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Investigating changes in within-person effects between attitudes and travel behaviour during the COVID-19 pandemic

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ABSTRACT

Attitudes have been used as explanatory variables of travel behaviour for decades, typically under the assumption that there is a causal effect of attitudes on behaviour. However, recent research has shown that the relationship between attitudes and travel behaviour is bi-directional. In this study we use a longitudinal modelling technique on panel data to 1) separate within-person effects from between-person associations and 2) test whether the within-person effects changed during the COVID-19 pandemic. We find that the within-person effects were weaker during the pandemic than they were before the pandemic. In addition, the within-person effects were much smaller than would be expected based on methods that do not separate within-person effects from between-person associations. This means that researchers should be careful when basing policy recommendations on cross-sectional correlations between attitudes and behaviour for two reasons: first, the problem of endogeneity, and second, the highly relevant separation of within-person effects from between-person relations.

1. Introduction

Many studies in the field of travel behaviour research use attitudes as explanatory variables of travel behaviour (Bohte et al., 2009; De Vos, 2022; Hoffmann et al., 2017; van Acker et al., 2010). Eagly & Chaiken (1993, p.1) define attitudes as “a psychological tendency that is expressed by evaluating a particular entity with some degree of favour or disfavour”. Following the theory of planned behaviour (Ajzen, 1985, 1991), researchers typically work under the assumption that attitudes affect behaviour when they cannot empirically validate the direction of the effects. However, research in the last decade has shown that this theoretical assumption does not hold up to empirical scrutiny (Chorus & Kroesen, 2014; Kroesen & Chorus, 2018): using longitudinal data they show that the reverse effect, of behaviour on attitudes, is generally at least as strong as the assumed effect of attitudes on behaviour.

Even though this finding is very consistent, all evidence is based on data estimated before the COVID-19 pandemic. Research has however shown that the pandemic has resulted in unprecedented changes to travel behaviour (Beck & Hensher, 2020; de Vos, 2020) and travel attitudes (e.g. Beck et al., 2021; de Haas et al., 2020; de Palma et al., 2022; Eisenmann et al., 2021). More recent research has indicated that some of the behavioural changes are likely to have a structural component which will outlast the pandemic itself (Faber et al., 2023; Hensher et al., 2023). Importantly, these changes might also have affected the relationship between attitudes and behaviour. The relationship could have grown weaker, due to an increasing influence of other factors (for example, lockdown policies or fear of infection). These factors might have put constraints on the relationship between attitudes on behaviour as people were

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unable to exhibit their desired behaviour. However, one might also expect the relationship to have become stronger, as attitudes were pushed to unprecedented extremes and, assuming a non-linear relationship, these extremes could have a relatively larger effect on behaviour than more moderate attitudes. The nature of the relationship between attitudes and travel behaviour is important, as relatively large bi-directional effects would imply that the temporary deviations in the attitudes and behaviour seen during the pandemic would have a structural effect on the attitudes and behaviour post-pandemic. Therefore, it is important to consider whether the relationship between attitudes and travel behaviour changed during the COVID-19 pandemic.

This paper contributes to the existing literature on attitudes and travel behaviour by studying the changes in the relationship between the two concepts during the pandemic. To achieve this contribution, we use panel data collected from the Netherlands Mobility Panel (MPN), collected between 2014 and 2021. This dataset enables us to estimate the relationships between attitudes and travel behaviour both before the pandemic (2014 – 2018) and during the pandemic (2018 – 2021).

In addition, this paper makes another contribution to the literature on the relationships between travel attitudes and travel behaviour. Almost all previous studies with panel data that examine the longitudinal relationship between attitudes and behaviour in the field of travel behaviour research have used cross-lagged panel models (CLPM). This method is unable to separate between-person from within-person processes[1] (Hamaker et al., 2015). Between-person processes refer to all mechanisms that result in differences in a variable, such as attitudes, across different individuals. As an example, we might consider two individuals, Alice and Bob. Alice has lived her whole life in a very rural area. As a result, she is likely to use the car more and have more favourable attitudes towards the car. Conversely, Bob has lived his whole life in a very densely developed city. As a result, he is likely to use public transportation more and have more favourable attitudes towards public transport. Within-person processes refer to changes in a variable that occur within the individual. For example, if Bob moves from his city towards a rural area, he is likely to start using the car more and as a result develop more favourable attitudes towards the car (Faber et al., 2021; Kroesen, 2019). Thus, there is a within-person effect of residential environment on travel attitude. Another useful example to illustrate the difference between within-person and between-person relations is given by Hamaker (2012): the between-person correlation between typing speed and typing errors is negative, as better typists both type faster and make fewer mistakes. However, if someone would be instructed to type faster, then they will make more typing errors. The within-person effect of typing speed on typing errors is thus positive. For more information on this topic, the reader is referred to the accessible paper by Hamaker (2012).

Since the previously used CLPM is unable to separate within-person processes from between-person processes, due to its assumption that there are *no* stable between-person differences. Since the causal mechanism between attitudes and behaviour, if such exists, takes place within the individual, disentangling between-person relations from within-person relations is highly relevant (Chorus & Kroesen, 2014; De Vos, 2022; Selig & Little, 2012). Furthermore, policy implications often revolve around policies that impact attitudes, with the end goal of indirectly changing travel behaviour through the within-person effect of attitudes on behaviour. The efficacy of such policies however depends on the existence of such within-person effects from attitudes on behaviour. As the CLPM can not distinguish within-person from between-person processes, this model is likely to overestimate the strength of this within-person relationship. For this reason, this paper uses an extension to the CLPM, the so-called random-intercept cross-lagged panel models (RI-CLPM), introduced by Hamaker et al. (2015). The chief benefit of the RI-CLPM is that it does allow us to separate between-person from within-person processes.

The rest of this paper is laid out as follows. Section 2 provides an overview of the literature on the relationship between travel attitudes and travel behaviour, as well as the literature on the effects of the COVID-19 pandemic on both attitudes and behaviour. The section culminates in two hypotheses that serve to guide our further analyses. Section 3 contains a description of the data and research methods used in this paper, and Section 4 presents the results from the analyses. The conclusions can be found in Section 5.

2. Literature overview

This section provides an overview of the literature on the relationships between attitudes and behaviour in the field of travel behaviour research. It starts by briefly summarizing the use of attitudes in travel behaviour research, which is followed by a discussion of the recent research stream that investigates the bi-directional causal relations between the two concepts. Afterwards, we discuss recent papers on the effects of the COVID-19 pandemic on both travel attitudes and behaviour. Finally, we state two guiding hypotheses that serve to focus the remainder of the paper.

2.1. Attitudes in travel behaviour research

Attitudes are broadly defined as the degree to which someone evaluates a certain object or behaviour as favourable or unfavourable (Ajzen, 1991; Eagly & Chaiken, 1993; van Acker et al., 2010). Such evaluations consist of affective, cognitive, and behavioural components (Ostrom, 1969; Parkany et al., 2004). The affective component refers to feelings towards the object in question, the cognitive component refers to beliefs and perceptions and the behavioural component considers overt actions and ways of behaving oneself (Ostrom, 1969; Rosenberg et al., 1960). In the social sciences, especially the field of social psychology, attitudes have been studied extensively (Bohner & Dickel, 2010). In line with the widely used theory of planned behaviour (Ajzen, 1985, 1991), attitudes are typically assumed to have a causal effect on behaviour. After the re-introduction of attitude research to the field of travel behaviour research, influenced by the work of Kitamura et al. (1997) and Gärling et al. (1998), this assumption has also taken hold in this field (van Acker et al., 2010).

Under this assumption, the concept of attitudes has played a notable role in travel behaviour research, for example in research that applies the theory of planned behaviour to the field of travel behaviour (Bamberg, 2006; Eriksson & Forward, 2011; van Acker et al., 2010), in research studying the effects of the built environment on travel behaviour (Cao et al., 2009; van Wee & Cao, 2022), and in the research on- and applications of hybrid choice models (Ben-Akiva et al., 2002; Chorus & Kroesen, 2014).

2.2. Bi-directional relationships between attitudes and behaviour

The theoretical assumption that attitudes cause behaviour has been challenged in the field of travel behaviour studies by a recent line of research, which uses panel data to empirically estimate the bi-directional effects between attitudes and behaviour. Generally, this research line has found that the reverse effect – namely that of behaviour on attitudes – is at least as strong as the assumed effect of attitudes on behaviour (Faber et al., 2021; Kroesen et al., 2017; Olde Kalter et al., 2020). These results imply that using attitudes as pure independent variables of behaviour will result in an overestimation of the effect of attitudes on behaviour. As a result, the effects of any other variables in the analysis are likely to be underestimated.

There are several theoretical explanations for the effect of behaviour on attitudes. Most often, researchers refer to either cognitive dissonance or learning theories as explanations for the reverse causal effect (Van Wee et al., 2019). Notably, both these theories and the theories underpinning the original causal effect borrow heavily from social psychology and the causal effect of these theories is assumed to occur at the level of the individual. For this reason, research would ideally investigate the direction of the effects between travel behaviour and attitudes within the individual (Hamaker, 2012; Vos, 2022). However, such research is very rare in the literature. (Olde Kalter et al., 2021) studied within-person relationships between mode preferences and mode use of young adults, and they too found that the effect of mode use on mode preferences where stronger than the reverse effect. (Kroesen & Chorus, 2020) found no strong within-person relations between attitudes and behaviour. Kroesen et al. (2023) studied the within-person relations between train use and train attitudes during the COVID-19 pandemic. They found a reciprocal influence, where again the effect of mode use on attitudes was stronger than the reverse effect.

2.3. The effect of the COVID-19 pandemic on travel attitudes and behaviour

The COVID-19 pandemic has had a tremendous impact on our travel behaviour. Worldwide, people travelled less often and in different ways than before (e.g. Beck & Hensher, 2020; de Haas et al., 2020; Downey et al., 2022; Hensher et al., 2023; Kolarova et al., 2021; Rafiq et al., 2022). A part of this effect was temporary, due for example the lockdown policies restricting mobility or the fear of COVID-infections keeping people at home. However, some part of the effect seems to be structural in nature, outlasting the pandemic, as society has adapted to some changes in activity-travel, such as working from home (Bohman et al., 2021; Faber et al., 2023; Javadinasr et al., 2022; Manser et al., 2022).

Not all travel modes seem to be equally affected by the pandemic. Public transport use saw sharp declines (Tirachini & Cats, 2020) as people tended to avoid shared transport options (Bohman et al., 2021) and, in many countries, public transport commuters were more likely to be able to work from home (Hensher et al., 2023). Simultaneously some areas saw a shift towards the use of active modes (Campisi et al., 2022; Currie et al., 2022) as people made more short-distance trips.

The pandemic also affected travel-related attitudes (de Haas et al., 2020; van Wee & Witlox, 2021). Attitudes towards public transport have become more negative, which is probably caused by perceptions of comfort and safety which have shifted as a result of the pandemic and the (perceptions of) infection risk in shared modes of transport (Thomas et al., 2021; Tirachini & Cats, 2020). Attitudes related to private cars and the active modes generally became more positive during the pandemic (de Haas et al., 2020).

2.4. Research hypotheses

The above information culminates in two hypotheses that are set to guide the further analyses in this paper, cohering to the two knowledge gaps introduced in the introduction.

The literature convincingly shows that the COVID-19 pandemic has affected both travel-related attitudes and travel behaviour. In general, people became less mobile, shifted away from public to private forms of transport, and there was a small shift to active transport. Attitudes towards public forms of transport became less favourable. We hypothesize that the pandemic has also resulted in a change in the relationship between attitudes and behaviour. Such a change might affect the extent to which the (partly temporary) deviations above will continue to affect both travel attitudes and travel behaviour in the future. To investigate this hypothesis, we estimate a model with two sets of parameters: one set before the pandemic and one set during the pandemic. Both sets can then be compared to one another. The above information is summarized in hypothesis 1, below:

H1 The relationships between travel mode attitudes and travel behaviour have changed during the COVID-19 pandemic

There is a =growing body of literature that uses panel methods to show that there is a bi-directional relationship between travel attitudes and behaviour. However, there is limited research on the within-person effects between the two concepts. This is particularly relevant given that these within-person estimates provide a better approximation of the (assumed to be) causal process between attitudes and behaviour, as these psychological processes are assumed to take place within the individual (Chorus & Kroesen, 2014; Vos, 2022). Hence, the separation of between-persons and within-persons relations provided by the RI-CLPM is theoretically highly relevant. We hypothesize that such a separation will result in different estimates for the effects between travel mode attitudes and travel behaviour. To investigate this hypothesis, we can compare the results from a method that does not separate between-person from within-person relationships to those from a method which does separate the two. This results in the second guiding hypothesis stated below:

H2 Separating between-person correlations from within-persons effects results in different estimates for the effects between travel mode attitudes and travel behaviour

3. Research methods

This section introduces the methods and data that are used to investigate the hypotheses mentioned above. First, the data are introduced in Section 3.1. Then the operationalisation of the variables is described in Section 3.2, followed by an introduction of the research methods in Section 3.3 and the estimation procedure in Section 3.4. Finally, we introduce some core concepts of graph theory in Section 3.5, which we use to facilitate the interpretation of our results.

3.1. Data & sampling

This study uses data from the Netherlands Mobility Panel (MPN). The MPN is a longitudinal household panel that consists of a 3-day travel diary and a set of questionnaires (Hoogendoorn-Lanser et al., 2015). Travel behaviour was collected each year using the travel diaries, but data on travel mode attitudes were collected only in the waves of 2014, 2016, 2018, 2020 and 2021. This gives us five waves of data from the MPN to estimate the relations between travel behaviour and travel-related attitudes, of which three waves have been collected before the pandemic and two waves were collected during the pandemic. The time lag between the waves is two years for every wave pair, except for the last one between 2020 and 2021. As such, we would expect stronger relationships in this last wave-pair than in the previous ones. An overview of the measurements between 2019 and 2022 is given in Fig. 1, together with the COVID-19 hospital admission rate and the Oxford Stringency Index in the Netherlands, which measures the stringency of the governments' COVID-19-related policies.

Since there are seven years between 2014 and 2021, panel mortality will both reduce and skew the pure-stayer sample severely. For this reason, we do not use a pure-stayer sample. Instead, respondents that fully participated in both the questionnaire and the travel diary in at least two consecutive waves are included in the analysis. In total, the sample consists of 6141 unique respondents, with between 2644 and 4130 respondents per consecutive pair of waves. The handling of the resulting missing data is described in the section on research methods below. The number of respondents and the distribution of some socio-demographic variables for each wave-pair is given in Table 1. The socio-demographics presented here are those that were recorded in the first of the two waves.

3.2. Operationalisation

This paper investigates the bi-directional relationships between behaviours and attitudes that are specific to travel modes. Attitudes and behaviours of five distinct travel modes are studied: the car, the train, bus, tram, and metro (BTM), the bicycle, and walking.

Travel behaviour is operationalized as the total distance travelled using each mode, as measured using the 3-day travel diaries of the MPN where respondents record the trips they made and estimate the distance they travelled for each trip. Attitudes are measured using six indicators for each mode, whereas public transport uses indicators related to both the train and BTM. Each indicator is scored on a 5-point Likert scale, varying between 'strongly agree' (1) to 'strongly disagree' (5). The unidimensionality of the indicators is checked using principal axis factoring. Since we use data from several years and we want to estimate the relationships between constructs over time, we need to ensure that the scale is constructed consistently over time (Selig & Little, 2012). To do so, the final factor scores were based on the average of the factor loadings as calculated on data for a specific year. These final factor loadings are given in Table 2.

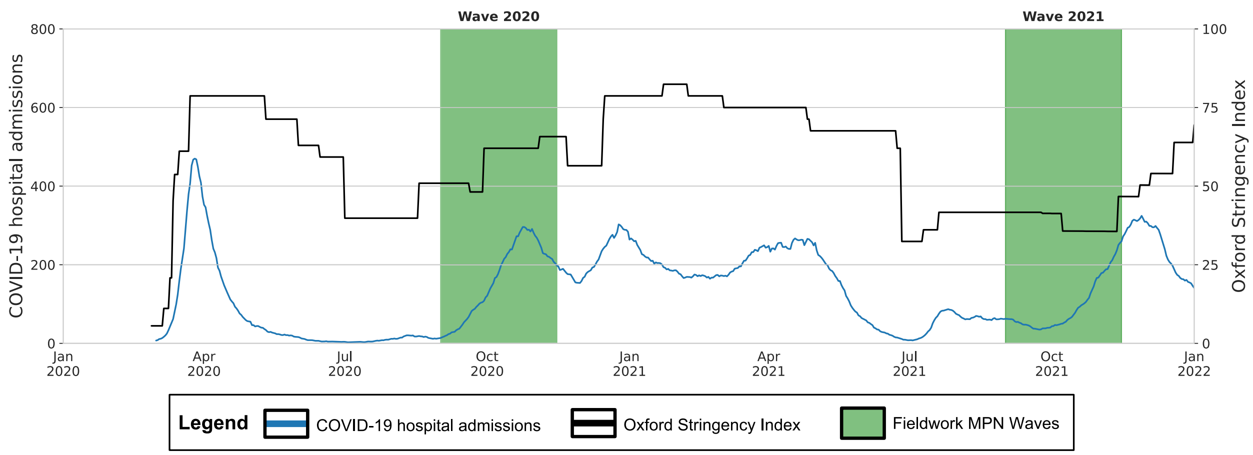

Fig. 1. Overview of the MPN measurements during the COVID-19 pandemic.

Table 1
Sample distribution across the four wave-pairs.

		2014–2016	2016–2018	2018–2020	2020–2021	Population (2019)
N	Complete Responses	2644	2833	4130	3917	–
Gender (%)	Male	46	46	47	47	49
Age (years)	Mean	45	45	48	49	49
	Median	46	45	50	52	49
Education	High	32	35	32	33	29
	Middle	48	41	38	37	42
	Low	20	24	30	30	29
Owns driver's license (%)	Yes	82	85	85	84	80
Urban density (%)	>2500 inh./km^2	17	18	21	18	24
	1500 – 2500 inh./km^2	28	35	33	34	30
	1000–1500 inh./km^2	25	18	18	17	16
	500–1000 inh./km^2	19	20	21	22	22
	< 500 inh./km^2	10	8	8	9	8
Household composition	Single	21	22	23	25	22
	Adults	28	28	33	35	49
	Adult(s) with children	51	50	44	40	28

The factor loadings are generally above the desired threshold value of 0.7. The internal reliability (Cronbach's Alpha) of each scale was then also tested and found to be more than acceptable in all cases (>0.8). The final scale used in the models was calculated using a weighted mean of the indicators, which scales the final variables between 1 and 5, corresponding to the minimum and maximum value of the indicators.

Table 3 contains the mean values for the attitudes and the mode use variables as collected using the Netherlands Mobility Panel. We see that the public transport attitudes were least positive on average, whereas car attitudes were most favourable. During the pandemic, this difference only grew, as the attitudes towards the car became slightly more favourable whereas attitudes towards public transport grew less favourable. In terms of mode use, the car was also dominant throughout the study period. During the pandemic, public transport use fell rapidly and its recovery in 2021 was the slowest of all.

3.3. Method

To determine the longitudinal relationship between the variables, we use a random-intercept cross-lagged panel model (RI-CLPM). The RI-CLPM is an extension of a cross-lagged panel model (CLPM; (Finkel, 2011). A CLPM is a structural equations model using longitudinal data, that specifies auto-regressive relationships. These are supposed to control for the stability of a variable over time. The cross-lagged relationships between the constructs are then supposed to represent the (causal) processes between the variables. As pointed out by (Hamaker et al., 2015), this approach assumes that the values for each variable for every person vary over time around the same mean. This assumption is problematic, as stable, time-invariant differences between individuals are observed in most variables.

Hamaker et al. (2015) therefore argue that researchers should not only control for temporal stability but also for time-invariant stability on the level of the individual. Effectively, doing so separates within-person differences over time from between-person differences over time. This is achieved by including random intercepts, which account for the trait-like, time-invariant stability of the variables. The random intercepts thus capture the between-person differences, allowing the (auto)-regressive structure to specifically capture within-person effects. These within-person effects are more likely to accurately represent the causal processes between attitudes and behaviour, which are assumed to occur on the level of the individual. Fig. 2 presents a schematic view of the (RI-)CLPM, where the CLPM structure in full borders is complemented by the additional RI structure with dashed borders.

We use an extension on the RI-CLPM discussed by (Mulder & Hamaker, 2020), as we want to control for the allotment of specific

Table 2
Latent travel mode attitude indicators and mean factor loadings across all included years.

	Car	Public Transport		Bicycle	Walking
		Train	BTM[1]		
Travelling by (mode) is comfortable	0.845	0.758	0.812	0.848	0.868
Travelling by (mode) is relaxing	0.791	0.749	0.810	0.871	0.885
Travelling by (mode) saves me time	0.781	0.692	0.729	0.666	0.444
Travelling by (mode) is safe	0.778	0.467	0.553	0.695	0.714
Travelling by (mode) is flexible	0.796	0.742	0.767	0.789	0.772
Travelling by (mode) is satisfying	0.856	0.792	0.821	0.885	0.894

1: bus, tram, and metro

Table 3
Mean values of attitudes and mode use over time.

		2014	2016	2018	2020	2021
Attitudes	**Car**	4.1	4.1	4.1	4.2	4.2
Attitudes are measured using a scale ranging from 1 to 5	**Public Transport**	3.0	3.0	3.0	2.9	2.9
	Bicycle	3.8	3.8	3.8	3.8	3.8
	Walking			3.7	3.8	3.8
Mode Use	**Car**	71.1	76.0	76.3	46.9	57.4
Km per person per three days	**Train**	14.0	15.95	12.75	3.08	6.57
	BTM	2.96	3.64	2.66	0.788	1.20
	Bicycle	8.62	7.32	8.35	6.60	7.32
	Walking	1.53	1.43	2.48	2.95	2.90

days of the week to our respondents. Each respondent is allotted three days of the week, which stay the same over time. We regress the random intercepts on the allotted number of days at the weekend to control for this variation, which ensures that the correlations between the random intercepts are not affected by measurement bias.

3.4. Model estimation procedure

The structural equation models are estimated using Lavaan (Rosseel, 2012), a statistical software package for the programming language R (R Core Team, 2017). Three consecutively more complex models are estimated and compared, to ensure that the more complex models provide a better fit to the data:

1. A CLPM
2. A RI-CLPM
3. A RI-CLPM where the random intercepts are regressed on allotted weekend days

As discussed previously in Section 3.1, the models are estimated using all respondents that participated in at least two consecutive waves where the attitudes are measured. As a result, the model must handle missing data and is therefore estimated using Full Information Maximum Likelihood (FIML).

All models described above can be seen as nested models, as the CLPM is a nested model of the RI-CLPM where the variance and covariance of all random intercepts are fixed to zero. Therefore, the estimated models' goodness-of-fit can be compared using the chi-square difference test. In addition, we look at more general goodness-of-fit indicators such as the CFI, RMSEA and SRMR as well as information criteria such as the BIC and AIC. The relevant goodness-of-fit statistics of the models are given in Table 4.

The RI-CLPM provides a very significant improvement on the CLPM, indicating that trait-like stability on the level of the individual exists within our variables. Adding the regression on the weekend days reduces the Chi-Square with 39.3 points at 9 additional parameters. This improvement is less drastic, but still statistically significant based on the Chi-square difference test. The parameter estimates and corresponding Z-values of both the CLPM and RI-CLPM are given in Appendix A.

3.5. Graph theory

This paper will make use of some core concepts that are part of graph theory to explore and present the results. We do this to facilitate the interpretation of our results: the final model estimates roughly 70 parameters for the regressive structure of each wave pair and nearly 600 parameters in total. By envisioning the models as a graph, we can visualize and summarize these parameters. To avoid any confusion, we do not use graph theory for the estimation of the model (such as discussed in Grace et al., 2012). We only use it

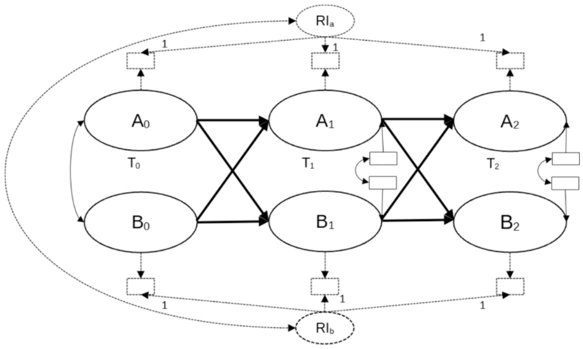

Fig. 2. Simplified schematic view of the (RI-)CLPM. The random intercept structure is dashed.

Table 4
Goodness-of-fit statistics for the structural equation models.

	Model 1	Model 2	Model 3
	CLPM	RI-CLPM	RI-CLPM; regress allotted weekend days
Est. parameters	548	593	602
Degrees of freedom	484	439	430
Df difference		45	9
Chi-square	5530	1168	1128
Chi-square difference test	–	4362 ($p < 0.001$)	40 ($p < 0.001$)
CFI	0.891	0.984	0.985
RMSEA	0.041	0.016	0.016
SRMR	0.053	0.029	0.029
BIC	133,909	129,940	129,978
AIC	130,225	125,953	125,931

to aid the interpretation of the outcomes. In this section, the main concepts from graph theory that we use are explained, both in general terms and in how they are used in this paper.

Graph theory is the study of graphs, which contain nodes (vertices) and edges (links) that connect pairs of nodes. Graph theory has been applied to many fields. In travel behaviour research, usage typically involves the analysis of road or transit networks (e.g., Derrible & Kennedy, 2011; Salas-Olmedo & Nogués, 2012).

In this paper, the nodes are the travel behaviour and travel attitude variables, and the edges are the standardized effects of the statistically significant paths between them. Doing so creates a weighted directed network of the significant effects between attitudes and behaviour. Using this network, we can calculate several useful statistics for the nodes in the network which summarize the available information. We use two main concepts:

1. **Weighted Outdegree:**
   a. This is the sum of the weights of the edges that depart from the node in question.
   b. In our network, the outdegree represents the extent to which a variable determines variation in other variables.
2. **Weighted Indegree:**
   a. This is the sum of all edges that arrive at the node in question.
   b. In our network, the indegree represents the amount of variation of the node that is explained by other variables.

Together, these concepts thus represent the extent to which a variable both affects and is affected by all other variables in the network.

4. Results

This section contains the results of the analysis. First, the relevance of separating within-persons from between-persons relations will be sketched and discussed in Section 4.1. Then, the changes in the relationship between attitudes and behaviour due to COVID-19 are interpreted in Section 4.1. Finally, Section 4.2 will contain the interpretation of the effects between attitudes and behaviour across the various travel modes.

4.1. Within-persons and between-persons relationships

As seen previously in Section 3.4, the RI-CLPM provides a better fit to the data than the CLPM. This indicates that stable, trait-like

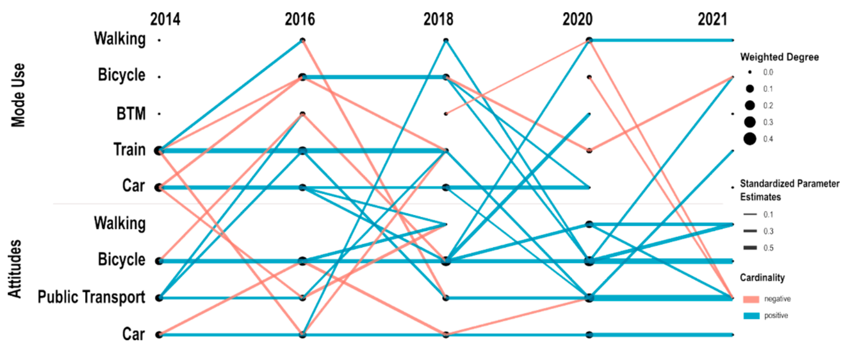

Fig. 3. Visualization of a graph of the within-person effects between attitudes and behaviour over time as estimated using a RI-CLPM.

differences in attitudes and travel behaviours exist. The identification and estimation of these stable, trait-like differences also has implications for the parameters that are estimated within the bi-directional regressive structure. Since the CLPM does not control for these stable differences, they will end up within the regressive structure. As a result, the CLPM will as a rule estimate larger bi-directional effects than the RI-CLPM. We can compare the results from the CLPM with those from the RI-CLPM to see the extent of this difference.

First, we look at the visual difference between the graphs of the regressive structures of both the CLPM and the RI-CLPM. To do so, we have created two graphs to summarize the two models' estimates. The graph using the parameter estimates from the RI-CLPM is given in Fig. 3, whereas the graph that uses the estimates from a CLPM is given in Fig. 4. As a reminder from section 3.5, the nodes are the variables in the model, and the edges represent the standardized parameter estimates for the within-persons relations between these variables. As a result, the graphs might be read as follows: in Fig. 3, we see a clear blue horizontal line for the car attitudes. This line extends throughout all years (2014 through 2021). This represents a positive within-person estimate for car attitudes on itself. In other words, if a persons' car attitude is above its expected value, then the next years' car attitude is also likely to be above its expected value. We see similar such horizontal lines for most variables, each indicating an autoregressive within-persons estimate. Aside from the horizontal lines, the figure contains several diagonal lines. An example is the positive effect from train use in 2014 to walking use in 2016. This effect indicates that if train use was higher than expected in 2014, then walking use is likely to be higher than expected in 2016. More generally, one might state that a busier looking figure, with more and thicker lines, indicates a more densely connected graph. This in turn means that there are more and stronger relationships between the variables contained within the model.

A visual inspection of both figures quickly shows that the RI-CLPM provides a much less densely connected network, indicating that this method produces fewer statistically significant relations between the variables in the model. Furthermore, the relations that are found to be statistically significant in both models are typically much weaker in the RI-CLPM than in the CLPM. Given the fact that the RI-CLPM both provides a better empirical fit to the data and provides theoretically more relevant estimates, the results from the RI-CLPM are to be preferred above those of a CLPM. Note then that these results confirm that the CLPM overestimates the strength of the (within-person) effects compared to the CLPM.

In the remainder of the results section, we will discuss and interpret the parameter estimates of the RI-CLPM to examine both whether the relationship between attitudes and behaviours changed during the COVID-19 pandemic (Section 4.2) and the extent to which there are relations between attitudes and behaviour across various travel modes (Section 4.3).

4.2. Changes during the COVID-19 pandemic

Before the node-specific attribute values are discussed, insights from a visual inspection of the graph of the RI-CLPM (Fig. 3) can be discussed. First, one can see that there are fewer lines during the measurements spanning 2018 through 2021 than during the measurements between 2014 and 2018. This indicates that fewer relationships were significant during the COVID-19 pandemic than before. One might thus conclude that in general, the relationships between attitudes and behaviour were weaker during the pandemic. One explanation for this finding is that people's behaviour was affected more strongly by other factors, meaning that they were unable to show the desired behaviour. If this is the case, then we would expect the effects to revert to the pre-pandemic effects relatively quickly. Alternatively, the attitudes measured during COVID-19 could have reflected more temporary dispositions towards travel modes, which have weaker effects on mode use.

Second, some horizontal positive edges (=carry-over effects) can be found throughout the graph. These indicate that higher or lower scores on these variables, compared to the individuals' average, carry-over to the next measurement. We see some differences here: bike attitudes seem to be the most stable throughout the seven years analysed here, whereas walking and BTM mode use have no

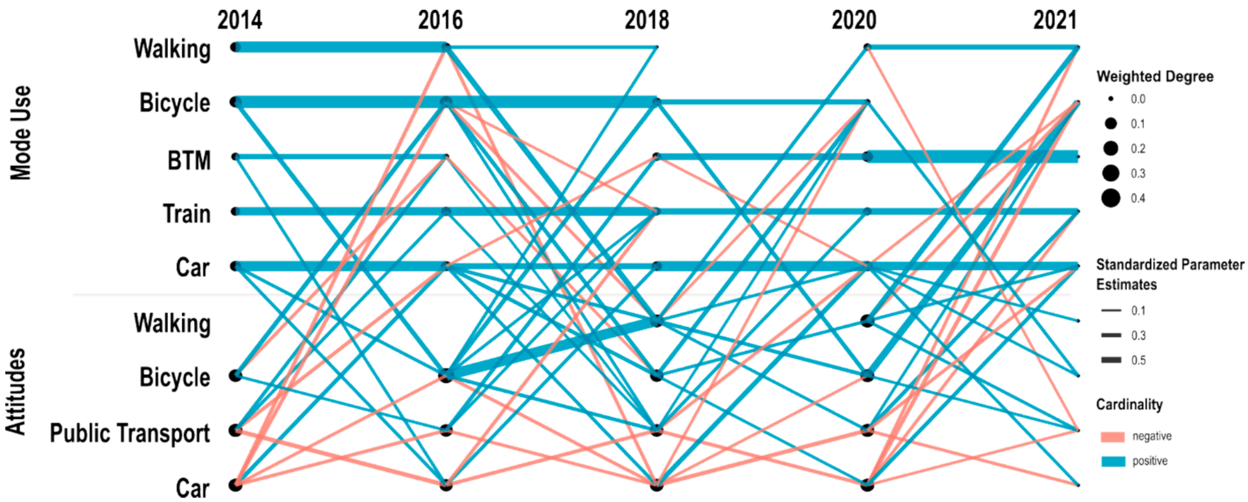

Fig. 4. Visualization of a graph of the effects between attitudes and behaviour over time as estimated using a CLPM.

significant auto-regressive parameters before 2018. During the pandemic, the carry-over effect of train use also disappears.

A further discussion and interpretation of more specific results will use node attribute values. First, we will investigate the changes in the relationship between attitudes and travel behaviour due to COVID-19. To further investigate the changes in effects, we look at the weighted outdegree of the variables, where we only count those edges that run from an attitude to a behaviour or from a behaviour to an attitude. In other words, we only use effects running between attitudes and behaviour (for example, from car attitudes to car use) and not effects within attitudes (for example, from car attitudes to public transport attitudes). The weighted outdegrees are given in Table 5. As explained in Section 3.5, the weighted outdegree represents the amount of variance that a variable explains in other variables. Since we only count edges that run from attitudes to behaviour or vice versa, these degrees thus represent the total variance that one variable explains in variables of the other concept (for example, the variance that car attitudes explain in all mode use variables combined).

When interpreting Table 5, we can see a sizeable decrease in weighted out-degree during the last wave-pair, collected fully during the COVID-19 pandemic. This can be interpreted as another sign that the within-person effects between attitudes and behaviour weakened during the COVID-19 pandemic.

4.3. Relations between travel modes

By incorporating the effects between mode use and attitudes across travel modes into one model, we can provide a more complete picture of the relationships between behaviour and attitudes in the context of travel behaviour research. In this section, we will first discuss the combined effects between attitudes and behaviour. Then, we will discuss which modes' behaviour and attitudes have larger effects on the behaviour and attitudes of the other modes. Finally, we will interpret the between-person correlations between travel distances and travel attitudes across the various travel modes.

From the graph presented in Fig. 3, it is not immediately clear whether there are stronger effects from attitudes to behaviour or vice-versa. This means that from this visual summary, the default theoretical assumption that it is solely attitudes that affect behaviour, and not vice-versa, seems at odds with our findings This result is further backed up by interpreting the net-degrees of the various variables. These net-degrees are the net difference between the sum of all incoming edges (=variance within the variable that is explained by other variables) and the sum of all outgoing edges (=variance that the variable explains in other variables). As above, we only use edges (=within-person effects) that run between attitude- and behaviour variables. If attitudes thus would have a stronger within-person effect on behaviour than vice-versa, we would expect net positive degrees for the attitude variables and net negative degrees for the behaviour variables. These net-degrees are given in Table 6.

For both the 2016 and 2018 nodes, the sum of the net degree of the behavioural variables is greater than the sum of the net degree of attitudes, but this trend is reversed in 2020. Substantively, this means that behaviours had a larger effect on attitudes in the years before 2020, but that the reverse is true in the years since 2020. As discussed in Section 4.2, the network is unfortunately not very stable year-on-year. However, based on these results one can at least draw the general conclusion that the effect of attitudes on behaviour is not stronger than the reverse effect. This further confirms earlier findings of studies using panel data on the nature of the relationship between travel attitudes and travel behaviour (Chorus and Kroesen, 2014; Kroesen and Chorus, 2018). This relationship is empirically estimated to be two-sided, and separating within-person processes from between-person processes does not change this conclusion.

Comparing the effects of variables on the various travel modes, we can see that for the 2016 nodes, which for their net-degree calculation only use the wave-pairs 2014 –>2016 and 2016 –>2018, car use was the strongest explanatory variable in the network, as it has the largest net degree. As a result, this variable had the strongest explanatory power before the COVID-19 pandemic. Public transport attitudes meanwhile had a strong net-negative degree only in 2018, which is probably the result of some structural change in the relationships between attitudes and behaviours due to COVID-19, as discussed in the previous section. A similar explanation can be used to explain the strong net-negative degree of BTM travelled distance for the 2020 nodes.

To complement the analyses of the within-person relations discussed above, we can look at the correlations between the various random intercepts, which capture the between-person relationships. These correlations are given in Table 7.

We see significant and strong correlations between the attitudes and behaviours of the various travel modes. In the quadrant to the

Table 5
Weighted outdegree of the nodes, counting only edges that run between attitude and behaviour nodes.

		2014 → 2016	2016 → 2018	2018 → 2020	2020 → 2021
Mode Attitude	Car	0.000	0.089	0.000	0.000
	Public Transport	0.111	0.043	0.000	0.072
	Bicycle	0.054	0.000	0.169	0.054
	Walking			0.000	0.000
	Sum	0.165	0.132	0.169	0.126
Mode Use	Car	0.054	0.125	0.023	0.000
	Train	0.067	0.067	0.064	0.000
	BTM	0.000	0.059	0.000	0.000
	Bicycle	0.000	0.000	0.041	0.031
	Walking	0.000	0.063	0.044	0.033
	Sum	0.121	0.314	0.172	0.064

Table 6
Difference between weighted out-degree and weighted indegree, counting only edges between attitude- and behaviour-related variables.

		2016	2018	2020
Mode Attitude	Car	0.022	0	0
	Public Transport	0.009	−0.131	−0.015
	Bicycle	0	0.041	−0.032
	Walking	–	−0.056	0
	Sum	0.013	−0.146	−0.047
Mode Use	Car	0.125	0.023	0
	Train	0.008	−0.031	0
	BTM	−0.046	0	−0.126
	Bicycle	0	0.041	0.031
	Walking	0.063	0.007	−0.010
	Sum	0.15	0.04	−0.105

bottom-left, the correlations between attitudes and travel distances are presented. As expected, attitudes and travel distances of the same mode are positively correlated. People who use a mode more also hold more favourable attitudes towards that mode. The correlations also show a clear divide between the car and the other modes. Car attitudes are negatively correlated with travel distances of all other modes, whereas PT attitudes are positively correlated with bike and walking travel distances, but negatively correlated with car distances. Attitudes to the active modes are only negatively correlated with local public transport use. As a result, we might conclude that people who generally favour the car and use it more are less likely to also favour the other modes and use those and vice-versa.

Similar conclusions can be drawn based on the right lower quadrant, where the correlations between the random intercepts of the travelled distances are shown. Car use is negatively correlated to the use of all other travel modes except for walking. The use of the train is relatively strongly positively correlated to cycling use. The correlation between train and bicycle use is much stronger than the correlation between train and BTM use. In The Netherlands, people often use bicycles as access- and egress modes of the public transport system. This would be one factor behind these positive between-person relations. However, given the shorter distance of trips made with busses, trams, and metros as compared to trains, these BTM modes are competitors of the bicycle as well. As a result, the positive relationship with train use is stronger than the relationship with BTM use.

In terms of attitudes (upper-left quadrant), we see a strong negative relationship between car- and public transport attitudes. Public transport and active modes' attitudes however are positively correlated. The correlation between bicycle and walking attitudes is very strong, indicating that people with favourable attitudes towards the one also have favourable attitudes towards the other.

5. Conclusion

This paper tried to answer two knowledge gaps in the literature on the relationship between travel attitudes and travel behaviour. The first knowledge gap considers whether this relationship changed during the COVID-19 pandemic. The second gap relates to the separation between within-person effects between travel attitudes and travel behaviour from the between-person correlations between these concepts. To address these knowledge gaps, we estimated a RI-CLPM on panel data from the Netherlands Mobility Panel spanning the years 2014 through 2021.

The results indicate that the relationship between attitudes and behaviour was weakened as a result of the COVID-19 pandemic, perhaps because other factors (such as constraints on mobility due to lockdown measures) played a larger role in determining behaviour and/or attitudes. As a result, we expect that the temporary deviations observed in both attitudes and behaviour during the pandemic will only have a diminished continued impact on the attitudes and behaviour post-pandemic. This could be considered good news, as it means that the more negative public transport and more positive car attitudes seen during the pandemic are unlikely to result in meaningful behavioural change post-pandemic.

Table 7
Correlations between random intercepts.

		Attitudes				Mode Use				
		Car	PT	Bike	Walk	Car	Train	BTM	Bike	Walk
Attitudes	Car									
	PT	−0.215								
	Bike	0.023	0.278							
	Walk	0.083	0.210	0.557						
Mode Use	Car	0.312	−0.174	0.038	0.123					
	Train	−0.110	0.138	0.080	0.023	−0.127				
	BTM	−0.046	0.145	−0.061	−0.030	−0.115	0.043			
	Bike	−0.165	0.209	0.414	0.075	−0.178	0.181	0.051		
	Walk	−0.155	0.061	0.139	0.354	0.000	0.023	−0.030	0.017	

Regarding the second gap, we find that the separation of within-person from between-person effects is highly relevant. We find that stable, trait-like differences between persons exist, both for attitudes and travel behaviour. The between-person correlations are strong and significant, indicating that these stable, trait-like differences are correlated with each other. For example, people with more favourable bicycle attitudes tend to use the bike more often and tend to have more favourable public transport attitudes. Due to the existence of such between-person relationships, methods that do not account for them will overestimate the strength of the within-person effects of changes in attitudes on travel behaviour and vice versa..

These results imply that researchers who are not able to separate within-person effects from between-person correlations should be careful when interpreting results regarding the relationship between attitudes and travel behaviour. In particular, they should be careful when recommending policies intended to somehow intervene and change travel-related attitudes with the end goal of indirectly influencing travel behaviour. These policies depend on within-person causal effects from attitudes on behaviour (De Vos, 2022), and our results show that these within-person effects *do exist*, but that they are much weaker than one would expect based on cross-sectional data for two reasons. First, the already known problem of endogeneity, where part of the relationship runs in the opposite direction (Chorus & Kroesen, 2014), and now second, the discovery that part of this relationship depends on between-person differences rather than within-person effects.

There are several interesting avenues for future research to explore. First, now that most of the COVID-19 pandemic seems to be in the past we are getting access to data collected in a post-pandemic world. This would allow for estimations of the relations between attitudes and behaviour not just before and during, but also after the pandemic. It would be interesting to see whether these post-pandemic relationships are more similar to the relationships before or during the pandemic. This information could be used to confirm or reject our suspicion that these relations will return to pre-pandemic levels and to see whether there are any lingering effects of COVID-19-related changes in attitudes on post-pandemic travel behaviour.

Second, it could be interesting to explore the within-person relationships between travel behaviour and different types of attitudes, such as attitudes related to climate change. Such research might for example find whether the increasing concerns relating to climate change will lead to changes in travel behaviour.

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CRediT authorship contribution statement

R.M. Faber: Conceptualization, Data curation, Formal analysis, Methodology, Visualization, Writing – original draft. **M.C. de Haas:** Conceptualization, Data curation, Formal analysis, Methodology. **E.J.E. Molin:** Conceptualization, Methodology, Supervision, Writing – review & editing. **M. Kroesen:** Conceptualization, Methodology, Supervision, Writing – review & editing.

Declaration of competing interest

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

Data availability

Data from the MPN is made available for research purposes two years after collection. As such, part of the data is available upon request already, and another part will be made available in the future

Appendix A. Estimation results

This appendix contains the parameter estimates for both the Cross-Lagged Panel Model and the Random Intercept Cross-Lagged Panel Model. In all tables, the independent variables are given in the rows and the dependent variables are given as columns. The tables contain both the parameter estimate and the corresponding Z-value, the latter of which is given within parentheses.

Cross-lagged panel model

2014 to 2016

Independent variables		Dependent Variable							
		Distance					Attitudes		
Distance		**Car**	**Train**	**Bus, tram, and metro**	**Bicycle**	**Walking**	**Car**	**Public Transport**	**Bicycle**
	Car	0.372 (10.4)	0.0117 (0.952)	−0.000554 (−0.162)	−0.0029 (−1.52)	0.000705 (1.23)	0.0265 (3.09)	−0.00535 (−0.571)	0.033 (3.51)
	Train	−0.00438 (−0.144)	0.314 (6.18)	0.00213 (0.309)	0.00151 (0.392)	0.00225 (1.64)	−0.033 (−1.88)	0.00201 (0.139)	0.0194 (1.22)

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Independent variables		Dependent Variable							
		Distance					Attitudes		
	Bus, tram, and metro	−0.132 (−1.63)	−0.000818 (−0.0182)	0.22 (2.68)	0.0123 (1.11)	0.00182 (0.417)	0.13 (2.44)	0.0326 (0.605)	0.00115 (0.0132)
	Bicycle	−0.0814 (−0.608)	0.187 (1.84)	0.00799 (0.232)	0.427 (11.0)	0.0066 (1.36)	0.0293 (0.457)	0.0498 (0.73)	0.482 (6.47)
	Walking	0.279 (0.583)	−0.293 (−1.17)	0.082 (1.34)	−0.0615 (−1.05)	0.386 (7.78)	−0.137 (−0.647)	−0.214 (−0.829)	−0.157 (−0.564)
Attitude	**Car**	0.151 (4.81)	−0.0249 (−1.43)	−0.00136 (−0.215)	−0.0146 (−4.33)	−0.00368 (−3.5)	0.575 (30.8)	−0.0615 (−3.72)	−0.0513 (−2.91)
	Public Transport	−0.11 (−2.58)	0.0472 (2.61)	0.0233 (4.82)	0.00131 (0.399)	1.69e-05 (0.0194)	−0.0918 (−6.4)	0.647 (37.1)	−0.0273 (−1.53)
	Bicycle	0.0273 (0.796)	−0.0158 (−0.839)	−0.018 (−3.2)	0.0192 (5.45)	0.00129 (1.51)	−0.00739 (−0.522)	0.0319 (1.97)	0.635 (32.4)

2016 to 2018

Independent Variables		Dependent Variables								
		Distance					Attitudes			
Dista		**Car**	**Train**	**Bus, tram, and metro**	**Bicycle**	**Walking**	**Car**	**Public Transport**	**Bicycle**	**Walking**
	Car	0.275 (6.21)	−0.00119 (−0.175)	−0.00409 (−2.25)	−0.00292 (−1.44)	0.00217 (1.19)	0.0277 (3.46)	0.00188 (0.251)	0.0474 (5.08)	0.0412 (3.48)
	Train	0.00632 (0.217)	0.227 (3.65)	−0.000104 (−0.0324)	0.00266 (0.638)	−0.00152 (−1.73)	−0.0154 (−1.47)	0.0271 (2.41)	0.0198 (1.66)	−0.0162 (−0.985)
	Bus, tram, and metro	0.0023 (0.0513)	−0.0261 (−1.13)	0.085 (1.65)	0.00535 (0.518)	−0.00394 (−0.536)	0.0444 (1.44)	0.0461 (2.06)	−0.0795 (−3.5)	−0.00947 (−0.231)
	Bicycle	−0.288 (−1.57)	−0.0935 (−2.11)	0.00564 (0.331)	0.594 (8.95)	−0.0005 (−0.075)	−0.0984 (−1.55)	0.177 (2.83)	0.396 (6.09)	−0.238 (−2.71)
	Walking	0.266 (0.487)	−0.0309 (−0.163)	−0.0613 (−1.64)	0.183 (1.74)	0.26 (5.75)	−0.82 (−3.61)	−0.271 (−1.21)	0.118 (0.399)	2.75 (6.91)
Attitude	**Car**	0.166 (4.61)	−0.0447 (−3.2)	0.00127 (0.389)	−0.00675 (−1.65)	0.00281 (0.695)	0.601 (36.9)	−0.0731 (−4.73)	−0.0145 (−0.832)	0.0325 (1.67)
	Public Transport	−0.031 (−1.0)	0.0289 (2.59)	0.0155 (2.91)	0.00421 (1.26)	0.00125 (0.53)	−0.0474 (−3.45)	0.621 (41.6)	0.0222 (1.37)	0.0365 (1.87)
	Bicycle	0.0459 (1.74)	0.0282 (2.66)	−0.00536 (−1.88)	0.0226 (4.33)	0.00855 (2.58)	−0.0464 (−3.61)	0.0589 (4.32)	0.634 (36.0)	0.356 (18.3)

2018 to 2020

Independent Variables		Dependent Variables								
		Distance					Attitudes			
Distance		**Car**	**Train**	**Bus, tram, and metro**	**Bicycle**	**Walking**	**Car**	**Public Transport**	**Bicycle**	**Walking**
	Car	0.156 (6.32)	−0.00201 (−0.696)	−0.00087 (−1.01)	−0.00188 (−0.824)	−0.00129 (−1.24)	0.0128 (1.91)	0.0035 (1.04)	0.00255 (0.572)	0.00257 (0.353)
	Train	0.0255 (1.11)	0.0832 (4.03)	−0.00272 (−1.44)	0.000643 (0.112)	−0.0014 (−0.548)	−0.0238 (−1.36)	0.0306 (1.94)	0.0171 (0.921)	0.00749 (0.447)
	Bus, tram, and metro	−0.134 (−2.87)	0.018 (0.607)	0.12 (2.42)	−0.00488 (−0.476)	−0.00906 (−0.976)	−0.15 (−1.62)	0.0266 (0.409)	−0.11 (−1.73)	0.0188 (0.346)
	Bicycle	−0.0356 (−0.537)	0.0245 (1.29)	−0.00507 (−0.456)	0.214 (7.38)	0.00298 (0.415)	−0.00141 (−0.0347)	0.0343 (0.85)	0.36 (5.94)	0.0752 (1.39)
	Walking	0.0728 (0.513)	−0.0564 (−1.41)	−0.102 (−0.151)	−0.0133 (−0.254)	0.106 (1.28)	−0.0923 (−0.559)	−0.129 (−1.69)	0.139 (1.86)	0.225 (1.86)
Attitude	**Car**	0.142 (8.1)	−0.00548 (−1.04)	−0.00284 (−0.498)	−0.011 (−2.4)	−0.00752 (−1.23)	0.568 (35.8)	−0.098 (−6.75)	−0.0375 (−2.43)	−0.0126 (−0.822)
	Public Transport	−0.0603 (−3.52)	0.0186 (3.78)	0.00366 (1.62)	0.00908 (1.97)	−0.000857 (−0.362)	−0.0598 (−4.76)	0.65 (39.9)	0.00312 (0.2)	−0.00119 (−0.081)
	Bicycle	0.0182 (0.951)	−0.00369 (−0.806)	0.00363 (1.21)	0.0344 (5.21)	0.00578 (1.83)	0.0292 (2.19)	0.00738 (0.458)	0.62 (32.6)	0.0495 (2.84)
	Walking	0.0481 (2.61)	0.000152 (0.032)	−0.00407 (−0.311)	−0.0107 (−2.58)	0.0143 (3.75)	−0.0208 (−1.59)	0.0412 (2.55)	0.0773 (4.09)	0.635 (34.9)

2020 to 2021

Independent Variables		Dependent Variables								
		Distance					Attitudes			
Distance		**Car**	**Train**	**Bus, tram, and metro**	**Bicycle**	**Walking**	**Car**	**Public Transport**	**Bicycle**	**Walking**

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Independent Variables		Dependent Variables								
		Distance					Attitudes			
	Car	0.315 (10.3)	−0.00461 (−0.835)	−0.00141 (−1.4)	−0.00741 (−2.29)	0.00093 (0.733)	0.0303 (3.6)	−0.0107 (−1.1)	0.0302 (3.05)	0.0276 (2.9)
	Train	−0.0571 (−1.51)	0.295 (5.18)	0.0171 (1.04)	0.000506 (0.059)	−0.00295 (−0.973)	0.00187 (0.0676)	0.0345 (1.39)	−0.0161 (−0.522)	0.00741 (0.276)
	Bus, tram, and metro	−0.0173 (−0.156)	0.0242 (0.344)	0.617 (4.18)	−0.0285 (−1.88)	−0.00703 (−1.01)	−0.0421 (−0.341)	0.0848 (1.23)	0.071 (0.58)	−0.00338 (−0.0226)
	Bicycle	−0.0518 (−1.36)	0.0253 (1.11)	0.00815 (1.1)	0.144 (1.87)	−0.0119 (−1.42)	−0.028 (−1.03)	0.0204 (0.73)	0.119 (2.87)	−0.0417 (−1.45)
	Walking	0.0446 (0.753)	−0.0067 (−0.271)	−0.00635 (−0.966)	−0.103 (−1.81)	0.0679 (2.12)	0.0145 (0.178)	−0.069 (−2.13)	0.062 (1.08)	0.122 (1.41)
Attitude	Car	0.103 (5.25)	−0.0239 (−2.24)	−0.00159 (−0.603)	−0.0227 (−3.18)	−0.00603 (−2.81)	0.623 (30.7)	−0.0328 (−2.45)	−0.00202 (−0.114)	−0.0251 (−1.43)
	Public Transport	−0.064 (−3.3)	0.0371 (4.46)	0.00364 (1.8)	0.00788 (2.26)	0.000966 (0.481)	−0.0412 (−3.37)	0.643 (43.6)	0.0131 (0.898)	0.00564 (0.365)
	Bicycle	−0.00581 (−0.304)	0.00878 (1.54)	−0.00125 (−0.728)	0.0505 (8.45)	−0.00163 (−0.961)	−0.0194 (−1.38)	0.0277 (1.97)	0.631 (34.1)	0.0334 (1.86)
	Walking	0.0538 (2.58)	0.00809 (1.18)	−0.000891 (−0.418)	−0.0121 (−3.11)	0.0148 (9.81)	0.0183 (1.29)	0.0414 (2.79)	0.0256 (1.43)	0.653 (34.1)

Random intercept cross-lagged panel model

2014 to 2016

Independent variables		Dependent Variable							
		Distance					Attitudes		
Distance		**Car**	**Train**	**Bus, tram, and metro**	**Bicycle**	**Walking**	**Car**	**Public Transport**	**Bicycle**
	Car	0.217 (5.59)	0.0136 (0.856)	0.00126 (0.286)	−0.00811 (−2.88)	0.00051 (0.625)	0.0115 (1.11)	−0.0221 (−1.98)	0.00706 (0.667)
	Train	−0.0313 (−0.946)	0.268 (5.14)	0.00354 (0.455)	−0.0101 (−2.12)	0.00405 (2.31)	−0.0497 (−2.64)	0.0199 (1.31)	0.0105 (0.558)
	Bus, tram, and metro	−0.175 (−1.63)	−0.00922 (−0.179)	0.147 (1.82)	0.00545 (0.337)	0.00515 (0.845)	0.0879 (1.29)	0.061 (0.907)	−0.0288 (−0.282)
	Bicycle	−0.198 (−1.02)	0.182 (1.27)	0.00111 (0.0211)	0.116 (1.57)	0.0111 (0.851)	0.043 (0.429)	−0.11 (−1.09)	0.19 (1.77)
	Walking	0.185 (0.276)	−0.335 (−0.946)	0.113 (1.19)	−0.055 (−0.402)	0.115 (1.33)	0.533 (1.62)	−0.615 (−1.67)	−0.335 (−0.89)
Attitude	**Car**	0.0934 (1.54)	−0.0388 (−1.34)	0.00816 (0.661)	−0.0128 (−1.62)	0.00137 (0.686)	0.11 (3.32)	0.0109 (0.364)	−0.0857 (−2.73)
	Public Transport	−0.168 (−1.6)	0.0937 (2.52)	0.0329 (3.41)	0.00541 (0.701)	−0.00235 (−1.15)	−0.048 (−1.52)	0.098 (2.38)	−0.02 (−0.507)
	Bicycle	−0.0255 (−0.418)	−0.0235 (−0.734)	−0.0299 (−2.84)	−0.00314 (−0.437)	0.0011 (0.574)	0.00104 (0.0395)	0.0162 (0.537)	0.193 (5.27)

2016 to 2018

Independent Variables		Dependent Variables								
		Distance					Attitudes			
Distance		**Car**	**Train**	**Bus, tram, and metro**	**Bicycle**	**Walking**	**Car**	**Public Transport**	**Bicycle**	**Walking**
	Car	0.121 (3.85)	−0.00643 (−0.74)	−0.00401 (−1.84)	−0.00467 (−1.86)	0.00275 (1.46)	0.011 (1.23)	−0.00467 (−0.503)	0.0316 (3.19)	0.0229 (2.25)
	Train	−0.0124 (−0.362)	0.176 (3.27)	−0.000667 (−0.205)	−0.00327 (−0.777)	−0.00142 (−1.43)	−0.0139 (−1.15)	0.0428 (3.45)	0.0247 (1.85)	0.0105 (0.669)
	Bus, tram, and metro	0.0101 (0.251)	−0.0282 (−1.16)	0.049 (1.36)	0.000917 (0.0879)	−0.00492 (−0.588)	0.0457 (1.37)	0.027 (0.868)	−0.105 (−3.77)	−0.0231 (−0.613)
	Bicycle	−0.215 (−0.764)	−0.323 (−3.46)	0.000557 (0.0198)	0.265 (2.84)	−0.0115 (−0.921)	−0.0288 (−0.262)	0.134 (1.15)	−0.0482 (−0.399)	−0.178 (−1.33)
	Walking	0.788 (1.14)	0.176 (0.559)	−0.122 (−1.3)	0.185 (0.856)	−0.0913 (−1.02)	−0.0258 (−0.0701)	−0.878 (−2.54)	−0.263 (−0.679)	−0.0947 (−0.28)
Attitude	**Car**	0.0231 (0.505)	−0.0608 (−2.44)	0.000694 (0.109)	0.00656 (0.926)	0.0145 (2.13)	0.106 (3.29)	−0.0307 (−0.967)	−0.0305 (−0.924)	−0.0187 (−0.589)
	Public Transport	0.0731 (1.13)	0.05 (2.12)	0.013 (1.03)	−0.00605 (−0.862)	−6.61e-05 (−0.0243)	0.000236 (0.00772)	0.0728 (1.7)	−0.0486 (−1.3)	−0.0982 (−2.7)
	Bicycle	0.0429 (0.96)	0.0317 (1.55)	−0.00364 (−0.608)	0.0051 (0.645)	0.00601 (1.71)	−0.0895 (−3.27)	0.0327 (1.07)	0.162 (4.44)	0.0995 (3.13)

2018 to 2020

(*continued on next page*)

(*continued*)

Independent Variables		Dependent Variables								
		Distance					Attitudes			
Independent Variables		Dependent Variables								
		Distance					Attitudes			
Distance		**Car**	**Train**	**Bus, tram, and metro**	**Bicycle**	**Walking**	**Car**	**Public Transport**	**Bicycle**	**Walking**
	Car	0.0688 (2.05)	0.00206 (0.618)	−0.00104 (−0.546)	−0.00105 (−0.371)	−0.00159 (−1.37)	0.00516 (1.33)	0.00643 (2.12)	−0.000617 (−0.16)	−0.000846 (−0.129)
	Train	0.0076 (0.308)	−0.0322 (−1.14)	−0.000344 (−0.103)	−0.01 (−1.31)	−0.00103 (−0.323)	−0.0307 (−1.43)	0.0653 (3.34)	0.017 (0.716)	0.0263 (1.07)
	Bus, tram, and metro	−0.0831 (−1.32)	0.0321 (1.03)	−0.0608 (−0.952)	−0.0166 (−1.0)	−0.0138 (−2.09)	−0.168 (−1.48)	0.0227 (0.244)	−0.137 (−1.39)	−0.0016 (−0.0186)
	Bicycle	0.187 (2.12)	−0.0833 (−2.43)	−0.0126 (−0.813)	−0.0654 (−1.71)	0.00309 (0.185)	0.0713 (1.25)	−0.0131 (−0.215)	0.149 (2.01)	0.0514 (0.646)
	Walking	0.0987 (0.698)	−0.0761 (−1.47)	−0.0369 (−0.112)	−0.0236 (−0.599)	0.0861 (1.4)	0.0171 (0.107)	−0.0883 (−1.14)	0.147 (2.15)	0.179 (1.92)
Attitude	**Car**	−0.0156 (−0.496)	0.0144 (1.29)	−0.000258 (−0.0626)	0.00702 (0.687)	−0.00845 (−0.773)	0.0984 (3.27)	−0.0669 (−2.17)	−0.0407 (−1.23)	−0.0192 (−0.567)
	Public Transport	0.0633 (1.87)	0.00497 (0.417)	−0.00788 (−1.81)	−0.00252 (−0.202)	−0.00715 (−1.21)	0.0121 (0.419)	0.157 (4.04)	−0.0226 (−0.664)	0.000701 (0.0199)
	Bicycle	0.0441 (1.17)	−0.0142 (−1.41)	0.0165 (2.43)	−0.0129 (−1.15)	0.0158 (2.31)	0.0587 (1.91)	−0.0161 (−0.445)	0.189 (3.99)	0.116 (2.84)
	Walking	−0.00187 (−0.0368)	0.00348 (0.201)	−0.0109 (−1.02)	−0.00542 (−0.454)	0.0153 (1.52)	−0.0543 (−1.48)	0.0392 (0.848)	0.105 (1.89)	−0.00346 (−0.0586)

2020 to 2021

Independent Variables		Dependent Variables								
		Distance					Attitudes			
Distance		**Car**	**Train**	**Bus, tram, and metro**	**Bicycle**	**Walking**	**Car**	**Public Transport**	**Bicycle**	**Walking**
	Car	−0.0738 (−1.2)	0.00436 (0.29)	0.00116 (0.606)	0.0025 (0.48)	0.00274 (1.25)	−0.0308 (−1.85)	0.0234 (1.6)	0.0291 (1.72)	−0.000633 (−0.0325)
	Train	−0.00862 (−0.0634)	−0.396 (−1.46)	0.0361 (1.19)	−0.0713 (−2.24)	−0.0101 (−1.18)	0.131 (1.8)	−0.0135 (−0.259)	−0.0934 (−1.1)	0.0562 (0.69)
	Bus, tram, and metro	0.598 (1.3)	0.0022 (0.00892)	0.243 (0.858)	−0.0586 (−0.837)	−0.0237 (−0.281)	0.201 (0.742)	−0.199 (−0.684)	0.265 (0.784)	−0.00219 (−0.00529)
	Bicycle	−0.00223 (−0.0577)	−0.0518 (−1.34)	0.00865 (0.955)	0.0299 (1.33)	−0.0109 (−1.49)	0.0362 (1.01)	−0.0574 (−2.2)	−0.0289 (−0.625)	−0.0574 (−1.46)
	Walking	−0.00931 (−0.18)	0.0382 (0.906)	−0.00905 (−1.13)	−0.0511 (−1.58)	0.0539 (1.97)	−0.0291 (−0.349)	−0.0912 (−2.01)	0.131 (1.49)	0.104 (1.17)
Attitude	**Car**	−0.0451 (−1.1)	−0.00272 (−0.148)	0.00181 (0.432)	−0.00407 (−0.509)	0.00194 (0.573)	0.186 (5.27)	0.04 (1.58)	0.0419 (1.21)	−0.0436 (−1.29)
	Public Transport	0.000293 (0.00879)	0.047 (3.39)	−0.000178 (−0.0486)	−0.0046 (−0.805)	−1.27e-05 (−0.00507)	−0.0179 (−0.727)	0.293 (11.3)	−0.0381 (−1.4)	0.00155 (0.0518)
	Bicycle	0.00466 (0.129)	−0.0171 (−1.22)	0.000178 (0.0445)	0.0169 (2.14)	0.000589 (0.195)	0.0176 (0.69)	−0.0422 (−1.66)	0.272 (7.1)	0.139 (3.69)
	Walking	−0.0143 (−0.323)	0.036 (1.9)	−0.00132 (−0.244)	−0.00418 (−0.568)	0.00395 (1.28)	0.0161 (0.544)	0.0619 (2.17)	0.0287 (0.712)	0.152 (3.33)

References

Ajzen, I., 1985. From intentions to actions: a theory of planned behavior. In: *Action Control,* pp. 11–39. Doi: 10.1007/978-3-642-69746-3_2.

Ajzen, I., 1991. The theory of planned behavior. In: *Organizational Behavior and Human Decision Processes,* vol. 50, pp. 179–211.

Bamberg, S., 2006. Is a residential relocation a good opportunity to change people's travel behavior?: Results from a theory-driven intervention study. Environ. Behav. 38 (6), 820–840. https://doi.org/10.1177/0013916505285091.

Beck, M.J., Hensher, D.A., 2020. Insights into the impact of COVID-19 on household travel and activities in Australia – The early days of easing restrictions. Transp. Policy 99, 95–119. https://doi.org/10.1016/j.tranpol.2020.08.004.

Beck, M.J., Hensher, D.A., Nelson, J.D., 2021. Public transport trends in Australia during the COVID-19 pandemic: An investigation of the influence of bio-security concerns on trip behaviour. J. Transp. Geogr. 96 https://doi.org/10.1016/j.jtrangeo.2021.103167.

Ben-Akiva, M., Mcfadden, D., Train, K., Walker, J., Bhat, C., Bierlaire, M., Bolduc, D., Boersch-Supan, A., Brownstone, D., Bunch, D.S., Daly, A., De Palma, A., Gopinath, D., Karlstrom, A., Munizaga, M.A., 2002. Hybrid choice models: progress and challenges. Mark. Lett. 13 (3), 163–175. https://doi.org/10.1023/A:1020254301302/METRICS.

Bohman, H., Ryan, J., Stjernborg, V., Nilsson, D., 2021. A study of changes in everyday mobility during the Covid-19 pandemic: As perceived by people living in Malmö, Sweden. Transp. Policy 106, 109–119. https://doi.org/10.1016/j.tranpol.2021.03.013.

Bohner, G., Dickel, N., 2010. Attitudes and attitude change *62*, 391–417. Doi: 10.1146/ANNUREV.PSYCH.121208.131609.

Bohte, W., Maat, K., van Wee, B., 2009. Measuring attitudes in research on residential self-selection and travel behaviour: a review of theories and empirical research *29*(3), 325–357. Doi: 10.1080/01441640902808441.

Campisi, T., Tesoriere, G., Trouva, M., Papas, T., Basbas, S., 2022. Impact of teleworking on travel behaviour during the COVID-19 Era: the case of Sicily, Italy. Transp. Res. Proc. 60, 251–258. https://doi.org/10.1016/J.TRPRO.2021.12.033.

Cao, X.J., Mokhtarian, P.L., Handy, S.L., 2009. Examining the impacts of residential self-selection on travel behaviour: A focus on empirical findings. Transp. Rev. 29 (3), 359–395. https://doi.org/10.1080/01441640802539195.

Chorus, C.G., Kroesen, M., 2014. On the (im-)possibility of deriving transport policy implications from hybrid choice models. Transp. Policy 36, 217–222. https://doi.org/10.1016/J.TRANPOL.2014.09.001.

Currie, G., Jain, T., Reynolds, J., Aston, L., 2022. Spatial impacts of COVID-19 on long term commuting in Melbourne. Australasian Transport Res. Forum. http://www.atrf.info.

de Haas, M., Faber, R., Hamersma, M., 2020. How COVID-19 and the Dutch 'intelligent lockdown' change activities, work and travel behaviour: Evidence from longitudinal data in the Netherlands. Transport. Res. Interdisciplinary Perspect. 6 https://doi.org/10.1016/j.trip.2020.100150.

de Palma, A., Vosough, S., Liao, F., 2022. An overview of effects of COVID-19 on mobility and lifestyle: 18 months since the outbreak. Transp. Res. A Policy Pract. 159, 372–397. https://doi.org/10.1016/J.TRA.2022.03.024.

de Vos, J., 2020. The effect of COVID-19 and subsequent social distancing on travel behavior. Transport. Res. Interdisciplinary Perspect. 5, 100121 https://doi.org/10.1016/j.trip.2020.100121.

De Vos, J., 2022. The shifting role of attitudes in travel behaviour research. Transp. Rev. 1–7 https://doi.org/10.1080/01441647.2022.2078537.

Derrible, S., Kennedy, C., 2011. Applications of Graph Theory and Network Science to Transit Network Design. *31*(4), 495–519. Doi: 10.1080/01441647.2010.543709.

Downey, L., Fonzone, A., Fountas, G., Semple, T., 2022. The impact of COVID-19 on future public transport use in Scotland. Transp. Res. A Policy Pract. 163, 338–352. https://doi.org/10.1016/J.TRA.2022.06.005.

Eagly, A.H., Chaiken, S., 1993. The psychology of attitudes. Harcourt brace Jovanovich college publishers.

Eisenmann, C., Nobis, C., Kolarova, V., Lenz, B., Winkler, C., 2021. Transport mode use during the COVID-19 lockdown period in Germany: The car became more important, public transport lost ground. Transp. Policy 103, 60–67. https://doi.org/10.1016/j.tranpol.2021.01.012.

Eriksson, L., Forward, S.E., 2011. Is the intention to travel in a pro-environmental manner and the intention to use the car determined by different factors? Transp. Res. Part D: Transp. Environ. 16 (5), 372–376. https://doi.org/10.1016/J.TRD.2011.02.003.

Faber, R., Merkies, R., Damen, W., Oirbans, L., Massa, D., Kroesen, M., Molin, E., 2021. The role of travel-related reasons for location choice in residential self-selection. Travel Behav. Soc. 25, 120–132. https://doi.org/10.1016/j.tbs.2021.07.003.

Faber, R., Hamersma, M., de Haas, M., Krabbenborg, L., Hoen, A., 2023. Estimating post-pandemic effects of working from home and teleconferencing on travel behaviour. Eur. J. Transp. Infrastruct. Res. 23 (1), 33–62. https://doi.org/10.18757/EJTIR.2023.23.1.6733.

Finkel, S., 2011. In: Causal Analysis with Panel Data. SAGE Publications. https://doi.org/10.4135/9781412983594.

Gärling, T., Gillholm, R., Gärling, A., 1998. Reintroducing attitude theory in travel behavior research: The validity of an interactive interview procedure to predict car use. Transportation 25 (2), 129–146. https://doi.org/10.1023/A:1005004311776.

Grace, J.B., Schoolmaster, D.R., Guntenspergen, G.R., Little, A.M., Mitchell, B.R., Miller, K.M., Schweiger, E.W., 2012. Guidelines for a graph-theoretic implementation of structural equation modeling. Article 3 (8). https://doi.org/10.1890/ES12-00048.1.

Hamaker, E.L., Kuiper, R.M., Grasman, R.P., 2015. A critique of the cross-lagged panel model. Psychol. Methods 20 (1), 102–116. https://doi.org/10.1037/a0038889.

Hamaker, E.L., 2012. Why researchers should think "within-person": A paradigmatic rationale RI-CLPM. In *Handbook of Research Methods for Studying Daily life,* pp. 43–61. https://www.researchgate.net/publication/266896375.

Hensher, D.A., Beck, M.J., Balbontin, C., 2023. Working from home 22 months on from the beginning of COVID-19: What have we learned for the future provision of transport services? Res. Transp. Econ. 98, 101271 https://doi.org/10.1016/J.RETREC.2023.101271.

Hoffmann, C., Abraham, C., White, M.P., Ball, S., Skippon, S.M., 2017. What cognitive mechanisms predict travel mode choice? A systematic review with meta-analysis. Transp. Rev. 37 (5), 631–652. https://doi.org/10.1080/01441647.2017.1285819/SUPPL_FILE/TTRV_A_1285819_SM6503.DOCX.

Hoogendoorn-Lanser, S., Schaap, N.T.W., Olde Kalter, M.J., 2015. The netherlands mobility panel: An innovative design approach for web-based longitudinal travel data collection. Transp. Res. Procedia 11, 311–329. https://doi.org/10.1016/j.trpro.2015.12.027.

Javadinasr, M., Maggasy, T., Mohammadi, M., Mohammadain, K., Rahimi, E., Salon, D., Conway, M.W., Pendyala, R., Derrible, S., 2022. The Long-Term effects of COVID-19 on travel behavior in the United States: A panel study on work from home, mode choice, online shopping, and air travel. Transport. Res. F: Traffic Psychol. Behav. 90, 466–484. https://doi.org/10.1016/j.trf.2022.09.019.

Kitamura, R., Mokhtarian, P.L., Laidet, L., 1997. A micro-analysis of land use and travel in five neighborhoods in the San Francisco Bay Area. Transportation 24 (2), 125–158. https://doi.org/10.1023/A:1017959825565.

Kolarova, V., Eisenmann, C., Nobis, C., Winkler, C., Lenz, B., 2021. Analysing the impact of the COVID-19 outbreak on everyday travel behaviour in Germany and potential implications for future travel patterns. Eur. Transp. Res. Rev. 13 (1), 1–11. https://doi.org/10.1186/S12544-021-00486-2/FIGURES/7.

Kroesen, M., 2019. Residential self-selection and the reverse causation hypothesis: Assessing the endogeneity of stated reasons for residential choice. Travel Behav. Soc. 16, 108–117. https://doi.org/10.1016/j.tbs.2019.05.002.

Kroesen, M., Chorus, C., 2018. The role of general and specific attitudes in predicting travel behavior – A fatal dilemma? Travel Behav. Soc. 10, 33–41. https://doi.org/10.1016/j.tbs.2017.09.004.

Kroesen, M., Chorus, C., 2020. A new perspective on the role of attitudes in explaining travel behavior: A psychological network model. Transp. Res. A Policy Pract. 133, 82–94. https://doi.org/10.1016/j.tra.2020.01.014.

Kroesen, M., Handy, S., Chorus, C., 2017. Do attitudes cause behavior or vice versa? An alternative conceptualization of the attitude-behavior relationship in travel behavior modeling. Transp. Res. A Policy Pract. 101, 190–202. https://doi.org/10.1016/j.tra.2017.05.013.

Kroesen, M., De Vos, J., Le, H.T.K., Ton, D., 2023. Exploring attitude-behaviour dynamics during COVID-19: How fear of infection and working from home influence train use and the attitude toward this mode. Transp. Res. A Policy Pract. 167, 103560 https://doi.org/10.1016/J.TRA.2022.103560.

Manser, P., Stutzmann, N., Sieber, L., Bischoff, J., Bützberger, P., 2022, May 22. Agent-based simulation of mobility behaviour in-duced by working from home. *STRC 2022*.

Mulder, J.D., Hamaker, E.L., 2020. Three Extensions of the Random Intercept Cross-Lagged Panel Model. Struct. Equ. Model. Multidiscip. J. 28 (4), 638–648. https://doi.org/10.1080/10705511.2020.1784738.

Olde Kalter, M.J., La Paix Puello, L., Geurs, K.T., 2020. Do changes in travellers' attitudes towards car use and ownership over time affect travel mode choice? A latent transition approach in the Netherlands. Transp. Res. A Policy Pract. 132, 1–17. https://doi.org/10.1016/j.tra.2019.10.015.

Olde Kalter, M.J., La Paix Puello, L., Geurs, K.T., 2021. Exploring the relationship between life events, mode preferences and mode use of young adults: A 3-year cross-lagged panel analysis in the Netherlands. Travel Behav. Soc. 24, 195–204. https://doi.org/10.1016/j.tbs.2021.04.004.

Ostrom, T.M., 1969. The relationship between the affective, behavioral, and cognitive components of attitude. J. Exp. Soc. Psychol. 5 (1), 12–30. https://doi.org/10.1016/0022-1031(69)90003-1.

Parkany, E., Gallagher, R., Viveiros, P., 2004. Are Attitudes Important in Travel Choice? *1894*(1894), 127–139. Doi: 10.3141/1894-14.

R Core Team, 2017. *R: A Language and Environment for Statistical Computing.* R Foundation for Statistical Computing. https://www.r-project.org/.

Rafiq, R., McNally, M.G., Sarwar Uddin, Y., Ahmed, T., 2022. Impact of working from home on activity-travel behavior during the COVID-19 Pandemic: An aggregate structural analysis. Transp. Res. A Policy Pract. 159, 35–54. https://doi.org/10.1016/J.TRA.2022.03.003.

Rosenberg, M., Hovland, C., McGuire, W. J., Abelson, R. P., Brehm, J. W., 1960. Attitude organization and change: An analysis of consistency among attitude components. *Yales Studies in Attitude and Communication, III.* https://psycnet.apa.org/record/1962-00924-000.

Rosseel, Y., 2012. lavaan: An R Package for Structural Equation Modeling. J. Stat. Softw. 48, 1–36. https://doi.org/10.18637/JSS.V048.I02.

Salas-Olmedo, M.H., Nogués, S., 2012. Analysis of commuting needs using graph theory and census data: A comparison between two medium-sized cities in the UK. Appl. Geogr. 35 (1–2), 132–141. https://doi.org/10.1016/J.APGEOG.2012.05.004.

Selig, J. P., Little, T. D., 2012. Autoregressive and cross-lagged panel analysis for longitudinal data. In: Laursen, B., Little, T. D., Card, N. A. (Eds.), *Handbook of developmental research methods,* The Gulford Press, pp. 265–278. https://www.researchgate.net/publication/259453465_Autoregressive_and_cross-lagged_panel_analysis_for_longitudinal_data.

Thomas, F.M.F., Charlton, S.G., Lewis, I., Nandavar, S., 2021. Commuting before and after COVID-19. Transport. Res. Interdisciplinary Perspect. 11, 100423 https://doi.org/10.1016/J.TRIP.2021.100423.

Tirachini, A., Cats, O., 2020. COVID-19 and Public Transportation: Current Assessment, Prospects, and Research Needs. J. Public Transp. 22 (1), 1–34. https://doi.org/10.5038/2375-0901.22.1.1.

van Acker, V., van Wee, B., Witlox, F., 2010. When transport geography meets social psychology: Toward a conceptual model of travel behaviour. Transp. Rev. 30 (2), 219–240. https://doi.org/10.1080/01441640902943453.

van Wee, B., Cao, X.J., 2022. Residential self-selection in the relationship between the built environment and travel behavior: A literature review and research agenda. Adv. Transport Policy Planning 9, 75–94. https://doi.org/10.1016/bs.atpp.2020.08.004.

Van Wee, B., De Vos, J., Maat, K., 2019. Impacts of the built environment and travel behaviour on attitudes: Theories underpinning the reverse causality hypothesis. J. Transp. Geogr. 80, 102540 https://doi.org/10.1016/j.jtrangeo.2019.102540.

van Wee, B., Witlox, F., 2021. COVID-19 and its long-term effects on activity participation and travel behaviour: A multiperspective view. J. Transp. Geogr. 95, 103144 https://doi.org/10.1016/J.JTRANGEO.2021.103144.

Vos, J. De., 2022. The shifting role of attitudes in travel behaviour research. 1–7. Doi: 10.1080/01441647.2022.2078537.