attitudes and subjective norms (as mentioned in Section 2.1).

These suggested triggers can be united with the mobility biographies theory, describing 'biographical key events' (as mentioned in Section 1.1). Biographical key events can be triggers on all three levels. To summarise: *"Triggers are the reason why people change what they know, feel or do. They are 'external initiators of internal processes' which lead to attitude change."* (Van Wee et al., 2019, p. 3). This is relevant for the context of this study, as COVID-19 can likely be seen as such a trigger. In Section 2.4 this will be further discussed.

2.4 COVID-19

As suggested in Section 1.1, the COVID-19 pandemic may also be considered a biographical key event. It has greatly affected daily routines and habits. In the Netherlands a study conducted using the Netherlands Mobility Panel shows a great decline in number of trips and distance travelled. Attitude towards traveling seems to have dropped, especially for shared modes (i.e. public transport). Attitude towards using public transport is significantly lower than for other modes, likely due to the fear of getting infected (De Haas et al., 2020).

Considering the clusters of triggers (personal, social and environmental) (Eagly & Chaiken, 1993; Van Wee et al., 2019), travel restrictions and risk perception due to COVID-19 are likely to have influences on all of them. Studies (e.g. Neuburger and Egger (2020)) show that there is a very significant increase in the perception of risk from traveling. Given the similarities to biographical key events and the triggers described by Van Wee et al. (2019), the assumption can be made that the increased perception of risk influences people's travel attitude. This is supported by a preliminary study by Nazneen, Hong, and Ud Din (2020).

Thus, people's travel behaviour has been changed by (governmental) travel restrictions – or in other words people's necessity to travel – and attitude is influenced by the increased perception of risk. Of course, as established, the changed attitudes affect travel behaviour as well.

Restrictions put in place regarding traveling, such as mandatory working from home or limited access to public transport, have large effects on people's travel behaviour. It can be argued that travel behaviour and attitude correlate less due to this factor. Mandatory teleworkers could still have a positive attitude towards public transport while reducing their travel. Similarly, there could be people who do not have the option to work from home, but would rather not travel. Using the same data from the NS Panel as this study (see further in Section 3.1), Ton et al. (n.d.) identified different teleworker typologies, such as a group that is 'forced and done with', meaning that those employees are forced to telework but would rather not.

Given this new – or at least currently much more relevant – 'necessity to travel', we argue that this factor should be taken into account to properly analyse the relations between travel behaviour, attitude and perception of risk. Therefore, we assume that this factor moderates the relations between the other factors, as it forces certain behaviour.

2.5 Reverse causality

A final concept that is not considered yet is the potential reverse causality between attitude and behaviour. Attitude is generally assumed to causally affect behaviour, not vice versa. However, based on the processes and triggers by Van Wee et al. (2019), it makes sense to also consider this reverse causality. A 'forced' change in behaviour can be seen as a trigger which influences one or more of the processes in the model by Van Wee et al. (2019). This connects to the perceived behavioral control which is taken into account in the theory of planned behaviour (Ajzen, 1991). However, in the theory of planned behavior no (indirect) relation between this perceived behavioral control and attitude was considered.

In the mean time it has been proven that this reverse causality exists (Kroesen et al., 2017; Van Wee et al., 2019). This shows that there is a bidirectional relationship between travel attitude and behaviour.

2.6 Conceptual model

Based on the findings in the literature review, a conceptual model for this study has been created. The conceptual model is shown in Figure 4. The bidirectional relationship between travel behaviour and attitude, as described in Section 2.5, is taken into account.

As described in Section 2.4, it is assumed that the COVID-19 pandemic has two main influences on travel behaviour; through the perception of risk and the necessity to travel. The perception of risk is assumed to behave similarly to attitude, therefore bidirectional relations between this perception and travel behaviour and attitude are considered. To allow analysing this, those three variables are considered for multiple instances in time. This way the effects from one variable to another to become distinguishable, which reveals the causal relations.

The necessity to travel, as mentioned in Section 2.4, is considered as a moderating factor. This means that it is expected that this factor influences all other relations and should thus be kept in mind.

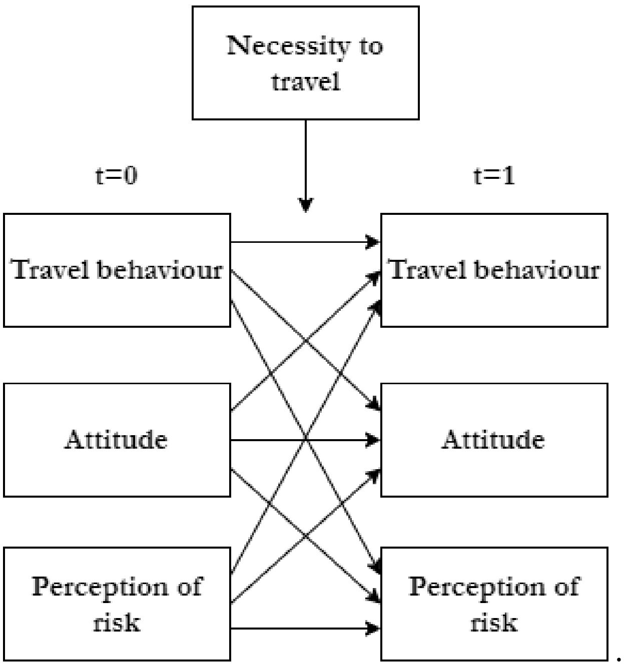

Figure 4: Conceptual model.

2.7 Hypotheses

Although the model will be used in an exploratory manner, meaning that all possible relations are examined, certain expectations can be made based on the literature. Stating these hypotheses beforehand helps identifying unexpected results, which are relevant for further analysis.

First of all, the autoregressive effects (e.g. travel behaviour at $t = 0$ on travel behaviour at $t = 1$; see Figure 4) are expected to be the highest, as they form the base for the predictors' values in the next wave. Thus, they are expected to be more influential than the cross-lagged effects. Literature suggests bidirectional relationships between travel behaviour and attitude. As discussed, Kroesen et al. (2017) found a stronger effect from behaviour to attitude than vice versa. Therefore, it is likely that this is true for this study as well.

The relations between risk perception and the other two predictors has not been looked into much in existing literature, therefore it is hard to hypothesise these. However, the expectation is that risk perception affects travel behaviour and attitude, and vice versa.

As risk perception could be seen as similar to attitude – both encompass people's personal evaluations – it is expected that a significant correlation between the two exists. However, the effect of risk perception is expected to be more present when considering train travel. The chance of getting infected with the coronavirus while traveling is very present in public transport, as opposed to (near) zero when traveling by car[1]. Thus, the effect of people's perception of risk is expected lower for car travel. Still, an effect is expected, as people with a higher perception of risk are likely to dislike travel in general. This raises the question if there is a direct effect between travel behaviour and risk perception.

It could be argued that risk perception influences attitude, which in turn affects travel behaviour. Therefore, risk perception and behaviour could be correlated, but not have direct relations. However, this assumes an almost full correlation between risk perception and attitude. Likely, risk perception and travel behaviour have direct bidirectional relationships. One could still have a positive attitude towards train travel, but currently use it less due to high perception of risk. The other way around it could be argued that risk percpetion changes when actually experiencing train travel, i.e. when traveling more risk perception could change. Furthermore, as risk perception is expected to mainly influence train travel, this will possibly lead to an increase in car travel to substitute it. Thus, while the effects between travel behaviour and risk perception are expected to be negative, for car travel it could actually be positive.

Finally, as mentioned in Section 2.4, the necessity to travel of the respondents could also be an important factor. We expect that there are significant differences in the relationships when comparing these groups. Because behaviour is more rigid, it will have less of an influence on the other predictors. Therefore, the cross-lagged relations with travel behaviour are likely to be lower (closer to zero). Furthermore, the effects of risk perception are likely less significant for people who have to travel, as they cannot change that. The opposite direction can still exist, as behaviour and attitude can still influence the perception of risk. However, this is not backed up by evidence in scientific literature, thus an exploratory approach will be used.

[1]Assuming traveling alone by car. If multiple people share a car the chance increases, but the number of people encountered is likely still much lower than compared to public transport.

3 Research design

In this chapter the design of this study is described. First in Section 3.1 the data from the NS Panel is discussed. Next, in Section 3.2 the methodology used in this study is elaborated upon. The cross-lagged panel model that will be used is explained in Section 3.3. The specific operationalisation for this study is described in Section 3.4. This leads to the structural model for the study, which will be specified in Section 3.5. Finally, some adjustments to the model are discussed in Section 3.6.

3.1 NS Panel

For this study, panel data from the NS Panel is used. Anybody can freely sign up for the NS Panel and choose to participate in the surveys or not [2]. To improve the representativeness of the panel data, respondents are controlled for their socio-demographic characteristics and travel frequencies. This has also been validated by an external panel.

In 2020, a longitudinal survey was set up to get insight into travel related metrics during the COVID-19 pandemic. In April, June, September and December of that year respondents were asked several questions related to traveling at that moment. Most questions relate to traveling by train, but the survey also includes questions about other modes of transport and working from home. It includes – among others – questions relating to travel behaviour and frequency; questions about travel attitudes; questions regarding perception of risk and motives to travel. In the first wave (April) respondents were also asked to look back at February of that year ('before' COVID-19). The questions in these four waves are roughly the same, which allows to analyse the changes during the year.

The data from the panel that will be used in this study are the entries from the respondents that participated in all four waves ($N = 14778$). For privacy reasons most socio-demographic factors are not available. However, the sample is weighted to represent the train traveling population.

3.2 Methodology

The data from the NS Panel will be used to answer the research question (see Section 1.2). Given the scientific knowledge obtained in Chapter 2, we are interested in how travel behaviour, attitude and risk perception develop during the pandemic and what influences those developments. Furthermore, we want to identify the the bidirectional relations between the three predictors and quantify them.

To gain insight into the development of travel behaviour, attitude and perception of risk during the pandemic, these will be plotted out. Analyses will be done for multiple categories (e.g. train or car travel).

To further analyse the causality between travel behaviour, attitude and risk perception, the bidirectional relationships will need to be analysed. To do so, a cross-lagged panel model will be set up. The cross-lagged panel model will be elaborated upon in Section 3.3.

To perform the quantitative research as described here, the predictors need to be operationalised. All respondents will have a value for each predictor, based on their survey

[2] To add to this, usually only a sample of the registered panel members are selected for each survey, based on their characteristics. For this panel study however, all registered members where asked to participate.

responses. In Section 3.4 the exact operationalisation based on the survey questions is described.

The performance of the models will be analysed by its goodness-of-fit indices. Based on the suggestions by Hu and Bentler (1999), the CFI and RMSEA indices are used. If they score within the cut-off values as suggested by Hu and Bentler (1999), the models can be considered a good fit for the data. If not, this means that there is room for improvement.

3.3 Cross-lagged panel model

Our goal is to gain insight into the causal relations between the three predictors (travel behaviour, attitude and perception of risk). To visualise these effects on each other over time, as is the main objective of this study, a more advanced methodology is required; the cross-lagged panel model (CLPM). *"The primary goal of cross-lagged panel analysis is to investigate the causal direction of the relation between two variables over time."* (Newsom, 2015, p. 122). Thus, a CLPM should be suitable for this objective.

A CLPM allows to investigate hypotheses where two or more variables have multiple causal directions over time. This can be done to establish in which direction causality is present. A simple example of such a CLPM is shown in Figure 5. Here, y_2 and y_4 are the repeated measurement of y_1 and y_3, respectively. β_{21} and β_{43} are the related 'autoregressive' paths or effects. These link the past and future states to each other, meaning that they provide the basis for the next time step. To illustrate this, consider y_1 in Figure 5 to be the attitude towards train travel. In the next time step, change to this attitude would be relative to the previous value of attitude. Thus, it allows the model to control for a variable's past, allowing the assessment of the other effects.

β_{23} and β_{41} are the 'cross-lagged' paths or effects to which the model thanks its name. These model the causal effect from one to another variable over time. Considering y_1 as attitude again, and y_3 as travel behaviour (Figure 5), β_{23} would be the effect from previous travel behaviour (y_3) on current attitude (y_2).

As not everything can be described by the autoregressive and cross-lagged paths, error terms for y_2 and y_4 are put in the model: ζ_2 and ζ_4. These 'impulses' include the exogenous changes to the system (e.g. getting fired from one's job or the start of the COVID-19 pandemic). As these impulses likely affect both variables, the covariance between the two is also considered (ψ_{24}). Similarly, y_1 and y_3 are assumed to not be independent from each other, thus the covariance between those two is also taken into account (ψ_{13}) (Newsom, 2015; Zyphur et al., 2019).

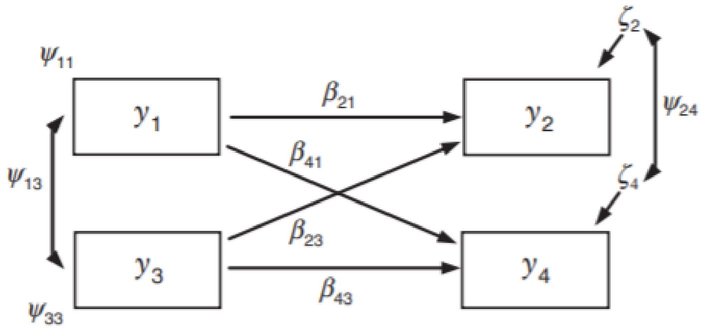

Figure 5: Example of a basic cross-lagged panel model (Newsom, 2015).

This model generates the following two structural equations (Equation 1) (Newsom, 2015):

$$
\begin{aligned}
y_2 &= \beta_{21} y_1 + \beta_{23} y_3 + \zeta_2 \\
y_4 &= \beta_{43} y_3 + \beta_{41} y_1 + \zeta_4
\end{aligned}
\tag{1}
$$

These show how y_2 and y_4 are calculated; the autoregressive paths, plus the cross-lagged paths, plus the exogenous variables. Note that the betas indicate how strong the autoregressive and cross-lagged effects are. Those values help in answering what the direction of causality is.

3.4 Operationalisation

To create a cross-lagged panel model for this study and perform the analyses, the different variables need to be operationalised first. In this section the four main variables (travel behaviour, attitude, perception of risk and necessity to travel) are described. Afterwards, the full cross-lagged panel model can be established.

Travel behaviour

Travel behaviour is surveyed in the panel on a four-point scale:

Last week, how often did you use each of the modes of transport below as main mode of transport when traveling from A to B? [3]

1. Not
2. 1 day
3. 2 to 3 days
4. 4 or more days

The question is asked for multiple modes, but for this study only *Car / motorcycle* and *Train* are used.

There are other survey questions that measure travel behaviour in another way, but those are either not consistently asked across waves or do not clearly separate car and train travel. Furthermore, this questions covers the intended insight of this study well. The only downside to this question is that is does not differentiate the number of trips on a day. If a respondent changes from two train trips on a day to one, this will not show up in their answer.

Attitude

Attitudes towards different modes of transport are also measured in the NS Panel survey. Two survey questions are selected to be combined into one attitude variable:

I like to travel by (car / train).

1. Strongly disagree
2. Disagree
3. Neutral
4. Agree
5. Strongly agree

[3] Order of answers has been reversed so that more traveling equals a higher value.

How do you currently (during Corona) think about the means of transport or alternatives to transport below?

1. Very negative
2. Negative
3. Neutral
4. Positive
5. Very positive

This last question is asked for multiple modes (and alternatives to travel), but only *The car* and *The train* are taken into account.

Both variables are measured on a five-point Likert scale in the same direction (i.e. higher score equals a more positive attitude). Therefore, they can be combined into one by taking their sum score, divided by two[4]. To test the consistency of the two questions Cronbach's alpha has been calculated. In Table 1 these values are presented for both modes and the four waves. The presented Cronbach's alpha values are all relatively high, thus good consistency is assumed.

Table 1: Cronbach's alpha for the attitude variable pairs.

	April	**June**	**September**	**December**
Car	.795	.830	.832	.809
Train	.673	.767	.809	.760

There are some other questions available in the panel dataset. However, these are not available for the different modes or are not available in all waves. Therefore, only these two questions together make up attitude.

Perception of risk

To measure the perception of risk of getting COVID-19, the survey asked respondents to rate the following statement:

I am afraid of getting infected.

1. Strongly disagree
2. Disagree
3. Neutral
4. Agree
5. Strongly agree

This question is selected for its generality. Other questions for risk perception in specific situations, e.g. traveling by train. However, to properly compare the effect of risk perception for train and car travel, a general variable is needed.

Necessity to travel

In order to differentiate between respondents who are able to work or study from home and those who cannot, a moderating variable is used.

Do you currently have the option to work from home or study at home?

[4]Thus the scale of this variable remains 1 to 5.

1. Yes
2. No, I do not work/study
3. No, I have to be physically present at my work/study place
4. No, my company/school would rather not have me work from home
5. No, I do not have the facilities at home to work/study at home
6. No, other: (open answer)

This metric gives insight into the necessity to travel of the respondents. Unfortunately, this question was only asked in the first three waves (April, June and September, not in December). However, number of respondents who are able to work from home are reasonably constant. Therefore, it is assumed that respondents who answered consistently in April, June and September are also consistent in December. This assumption allows to use one variable as moderator for the necessity to travel.

Specifically, cases are selected for two groups. The first group are respondents who did not have the necessity to travel during the three waves. This corresponds to answer options 1 and 2 in the survey. The second group are respondents who did have to travel for their studies or work during the three waves. Answer options 3, 4 and 5 correspond to this group.[5] Only if the respondents answered within the related group in all three waves, they are placed in that group. All other cases are disregarded when taking necessity to travel into account. Table 2 shows the number of cases in each group and the fraction of all respondents. It makes clear that a limited percentage of cases is used in both groups.

Table 2: Number of cases in necessity to travel groups.

Group	N	
All respondents	14 778	100.0%
No necessity to travel	4 247	28.7%
Necessity to travel	987	6.7%

3.5 Model specification

Based on the conceptual model (Section 2.6) and given the described base cross-lagged panel model (Section 3.3), the operationalised metrics (Section 3.4) can be used in the structural model created for this study. The structural model is presented in Figure 6. Autoregressive paths between the four waves for each predictor (x, y and z) are shown, e.g. β_{x1x2}. Cross-lagged effects are considered for all three predictors, e.g. β_{x1y2}. This way, the causal relations between all three predictors can be analysed. Furthermore, for wave two, three and four impulses are considered, e.g. ζ_{x2}. Correlations are taken into account between the predictors in the first wave and between the impulses.

3.6 Model adjustments

As the model specified in Section 3.5 is (partly) used for exploratory research, some changes will be made to it to find out if those make the model better or to provide more results. Multiple steps can be taken to potentially improve the model. In this Section those steps are discussed.

[5]Note that answer option 6 (open answer) was disregarded as answers were not clear and/or consistent and could therefore not objectively be assigned to either group.

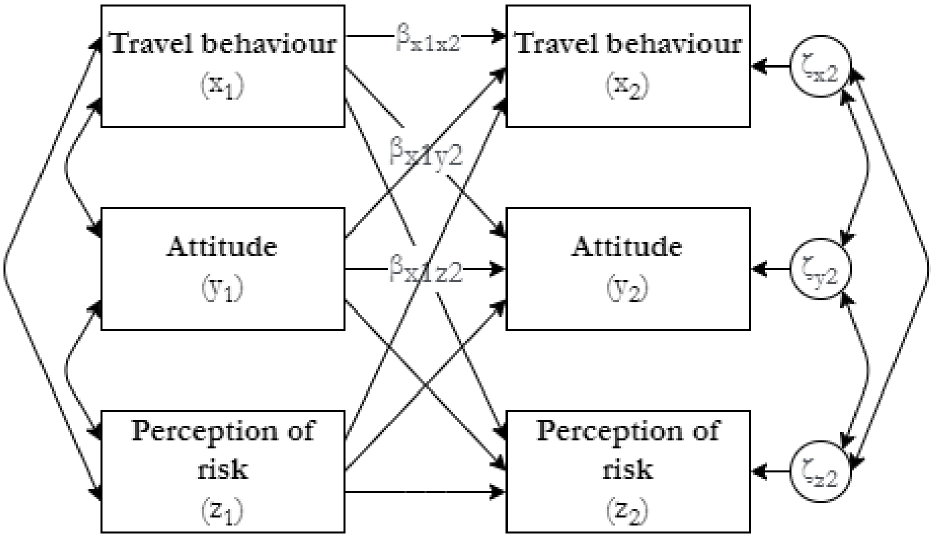

Figure 6: Structural model.
Note: Only first two waves are shown; wave 3 and 4 are similar to the second wave. Not all relations are labeled to avoid clutter.

Constraining the regression estimates

In Section 4.3 it has been shown that both the autoregressive and cross-lagged effects remain rather stable across the three waves. In other words, the regression estimates do not differ much from wave to wave. Therefore, it could be argued that those regressions are actually equal. To test this, constraints are put on the regressions between all waves; all three instances of each regression are to be estimated as one value. This is done for both the autoregressive as the cross-lagged regressions. As a result, the unstandardised regression weights are estimated as one value for the three instances between waves.

Doing so increases the degrees of freedom as less variables are to be estimated, which gives the model more power to find statistical significant results. To test whether adding the constraints and thus increasing the degrees of freedom actually makes the model better, a chi-squared test will be performed. The results of adding constraints to the regressions between waves are shown in Section 4.4.

Necessity to travel

The dataset contains questions relating respondents' necessity to travel. As elaborated upon in Section 3.4, two groups have been constructed; a group with the necessity to travel to work or school and a group which does not have this necessity. The models can be estimated with only taking either group into consideration. That way, the differences between both groups can be analysed. Large differences between these groups can cause the model with all respondents to be less fitting, as it will make one estimate (per regression) for all respondents. To test this, we will check if the model fit is improved by adapting the model to take these groups into account.

The two groups will be tested for statistical difference from each other. A chi-squared test will show if the same results would have been expected without considering the two groups. If this is not the case, it shows that the two groups are significantly different from each other.

Car and train travel in one model

The base model as specified in Section 3.5 considers either car behaviour and attitude or train behaviour and attitude, but not both simultaneously. The consequence of this is that the relations between the two modes (e.g. the effect of car attitude on train attitude) cannot be analysed. By combining the two models this can be done. Including both increases the amount of predictors per wave from three to five (as risk perception is not specific to a mode, this remains a single predictor).

4 Results

In this Chapter the results based on the data will be presented. First, in Section 4.1 the representativeness of the dataset will be discussed. Then, in Section 4.2 the developments during the pandemic will be analysed. Next, in Section 4.3 the bidirectional relationship will be estimated using the base cross-lagged panel model. Three adjustments to the base model are carried out; putting constraints into the model in Section 4.4, grouping by necessity to travel in Section 4.5 and combining car and train travel into one model in Section 4.6. Finally, a synopsis of the results is presented in Section 4.7.

4.1 Representativeness of the dataset

When analysing survey data, it is important to know the representativeness of the respondents to the population. In this case the population consists of train travelers in the Netherlands. The NS Panel responses have been weighed for their representativeness to this population for every wave. However, as a further subselection of cases has been performed, namely only using the responses from respondents who participated in all four waves, this balance could have been disturbed. Unfortunately, the demographic data of the respondents is not available, therefore an analysis into the representativeness of the data could not be made. This should be taken into account when considering the results and its implications.

4.2 Developments during the pandemic

During the pandemic, public transport usage dropped significantly. Figure 7 shows mobility data obtained by Google (2021) for 2020, together with the mean reported train usage in the NS Panel. The mobility data compares the usage of public transport hubs to the baseline in January 202. When adjusting the axes of this data and the results of the NS Panel, the same trends are visible. Thus suggesting that the NS Panel follows the observed data well.

These statistics can be put into context by looking at the severity of the pandemic in the Netherlands in 2020. Figure 8 shows the deaths in the Netherlands in 2020 due to the coronavirus[6].

Comparing the two graphs show that trips significantly drop during the 'first wave' of the coronavirus in March and April. Afterwards, as the severity of the pandemic seems to drop, travel behaviour increases again. Travel behaviour seems to lag a bit behind the (reversed) trend of confirmed deaths. This suggests that it takes people some time to change their travel behaviour again. As at the end of 2020 the pandemic increases in severity again, travel behaviour clearly decreases again. However, as deaths drops again in November, travel behaviour remains roughly constant. This suggests again that it takes some time before travel behaviour changes. When the number of deaths increases again, travel behaviour drops again (according to Google (2021)), even though the numbers are similar to those in October. Overall this suggests that travel behaviour generally follows the trend of the severity of

[6]The statistic of confirmed deaths is used as new cases (infections) is not consistent throughout 2020. Especially in the beginning of the pandemic the number of cases is heavily under-reported due to lack of tests. Hospital admissions or occupation were also considered, but these statistics also have similar problems. A shortage of hospital beds skew these statistics. Confirmed deaths does have these problems in a lesser degree, and is therefore considered most representative of the situation in the Netherlands in 2020.

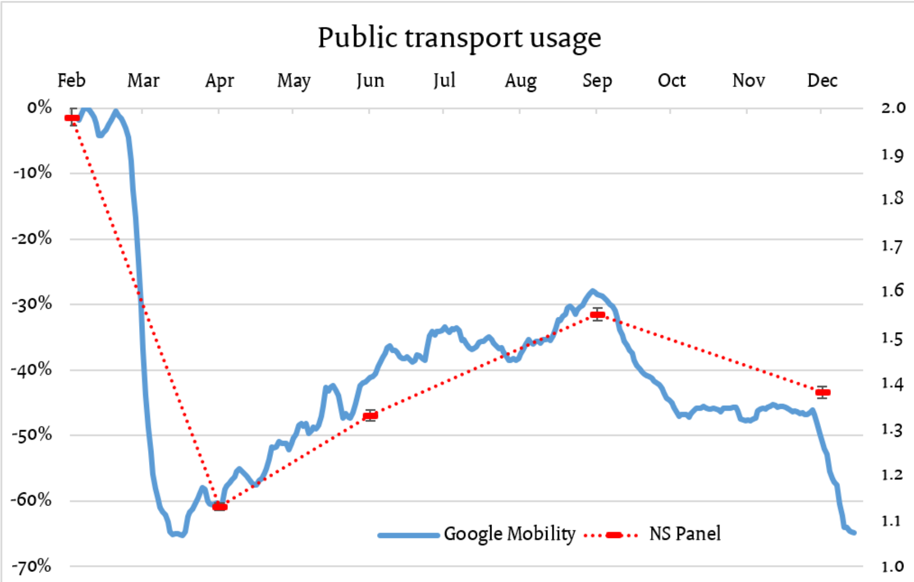

Figure 7: Public transport usage (7 day rolling average) in the Netherlands in 2020, compared to January 2020 (Google, 2021); Mean reported train usage in the NS Panel (including February) with 95% confidence interval.

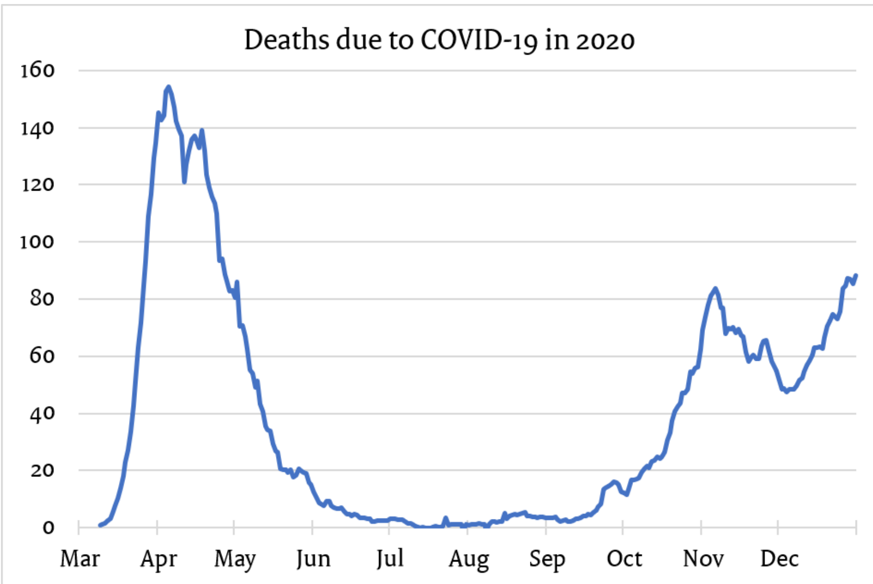

Figure 8: Deaths due to COVID-19 (7 day rolling average) in the Netherlands in 2020 (Our World in Data, 2021).

the pandemic. More specifically, it shows that an increase in severity is almost directly followed by a decrease in travel. On the other hand does a decrease in severity not directly lead to an increase of travel again. It takes some time before people start traveling more again.

To further analyse the developments of travel behaviour, attitude and risk perception during the pandemic for car and train travel, its means and confidence intervals are analysed. This gives insight into the average value for each wave, as well as the degree of dispersion at the given time. In Figure 9, Figure 10 and Figure 11 the developments of respectively travel behaviour, attitude and risk perception are shown.

Looking at travel behaviour, a large difference between car and train travel is that the behaviour of train travel is affected much more than car travel. This can likely be largely attributed to travel restrictions for public transport. However, the perception of risk of getting infected in public transport may also contribute. During the pandemic (from April onward), an increase in travel can be seen in June and September followed by a decrease again in December. The increase in car travel appears to be earlier than train travel. This could be because people feel safer in their car than in public transport. Another reason could be the relaxation of restrictions on public transport. For most of 2020 the advice was to only travel by public transport when strictly necessary. Overall, travel by train remains significantly lower during the pandemic as compared to before and compared to travel by car. From June on there is more car travel than before the pandemic (February), likely because people substitute their train travel for car travel.

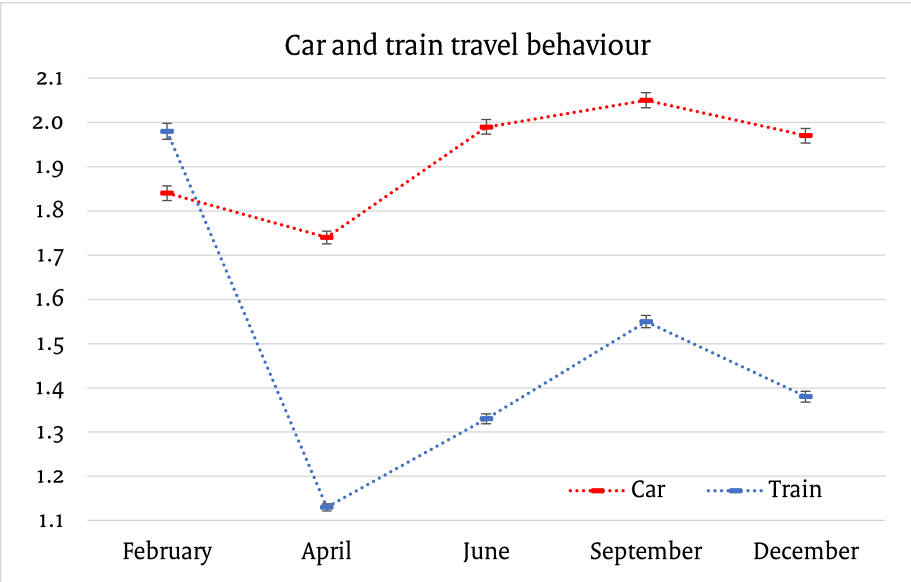

Figure 9: Development of travel behaviour values in the dataset; sample means with 95% confidence interval. A higher value indicates a more trips made.

Also comparing attitudes shows different trends for car and train travel (Figure 10). Interestingly, train attitudes clearly fluctuate more, suggesting a larger effect of the pandemic on people's attitudes towards train travel. The same trend as for train travel behaviour seems to be present; an increase in June and September followed by a decrease again in December. This indicates that there could be causal relationships between travel behaviour and attitude, which will be looked into in Section 4.3. Car attitudes also seem to follow the same trend, however this trend seems less significant. This shows again that car travel is less affected by the pandemic than train travel.

Furthermore, similarly to travel behaviour, for both car and train it seems to take some

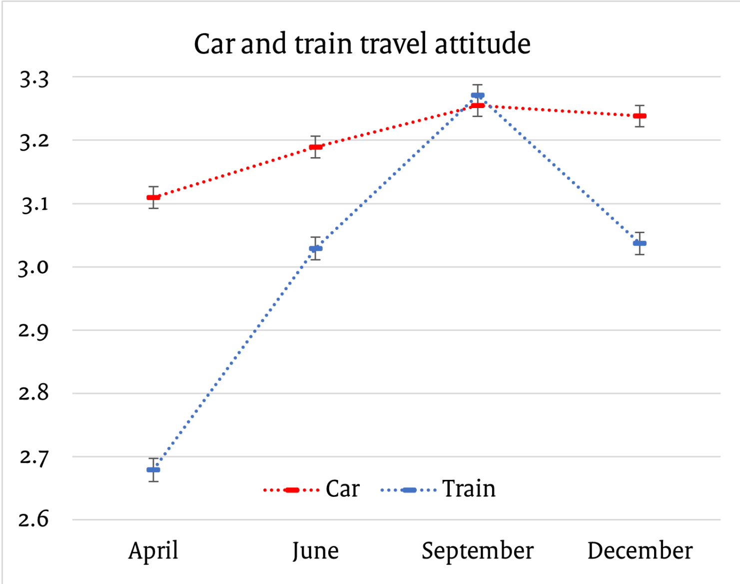

Figure 10: Development of attitude values in the dataset; sample means with 95% confidence interval. A higher value indicates a more positive attitude.

time before attitudes increase. In June and September the severity of the pandemic did not differ much, while attitudes clearly do. Attitudes in June are even lower than those in December, when the pandemic was significantly more severe.

The development of risk perception (Figure 11) seems to follow a slightly different trend. From April to June the perception of risk decreases, but from June onward it only increases. Attitudes and travel behaviour are shown to be at their highest in September, while the risk perception by then has increased to almost the same level as April. In June the lowest perception of risk is shown, which seems logical compared to the severity of the pandemic at that time. But that is not fully logical with the similar severity statistics of September, where the risk perception has sharply increased again, even close to the number of April. In December the risk perception is even higher than in April. This is interesting as April showed the lowest attitudes and travel behaviour values. This could suggest that risk perception does not have a large relationship with travel behaviour and attitude. The results of the cross-lagged panel model (from Section 4.3) will give more insight into the relationship of risk perception with attitude and behaviour.

Another explanation could be that it takes time for people to change their behaviour and attitudes, while risk perception may be dependent on the development of the statistics. The development of the severity statistics may play a role here, as increasing number of deaths for example can likely be seen as more risky than a similar number while the trend is decreasing. This could also be the reason for the higher value in December compared to April. In April the number of deaths was already decreasing, while in December the number was increasing.

4.3 Bidirectional relations

Following the setup of the structural model as described in Section 3.5, the cross-lagged panel model was built in Amos Graphics. For both car and train travel a separate model has been built, following the same design. The results of these first models are presented below.

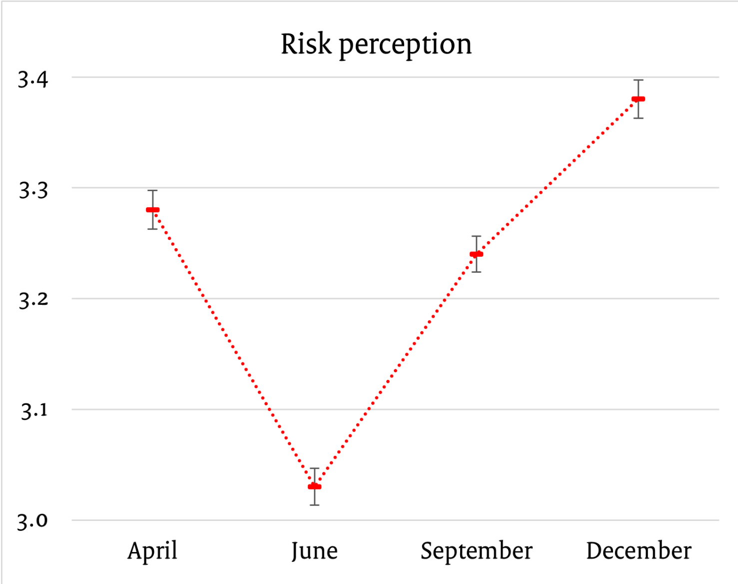

Figure 11: Development of risk perception values in the dataset; sample means with 95% confidence interval.

Car travel

In Figure 12 the cross-lagged panel model for car travel and its results are shown. As expected, the autoregressive effects are rather large (.46 to .71). This is as expected, as it means that the previous state of the predictor explains the current state for a large part. The cross-lagged effects are much smaller. Between behaviour and attitude there are clear effects (.11 to .30), which are all significant. The effect from attitude to behaviour appears to be larger than vice versa in all waves, which is opposite to the findings of Kroesen et al. (2017). This would mean that the causal relation between attitude and behaviour is stronger, thus that attitude has more of an influence on behaviour than the other way around. Still, there is a significant effect from behaviour to attitude, so only considering attitude affecting behaviour would be incorrect.

The cross-lagged effects both from and to risk perception are very close to zero (-.01 to .08). Positive values were not expected, as these would mean that a higher risk perception increases behaviour or attitude, or vice versa. Likely, the relationships between risk perception and the other predictors are very small. Some of the relations between behaviour and risk perception are not significant[7]. These results tell that risk perception has little influence on people's travel behaviour and attitude towards the car. Similarly, risk perception does not seem to be much affected by travel behaviour nor attitude.

This is also shown when looking at the correlations. The correlations between attitude and behaviour (in April) and its error terms (dispalyed as 'e'; in June, September and December) are much larger than for risk perception and its error terms, which are all close to zero. This means that there is little overlap between risk perception on the one hand and car travel behaviour and car attitude on the other.

One explanation here could be that the effect of risk perception is small for car travel, as traveling by car itself does not create significant infection risks[8].

[7]The significance of all regression weights is shown in Table 8.
[8]Assuming people mostly travel alone by car.

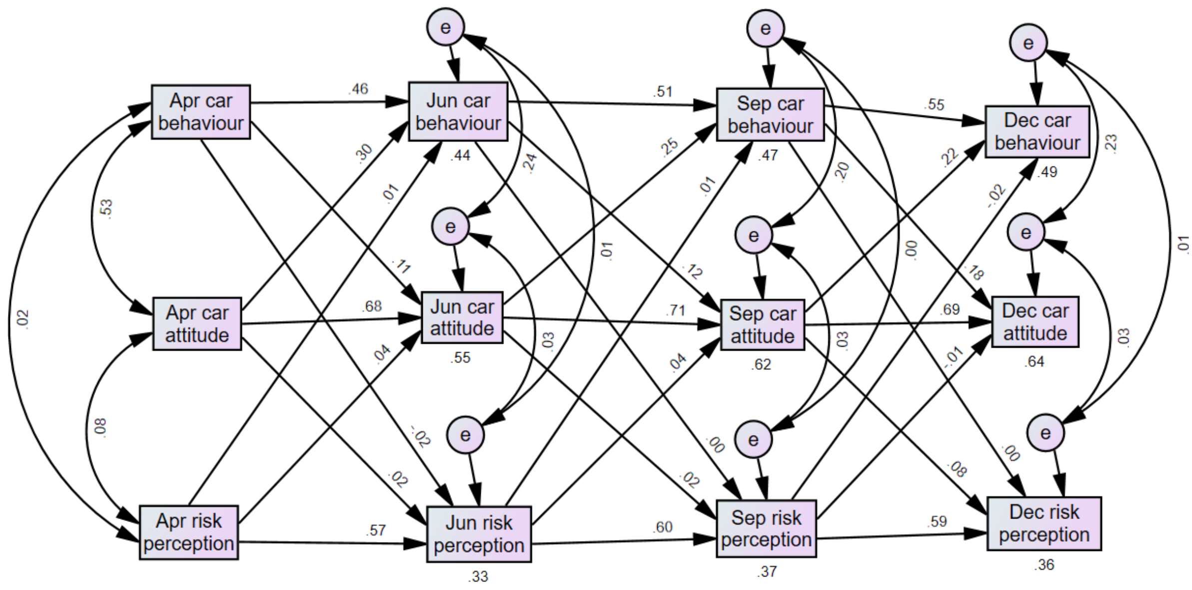

Figure 12: Standardised estimates of the cross-lagged panel model for car travel.

Train travel

The same model setup as for car travel is used, but with the specific behaviour and attitude variables for train travel. In Figure 13 the model and its estimates are shown. Here the autoregressive effects are also rather large (≥ .46) as expected. Interestingly, the cross-lagged effects between behaviour and attitude appear to be smaller here than in the car travel model. This could be caused by an increased influence of other factors for train travel behaviour and train attitude. In the first two waves the effect from attitude to behaviour is larger than vice versa (similar to car travel), but in the third wave the opposite is true. There is no clear direction of causality between the two, but bidirectional relationships have been shown, as all these effects are significant.

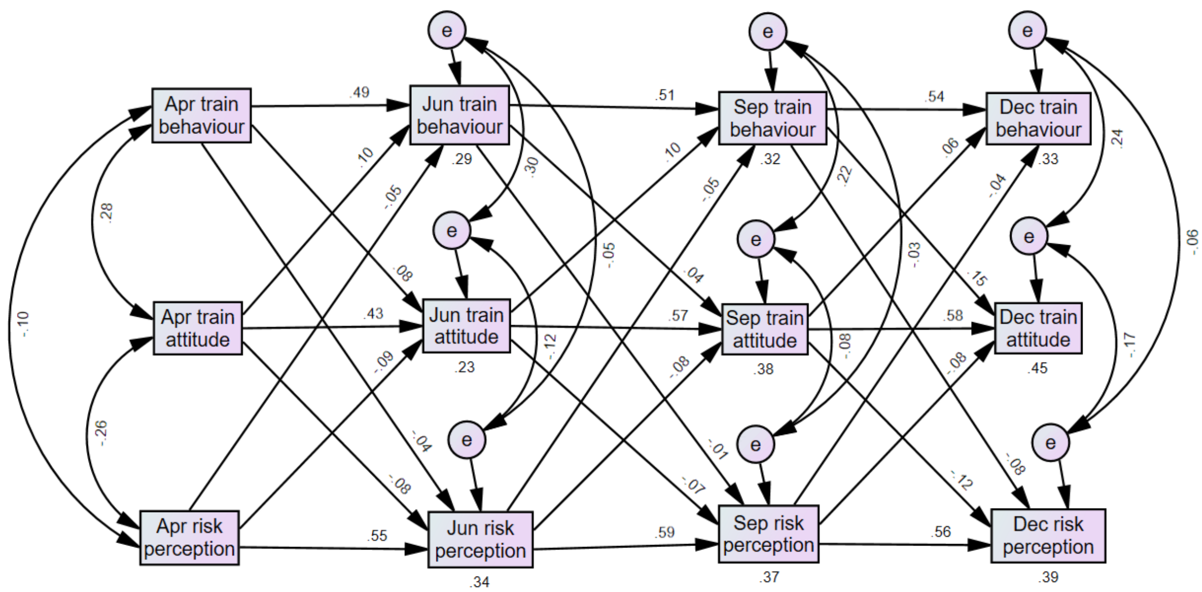

Figure 13: Standardised estimates of the cross-lagged panel model for train travel.

The cross-lagged effects from and to risk perception are larger in the train travel model, but still relatively close to zero (-.12 to -.01). However, as opposed to the car model, all but one of these effects are significant (only June behaviour to September risk perception is not significant). Especially between attitude and risk perception stronger relationships are visible. These relations go both ways, showing that attitude negatively affects risk perception and that risk perception negatively affects attitude. Although smaller (and one not significant effect), the same seems to be true for behaviour and risk perception. Both negatively influence each other, which means that there are also bidirectional relationships here. This is more in line with the expectations (Section 2.7) and shows that train travel is more affected by people's risk perception. It proves that people change their attitude and behaviour based on risk perception of the coronavirus.

Model fit

To test the models' goodness-of-fit, the CFI and RMSEA indices are used. Table 3 shows these indices. The values show that the fit of both models is flawed. This means that the models are likely misspecified. This could be because relations are assumed that in reality do not exist or that important factors are left out. Even though the model fit is not indices do not show a good model fit, this does not mean that the results are false. However, it does mean that currently the data does not fully support the model. In Section 4.4 the models will be adapted to see if a better model fit can be reached.

Table 3: Model fit indices for the base car and train travel models.

Model fit index	Car	Train
CFI[a]	.893	.881
RMSEA[b]	.170	.145

[a] CFI > .95 indicates good model fit (Hu & Bentler, 1999).
[b] RMSEA < .06 indicates good model fit (Hu & Bentler, 1999).

4.4 Bidirectional relations with constraints

As elaborated upon in Section 3.6, constraints are added to the regressions between all waves that represent the same relation. Thus, the unstandardised estimates of these regressions will be calculated as one estimate[9]. Below the results for car and train travel are presented.

Car travel

The standardised estimates of the constrained car travel model are shown in Figure 14. On first sight there are no large differences. That was to be expected, as large differences would mean that the model had changed significantly. In terms of significance, all but the relations between travel behaviour and risk perception (both ways) are statistically significant.

To compare the new model with the base model, the model fit is examined again. Table 4 shows the model fit indices for both models. Interestingly, the CFI index suggests the

[9]Note that the standardised estimates do vary as the unstandardised estimates are constrained. Standardised estimates are corrected for the relative influence they have on the dependent variable. As this is different from variable to variable, the standardised estimates will differ even if the unstandardised estimates are the same.

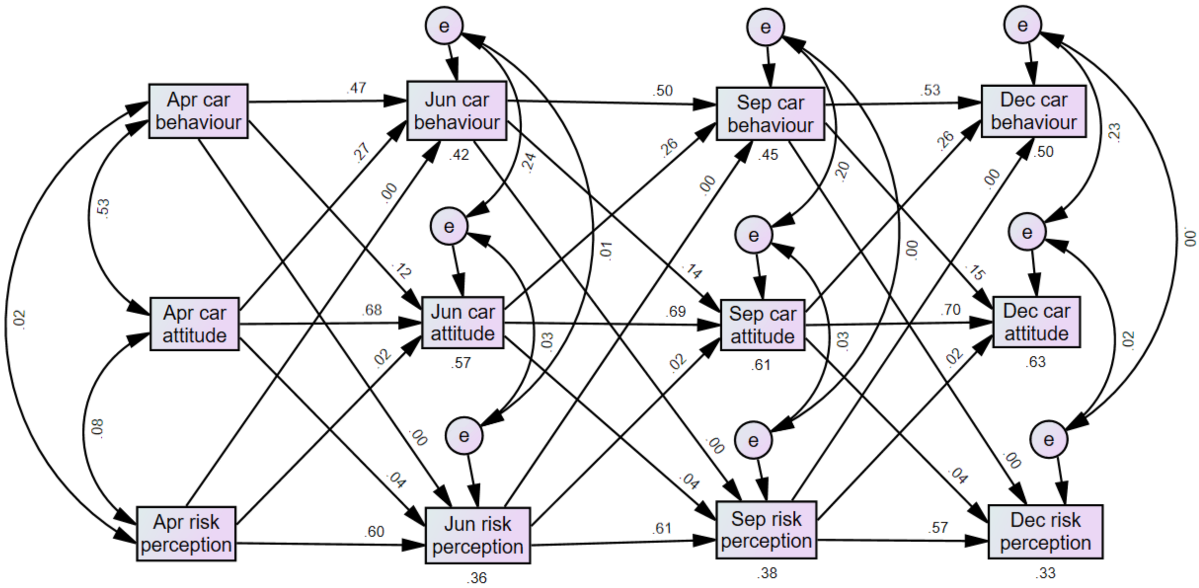

Figure 14: Standardised estimates of the cross-lagged panel model for car travel, using constraints.

model fit has decreased while the RMSEA index suggests the opposite. This does not allow to declare one model as better fitting the data than the other.

Table 4: Model fit indices for the base and constrained car travel models.

Model fit index	Base model	Constrained model
CFI[a]	.893	.889
RMSEA[b]	.170	.134

[a] CFI > .95 indicates good model fit (Hu & Bentler, 1999).
[b] RMSEA < .06 indicates good model fit (Hu & Bentler, 1999).

To fully compare the two models, a chi-squared test is performed. The chi-square values and degrees of freedom of the base and constrained model are shown in Table 5. Based on a probability of .05, the critical chi-square value is 28.869. Thus, with a found value of 397, the increase in degrees of freedom does not warrant the loss in predictive power. Therefore, the model is to be rejected.

Table 5: Chi-square values and degrees of freedom for base and constrained car travel models.

Model	Chi-square	Degrees of freedom
Base model	11 501	27
Constrained model	11 898	45
	+ 397	+ 18

Train travel

The standardised estimates of the constrained train travel model are shown in Figure 15. Similar to the car model, no large differences seem to have occurred. All estimated regressions are statistically significant.

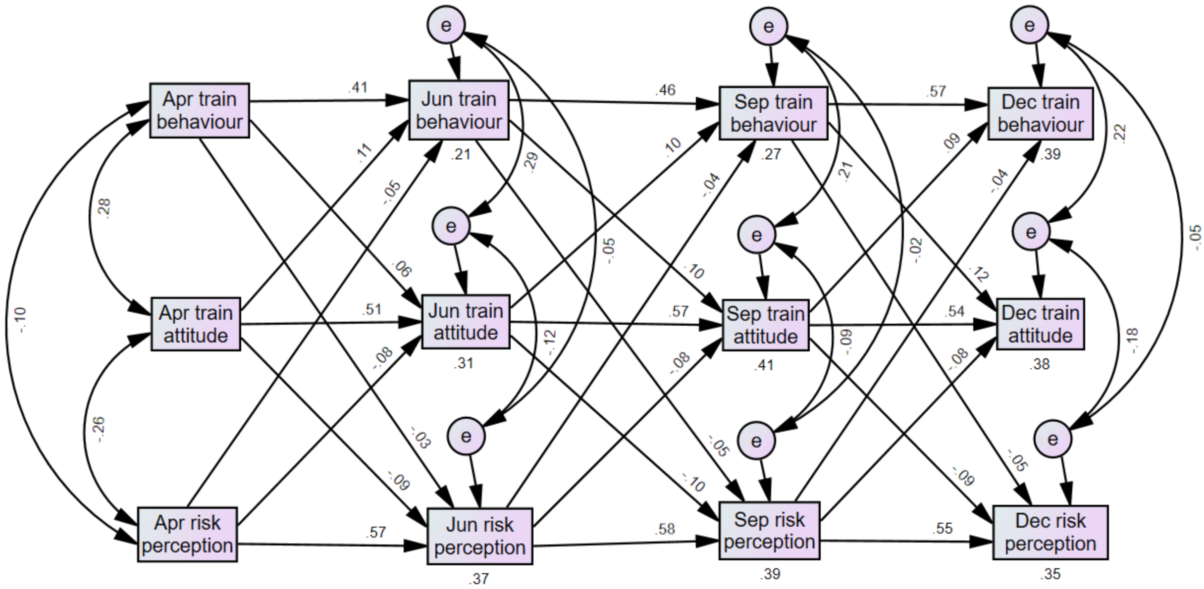

Figure 15: Standardised estimates of the cross-lagged panel model for train travel, using constraints.

Table 6 shows the model fit indices of the base and constrained train travel model. Similar to the car travel model, the CFI index indicates a worse model fit while the RMSEA index indicates a better model fit. Given those results we are unable to declare one of the two models a better fit.

Table 6: Model fit indices for the base and constrained train travel models.

Model fit index	Base model	Constrained model
CFI[a]	.881	.861
RMSEA[b]	.145	.122

[a] CFI > .95 indicates good model fit (Hu & Bentler, 1999).
[b] RMSEA < .06 indicates good model fit (Hu & Bentler, 1999).

To better compare the two models a chi-squared test is performed. Table 7 shows the chi-square values and degrees of freedom of the base and constrained model. Based on a probability of .05, the critical chi-square value is 28.869. Thus, with a found value of 1 450, the constrained model for train travel also loses too much predictive power compared to the gained degrees of freedom. Therefore, the constrained train travel model is also to be rejected.

Table 7: Chi-square values and degrees of freedom for base and constrained train travel models.

Model	Chi-square	Degrees of freedom
Base model	8 453	27
Constrained model	9 903	45
	+ 1 450	+ 18

4.5 Bidirectional relations considering necessity to travel

As described in Section 3.6, the models will also be estimated when only taking into account the respondents who have the necessity to travel or those who do not have this necessity. Note that these two groups do not encompass all respondents, as mentioned in Section 3.4. Thus, only a subset of the respondents will be used for these estimations (the number of respondents is shown in Table 2).

As the constrained models have been rejected (see Section 4.4), the base model (as used in Section 4.3) will be used for the group analysis. This is again done separately for car travel and train travel.

Car travel

The full results of the group analysis for car travel are presented in Table 8, together with the results without groups ('All respondents'). People with a necessity to travel have higher autoregressive effects between behaviour (strongest for June to September; .620 to .461). This was expected, as it means that the behaviour of people who have to travel remains more similar than of those who do not have to travel.

For attitude the No necessity group has higher autoregressive effects. The autoregressive effects of risk perception are also higher for the group that does not need to travel, but the differences are slim. This is an intereseting result, as it means that the people who have more choice in their behaviour have a more constant attitude and risk perception.

The effect from attitude to behaviour was also expected to be lower for the Necessity group, again because their behaviour is more rigid, thus expected to be less impressionable. This is indeed the case in the first two instance, but from September to December the opposite is true; attitude influences the behaviour of the people need to travel more than those who do not. Of course, even people with a necessity to travel can change their behaviour (e.g. use a different mode), but this is still an unexpected results, as the No necessity group has likely more options to change their behaviour (e.g. travel less).

The reversed effect – behaviour to attitude – is more consistent; the group Necessity has higher regression weights for these. This is also an interesting result, as it means that the fact that people are required to travel influences their attitude more. As this effect is positive, it also means that the people who need to travel generally get higher attitudes from travelling more. This partly confirms findings by Kroesen et al. (2017), as it clearly shows that an increase travel behaviour (i.e. higher usage) increases attitude.

It is harder to make conclusions about risk perception and its relationships, as most values are not significant when analysing the two groups. This is likely due to the lower group sizes. However, this also shows that the effect of risk perception is relatively low and inconsistent. It can be concluded that risk perception does not have significant effects on travel behaviour and attitude, in most cases.

Train travel

The results of the group analyses and the original results with all respondents are presented in Table 9. As is true for the car travel model, the autoregressive effects are clearly larger for the Necessity to travel group compared to the No necessity to travel group. The findings in the car travel model of higher attitude and risk perception autoregressive effects is less present in the train travel model; there is no one relation consistently higher between the groups. Thus this identified effect in the car travel model is not present in the train travel

Table 8: Standardised regression weights in the base car travel model for all respondents and the groups 'necessity to travel' and 'no necessity to travel'.

Car travel regression				All respondents		Necessity		No necessity	
April → June	Behaviour	←	Behaviour	.455	*	.583	*	.426	*
		←	Attitude	.296	*	.246	*	.300	*
		←	Risk perception	.011		-.011		.018	
	Attitude	←	Behaviour	.109	*	.134	*	.106	*
		←	Attitude	.676	*	.664	*	.691	*
		←	Risk perception	.045	*	.017		.033	*
	Risk perception	←	Behaviour	-.019	*	-.008		-.014	
		←	Attitude	.023	*	.048		-.002	
		←	Risk perception	.572	*	.571	*	.629	*
June → September	Behaviour	←	Behaviour	.509	*	.620	*	.461	*
		←	Attitude	.254	*	.161	*	.281	*
		←	Risk perception	.009		-.012		.015	
	Attitude	←	Behaviour	.119	*	.145	*	.102	*
		←	Attitude	.712	*	.685	*	.735	*
		←	Risk perception	.036	*	.009		.039	*
	Risk perception	←	Behaviour	-.001		-.021		-.008	
		←	Attitude	.019	*	.030		.011	
		←	Risk perception	.604	*	.629	*	.634	*
September → December	Behaviour	←	Behaviour	.550	*	.588	*	.535	*
		←	Attitude	.225	*	.232	*	.209	*
		←	Risk perception	-.017	*	-.013		-.014	
	Attitude	←	Behaviour	.179	*	.205	*	.154	*
		←	Attitude	.688	*	.673	*	.726	*
		←	Risk perception	-.010	*	.046	*	-.009	
	Risk perception	←	Behaviour	.001		.017		-.018	
		←	Attitude	.076	*	.028		.073	*
		←	Risk perception	.591	*	.627	*	.633	*

* An asterisk indicates a significant value ($p < .05$).

model. This could be explained due to the fact that train travel was more volatile during the pandemic, as is also shown in Section 4.2.

Similarly to car travel, the effect from attitude to behaviour is not very consistent. It was expected that attitude has less effect on behaviour for the Necessity group, as behaviour was assumed to be more rigid. However, this is not consistently the case. Attitude does have a higher role for this group from April to June. For June to September and September to December, attitude does have a much larger effect on behaviour for the people who are not required to travel. This is in line with the expectations.

Behaviour to attitude, which was consistently higher for the Necessity group in the car travel model, does not show the same effect in the train travel model. Thus, for train travel there is no clear influence from the necessity to travel on the relationship behaviour to attitude. One of the results (June to September for group Necessity) is not even significant.

Risk perception shows more significant regressions here, although mostly for attitude and risk perception. The regression weights from attitude to risk perception do fluctuate

Table 9: Standardised regression weights in the base train travel model for all respondents and the groups 'necessity to travel' and 'no necessity to travel'.

	Train travel regression			All respondents		Necessity		No necessity	
April → June	Behaviour	←	Behaviour	.492	*	.635	*	.367	*
		←	Attitude	.098	*	.144	*	.119	*
		←	Risk perception	-.049	*	.000		-.028	
	Attitude	←	Behaviour	.079	*	.089	*	.087	*
		←	Attitude	.426	*	.494	*	.444	*
		←	Risk perception	-.088	*	-.095	*	-.100	*
	Risk perception	←	Behaviour	-.038	*	.017		-.037	*
		←	Attitude	-.083	*	-.151	*	-.053	*
		←	Risk perception	.549	*	.540	*	.611	*
June → September	Behaviour	←	Behaviour	.507	*	.674	*	.419	*
		←	Attitude	.103	*	.054	*	.133	*
		←	Risk perception	-.053	*	-.029		-.061	*
	Attitude	←	Behaviour	.040	*	.031		.041	*
		←	Attitude	.573	*	.619	*	.601	*
		←	Risk perception	-.078	*	-.051	*	-.094	*
	Risk perception	←	Behaviour	-.007		.037		.001	
		←	Attitude	-.075	*	-.083	*	-.050	*
		←	Risk perception	.587	*	.612	*	.622	*
September → December	Behaviour	←	Behaviour	.544	*	.706	*	.440	*
		←	Attitude	.061	*	.053	*	.107	*
		←	Risk perception	-.037	*	.001		-.041	*
	Attitude	←	Behaviour	.146	*	.175	*	.107	*
		←	Attitude	.584	*	.598	*	.640	*
		←	Risk perception	-.078	*	-.048	*	-.077	*
	Risk perception	←	Behaviour	-.084	*	-.079	*	-.038	*
		←	Attitude	-.123	*	-.076	*	-.140	*
		←	Risk perception	.558	*	.608	*	.600	*

* An asterisk indicates a significant value ($p < .05$).

quite a lot, but no clear difference between the two groups becomes clear. Reversed – the regressions from risk perception to attitude – is consistently higher (in absolute sense) for the group No necessity. Thus, the group of respondents who are not required to travel have a larger (negative) impact on their attitude based on their risk perception.

Model fit

For both the car and train travel models, there is a significant difference between the groups necessity to travel and no necessity to travel. This is shown in Table 10, wherein the critical chi-square value (with a probability of .05) is 41.337. These values are obtained by comparing the models with groups to the models where the groups are assumed to be equal.

To check the model fit, the same model fit indices are used again. Table 11 shows the model fit indices. The model fit has been improved compared to the base model, but does not reach the cutoff values suggested by Hu and Bentler (1999). Still, the model has clearly improved its goodness-of-fit, and therefore can be accepted. This does not mean that the

Table 10: Chi-square values and degrees of freedom for car and train travel models using necessity to travel groups.

Model	Chi-square	Degrees of freedom
Car travel	102	27
Train travel	302	27

base model has to be rejected now, as they both can be used for different purposes (i.e. when needing to compare the two groups or not).

Table 11: Model fit indices for the car and train travel models using necessity to travel groups.

	Car travel		Train travel	
Model fit index	**Base model**	**Groups model**	**Base model**	**Groups model**
CFI[a]	.893	.898	.881	.892
RMSEA[b]	.170	.118	.145	.101

[a] CFI > .95 indicates good model fit (Hu & Bentler, 1999).
[b] RMSEA < .06 indicates good model fit (Hu & Bentler, 1999).

4.6 Car and train travel relations

In the previous Sections the results of car and train travel have been reported separately. This allows to see the developments and effects within each mode, but does not give insight into the relation between the two. In this Section both modes are considered in a single model, including all possible effects (e.g. train attitude on car behaviour). Table 12 shows the standardised regression weight estimates of this model. Only the new regressions are presented, i.e. those between car and train travel predictors.

The results show that all statistically significant results have a negative value. This shows that the two modes negatively influence each other, e.g. higher train attitude leads to lower car attitude. For the bidirectional relationships between car and train travel behaviour, this is to be expected. People who travel more by car are likely to travel less by car and vice versa. That the regressions between car and train travel attitude are also negative, shows that there are negative bidirectional relations between the attitudes towards both modes. In other words, a higher attitude for one mode leads to a lower attitude for the other mode. All of the mentioned regressions but one are statistically significant (only car behaviour in September on train behaviour in December is not).

Finally, there are the regressions between attitude and behaviour, Table 12 shows that about half of these are not statistically significant. All significant results are negative, thus showing that attitude and behaviour also negatively influence each other. The non-significant results are mostly those of car travel on train travel. This suggests that train travel attitude and behaviour has a larger influence on car travel attitude and behaviour than vice versa. This makes sense with the context of the pandemic in mind. As shown in Section 4.2, train travel was much more affected than car travel. The changes in train travel behaviour (and attitude) lead to changes for car travel. The opposite is much less present; the main caustation is from train to car travel.

To check the goodness-of-fit for this combined car and train travel model, the model fit indices are used again. Table 13 shows the indices together with the indices for the base car and train travel models. The model fit indices for the combined model indicate a better

Table 12: Standardised regression weights between car and train travel.

Regression					Weight	
June ← April	Car ← Train	Behaviour	←	Behaviour	-0.032	*
			←	Attitude	-0.028	*
		Attitude	←	Behaviour	-0.003	
			←	Attitude	-0.051	*
	Train ← Car	Behaviour	←	Behaviour	-0.017	*
			←	Attitude	-0.090	*
		Attitude	←	Behaviour	-0.013	
			←	Attitude	-0.092	*
September ← June	Car ← Train	Behaviour	←	Behaviour	-0.021	*
			←	Attitude	-0.012	
		Attitude	←	Behaviour	-0.009	
			←	Attitude	-0.048	*
	Train ← Car	Behaviour	←	Behaviour	-0.016	*
			←	Attitude	-0.098	*
		Attitude	←	Behaviour	-0.018	*
			←	Attitude	-0.076	*
December ← September	Car ← Train	Behaviour	←	Behaviour	-0.014	*
			←	Attitude	0.006	
		Attitude	←	Behaviour	0.003	
			←	Attitude	-0.014	*
	Train ← Car	Behaviour	←	Behaviour	-0.006	
			←	Attitude	-0.030	*
		Attitude	←	Behaviour	-0.024	*
			←	Attitude	-0.074	*

* An asterisk indicates a significant value ($p < .05$).

model than the base models, thus including the regressions between car and train travel improve the model. However, the indices are still below the cut-off values as proposed by Hu and Bentler (1999), suggesting a less than good model fit.

Table 13: Model fit indices for the base car and train travel models and the combined model including car and train travel.

Model fit index	Only car	Only train	Combined
CFI[a]	.893	.881	.897
RMSEA[b]	.170	.145	.121

[a] CFI > .95 indicates good model fit (Hu & Bentler, 1999).
[b] RMSEA < .06 indicates good model fit (Hu & Bentler, 1999).

4.7 Results synopsis

The results from this study, presented in this Chapter, provide some interesting insights. In this Section a short synopsis of the most relevant results is presented together with the the literature review and the hypotheses (see Section 2.7) resulting from it.

The first hypothesis formulated was that the autoregressive effects would be the largest. The results clearly show that this is the case; the autoregressive effects are significantly larger than all other estimated regressions. This means that each of the three predictors parameters forms a stable base value for the parameter in the next wave. In other words, respondents who have have e.g. a high perception of risk in April, are likely to also have a high perception of risk in June.

The autoregressive effects where however not the main interest of this study; the cross-lagged effects are. One of the reasons for conducting this study were the findings of Kroesen et al. (2017). They showed that behaviour could have a stronger causal relation on attitude than attitude on behaviour, as regularly assumed. The results in this study do show that there are significant bidirectional relations, thus that behaviour does indeed affect attitude, as well as vice versa. However, there was no direction clearly stronger than the other. Thus, the results found here differ from those of Kroesen et al. (2017).

For the regression estimates related to risk perception less confident hypotheses were formulated. The literature review did not show clear causal relations. Still, the expectation was that risk perception influences and is influenced by both behaviour and attitude. The results show that this is mostly the case. However, the size of these regressions is rather small and there are – especially in the car travel model – some statistically insignificant results. On the one hand this tells us that there are (bidirectional) relationships between risk perception and both attitude and behaviour. On the other hand, it also shows that these effects are generally speaking rather small.

For car travel, the relationship between travel behaviour and risk perception seems almost nonexistent. In only two instances there is a statistically significant regression weight. These two are in opposite directions and both negative. Therefore, it can be argued that there is no or only little effects between travel behaviour and risk perception for car travelers.

In the train travel model only one of these regressions in insignificant. All of them are negative, meaning that a higher risk perception leads to less train travel and vice versa. Thus, this also shows that more train travel generally causes a reduction in risk perception. This is interesting as it points towards that more travel by train decreases one's perception of risk.

When looking at attitude and risk perception, there are also some interesting effects to be noted. Car travel attitudes have a positive effect on risk perception. Thus, a more positive attitude for car travel leads to a higher perception of risk. There was an expectation that the relationship with risk perception for car travel could actually be positive, as car travel could be a substitute for other – more riskful perceived – modes of transportation. However, it is very interesting that the results show a causation from attitude to risk perception, since this was not hypothesised. It shows that people with a higher attitude towards car travel generally have a higher perception of risk for getting infected with COVID-19. For train travel the opposite is the case. A higher attitude causes a lower risk perception.

In the opposite relation – risk perception on attitude – the train travel model shows similar results. Risk perception has a negative effect on attitude, as was expected. Car travel has more striking regressions. Between the first two waves the relationship is positive, similar to attitude on risk perception. However, between September and December there is suddenly a negative relation estimated. Although this is a rather small value ($-.010$), it is still statistically significant.

To further analyse the relationships, necessity to travel was also taken into account to see if there are different results between people who have to travel and those who do not. The results show that there are statistically significant differences. It was expected that the cross-lagged regressions would be closer to zero for the group that needs to travel, although this was not a strong expectation. With some exceptions this is true for attitude and behaviour, in both the car and train travel model. The autoregressive effects are generally larger, while the cross-lagged effects between the two are smaller. However, it needs to be noted that due to the lower sample sizes (see Table 2) quite some of these results are not statistically significant. This is especially true for the regressions involving risk perception. Therefore, it is not possible to generate hard conclusions based on these results.

Finally, the model combining car and train travel showed negative bidirectional relations between train and car travel behaviour and attitude. This shows that while these relations are positive within a mode (e.g. car behaviour on car behaviour), this is not true between modes (e.g. train behaviour on car behaviour). Significant relations are mostly present between two attitude or two behaviour pairs. Attitude on behaviour and vice versa were less often significant between car and train travel. Interestingly, the insignificant results were mostly present on regressions from car to train travel. This suggests that during the pandemic train travel influences car travel more than the other way around.

Lastly, it should also be noted that the goodness-of-fit values for all models did not reach their respective cutoff value. This means that the model fit was less than good for both the car and train travel models, even when taking into account the (no) necessity to travel groups. This does not mean that the found results are invalid, but it does mean that there are likely also other factors that play a role here.

5 Discussion and limitations

In this Chapter the results of this study are further discussed. This leads to a discussion of limitations, which could be improved upon in further research.

Developments during the pandemic

To gain insight into the developments of travel behaviour, attitude and risk perception during the pandemic, those parameters were analysed. To put them further into context, they were compared to Google Mobility data and confirmed deaths due to COVID-19. This gave some interesting initial results, mainly into the differences between car and train travel. As was expected, it became clear that car travel was much less affected by the pandemic than train travel. Car travel did even increase above pre-pandemic levels. This shows that the car is considered a valid safer alternative to public transport.

Another interesting finding is that travel behaviour and attitude do seem to quickly decrease when the pandemic becomes more severe. Contrary, when its severity decreases attitudes and behaviour do not instantly increase again, this takes some time. It should be noted that as the parameters are only measured at four moments, these conclusions are based on the rough trends that are visible. This is a limitation of the data, which could be improved upon if more data points were available.

The rough trend of risk perception is quite different from those of travel behaviour and attitude, and also from the mobility and severity statistics. The results suggest that risk perception is more dependent on the development of the (severity of) the pandemic, than the pandemic in absolute sense. Risk perception decreases when the severity of the pandemic is decreasing and increases when it shows a rising trend. Again, this is based on only four data points, thus drawing hard conclusions is not possible here. However, it is an interesting finding that could be further looked into.

Bidirectional relationships between travel behaviour and attitude

It is already mentioned that one of the motivations for this study were the findings of Kroesen et al. (2017). It is also mentioned that the results they found and the results of this study do not completely match up. While Kroesen et al. (2017) found a larger effect from travel behaviour on attitude than the other way around, this regression was not consistently found in this study. It could be that the COVID-19 pandemic played a disturbing role here, but it is definitely a reason to look further into this bidirectional relationship. One thing that can be concluded is that the relationship goes both ways, thus not only from attitude to behaviour, as is sometimes assumed in literature.

Differences between car and train travel

While there are numerous small differences between the car and train travel model results, there is one that stands out. That is the relation from attitude to risk perception. As described, for car travel this regression is positive, while for train travel it is negative. The results do not directly answer why this difference is present. However, it may be linked to the finding that traveling more generally leads to a lower perception of risk. The idea behind this is that people who travel more are less 'scared' of traveling. Reasons for this could be that they are the ones that actually experience traveling, therefore have a better understanding of the risks, and/or that when traveling more it becomes more of a habituation and therefore risks are less perceived.

Anyway, this same principle might be applicable to the case here. People with a higher attitude towards car travel are likely to travel more by car and therefore, as they thus likely travel less by train, do less experience more riskful travel modes (i.e. train travel). Vice versa people with a higher attitude towards trains likely travel more by train and then the same is true again: risk perception lowers.

However, as mentioned, this cannot be proven given the results from this study. Additionally, with the possible explanation given here, it would be logical that the regressions from travel behaviour to risk perception also show this effect, but this is less so the case. Overall, these results raise some interesting questions for which further research would be required.

Model fit

The goodness-of-fit indices for the estimated models did not reach the used cutoff values. As mentioned, this means that the model fit is less than good. Still, most of the results are statistically significant, but there are shortcomings to the model. Other factors might play an important role which are not included. For further research it would be wise to look into factors that could be included, to test if this improves the model fit.

Cross-lagged panel model adaptions

While the CLPM has been used in many studies, it is not without critique. Multiple adaptions to the base CLPM (as elaborated in Section 3.3) have been suggested in literature. Two large adaptions to the base CLPM are the general cross-lagged panel model (GCLM) and the random-intercept cross-lagged panel model (RI-CLPM). While different adaptions, these both aim at segregating between-person and within-person effects. This means that not only the population level is analysed, but also the more specific effects on individual level (Usami, 2021). Initially this was not taken into account in this study, as we were most interested in the general effects on population level. However, given that some estimated regressions do not always show a clear direction, it could be the case that there are large differences between respondents. Therefore, we believe that this study would benefit from a follow up study using these adapted forms of the CLPM.

Structural equations modelling requirements

When using a structural equations modelling technique such as the cross-lagged panel model, some assumptions are implicitly made. One of those is that the used data has a multivariate normal distribution. As for this study data on ordinal scales (e.g. Likert-scale) is used, this is not the case by definition. Thus, not all required assumptions are actually true. This does not mean that the findings are completely invalid, but results would be more meaningful if this assumption was rightfully assumed. Therefore, future research would, if possible, benefit from using data that is multivariate normally distributed.

Overall, this study gives further insight into the bidirectional relationships between travel behaviour, attitude and risk perception, even though it has some shortcomings and limitations. Given the suggested improvements for additional research made in this Chapter, even more insight into this field could be created.

6 Conclusion and recommendations

From both a scientific and societal viewpoint it is relevant to look into travel behaviour and attitudes for train and car travel. There are some knowledge gaps regarding the relationship between the two in scientific literature that this study contributes to. This is useful from a societal viewpoint as it helps to understand how policy related to travel behaviour can be the most effective. This is a large reason to look into car and train travel, as this is very relevant to the transportation related policy challenges society is currently facing.

The coronavirus pandemic created an environment where the usually quite rigid travel behaviour and attitude rapidly changed. Never before in recent history has such a shift in travel behaviour occurred. This created proper conditions to look into the relationship between the two.

The main objective of this study was to gain insight into the relationships between travel behaviour and attitude, for both car and train travel. Additionally, the perception of risk of getting COVID-19 was taken into account, as this was expected to be an important factor for travel during the pandemic. Literature review has shown that there are multiple theories on behaviour and attitude and how they interact. In earlier literature the two are mostly assumed static. Later on this shifted more towards the idea that attitude actively influences travel behaviour. More recently the idea that behaviour also influences attitude gains more ground. This is further analysed in this study. There was little literature available that takes this risk perception into account for travel evaluations. It was however coupled to the mobility biographies theory in which it could be a trigger.

To further answer what the specific relationships between the three predictors are, the data from the NS Panel was analysed. Train usage dropped massively compared to before the pandemic. Halfway through 2020 behaviour increased again, but when the pandemic became more serious again, this also dropped again. Interestingly, car travel initially dropped also a bit, but later increased to above pre-pandemic levels. This suggests that the car substitutes other modes of transport, such as public transport.

Attitude for car travel remained relatively stable during 2020 compared to train attitude. Attitude and behaviour seem to follow pretty similar trends. Interestingly, it does not follow the same trend as risk perception, which was expected. Risk perception is reported the lowest in June, with a sharp increase again in September. Train attitudes are however at their highest in September. Thus, either risk perception does not play an important role, or this effect is lagged.

To really get into the causality of the relations between the three predictors, a cross-lagged panel model was built. The results from the model shows that there are clear bidirectional results between travel behaviour and attitude. Thus, they both affect each other. However, the results do not allow to clearly state which of the two directions is stronger.

For policy perspectives this means that attitudes can be used to change behaviour, as is often done currently. The results do however also show that this is definitely not a one on one relation. In other words, attitude needs to be significantly affected to cause a meaningful behavioural change. Directly influencing people's behaviour is often seen as a taboo. However, the results also show that when behaviour is changed, attitude changes accordingly. When people are confronted with different travel behaviour, they are more likely to increase their attitude towards that behaviour.

The results also show that risk perception plays a rather small role for car travel, but a much more significant role in train travel. This was to be expected as traveling by car itself does not directly create infection risks, contrary to traveling by public transport. Still, the effects of risk perception are lower than those of travel behaviour and attitude. One especially interesting result was that car attitude has a positive causal relation on risk perception, while train attitude has a negative relation. A possible explanation for this phenomenon has been proposed, however this cannot be proven in this study.

The difference in results between people who are force to travel and those who do not has also been analysed. Here it became clear that people who need to travel generally have more stable parameters, i.e. those are harder to affect. Interestingly, the effects of risk perception on travel behaviour and attitude where especially lower. Thus, risk perception has less influence on the group which had to travel.

Overall, this study shows that there are bidirectional relations between travel behaviour, attitude and risk perception for both car and train travel. Although risk perception is mostly a factor for train travel. The results show the weight of regressions on each other. It makes it clear that risk perception is a less relevant factor than travel behaviour and attitude.

The study shows that travel behaviour and attitude are rather flexible during the pandemic. Risk perception plays a role, but not as large as the (bidirectional) relationship between behaviour and attitude. Therefore, number of trips will likely return to similar levels post-pandemic as pre-pandemic. However, due to the exposure to different behaviour (e.g. taking another mode of transport, but also working/studying from home) attitudes have likely shifted. Therefore, it could take some time before the number of train travelers returns to 'normal'. Therefore, the NS is recommended to anticipate for a return to a normal (i.e. pre-pandemic) level of travelers and trips. This return will however not be immediate, thus a few years of lower numbers is to be expected.

For policy-makers the results clearly show that behaviour itself also strongly influence attitude, and that it is not only the other way around. This is relevant as it means that it is not as simple as sometimes assumed to change travel behaviour. Therefore, it is recommended to look further than influencing certain attitudes to change behaviour.

On the other hand, these findings also show new opportunities. When people are exposed to a certain (new) behaviour, there attitude towards it is likely to change. Thus, by letting people experience a certain behaviour they may opt to change their current behaviour. Thus for policy-makers it can be recommended to look into ways to let people experience other travel behaviour in a way that they have a better idea of what that behaviour actually entails. Basically, people can be influenced by telling them why they should do something (i.e. influencing attitudes), but also by actually showing them (i.e. (temporarily) influencing behaviour).

This study provides some interesting results, but also generates new questions that cannot be answered as of now. In Chapter 5 already some suggestions for further research were made. For future research it is recommended to further analyse the bidirectional relation between travel behaviour and attitude. A clear stronger direction of the relation has not been found in this study, this could be the focus of future research. Improvements could be made to the used cross-lagged panel model and the required structural equations modelling assumptions. It could be interesting to focus on more or other modes of transport, to see if those show different results.

From a policy perspective it would be good the gain more insight in the future travel behaviour of people. For the NS it would be important to know what they can expect in terms of travelers. This study does already provide some predictions to the future, but these are no solid conclusions. Therefore, it is recommended that this is further researched. Scientifically this would also be very interesting, as this would give more insight into how travel behaviour can be predicted. A recommendation for future research is to look back on the pandemic after some time. This will allow to gain insight in how travel behaviour and attitudes have changed during and after the pandemic.

Lastly, the results do not clearly state what exact factor has lead to changes in travel behaviour and attitude. Risk perception definitely plays a role, but not everything can be explained by that predictor. Thus, this also leaves some questions. Future research could look further into what other factors may have influenced travel behaviour and attitudes during the pandemic and analyse those influences.

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