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Exploring attitude-behaviour dynamics during COVID-19: How fear of infection and working from home influence train use and the attitude toward this mode

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ABSTRACT

Research on the relationships between travel-related attitudes and travel behaviour has recently been reinvigorated by new theorizing as well as new empirical models. While traditional theories assume a rather static role of attitudes, i.e. acting as stable predispositions that cause behaviours in a unidirectional manner, recent models assume that attitudes and behaviours mutually influence each other over time. This study aims at better understanding attitude-behaviour dynamics by capitalizing on the circumstances presented by the ongoing COVID-19 pandemic. It assesses how the fear of COVID-19 infection and (the attitude towards) working-from-home influence train use as well as train use attitudes. To explore the (within-person) reciprocal relationships between these variables, random-intercept cross-lagged panel models were estimated using a 4-wave longitudinal dataset collected during the COVID-19 pandemic from a large panel of train travellers in the Netherlands. The results indicate that train use and the attitude towards train use reciprocally influence each other. Those with stronger fears of infection in one wave tend to use the train less in a subsequent wave, but higher use of the train in one wave also reduces the fear of infection in the next. We also found that working from home (WFH) and travelling by train operate as substitutes for one another. Moreover, people who work from home frequently become more fearful of infection. All the findings are consistent with cognitive dissonance theory that people develop attitudes that align with their behaviours. The paper concludes with several policy implications related to changing attitudes and promoting train use.

1. Introduction

Research on the relationships between travel-related attitudes and travel behaviour has recently been reinvigorated by new theorizing (De Vos & Singleton, 2020; De Vos et al., 2021; Kroesen and Chorus, 2020; Van Wee et al., 2019) as well as new empirical models (Kroesen et al., 2017; Olde Kalter et al., 2021). While traditional theories and models (e.g. the Theory of Planned Behaviour) assume a rather static role of attitudes, i.e. acting as stable predispositions that cause behaviours in a unidirectional manner, recent theories and models assume that attitudes can change and that attitudes and behaviours mutually influence each other over time (De Vos et al., 2021; Kroesen et al., 2017). Classic social-psychological theories such as cognitive dissonance theory support such a dynamic

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perspective, i.e. to resolve dissonance between attitudes and behaviours, behaviours may be aligned with attitudes *or* attitudes may be aligned with behaviours. The recently introduced travel mode choice cycle proposed by De Vos et al. (2021), which, among others, draws from cognitive dissonance theory, also explicitly supports bidirectional effects between behaviours and attitudes, via travel satisfaction.

In line with the goal to better understand attitude-behaviour dynamics, Van Wee et al. (2019) have proposed a conceptual model of attitude change. Based on the earlier work of Eagly and Chaiken (1993), they identify-three interrelated mechanisms that may drive attitude change, namely cognitive, affective and behavioural mechanisms. In short, attitudes may change because a person is exposed to *new knowledge*, or because the person experiences *new emotions* or *feelings* and/or because the person engages in *new behaviours*. Often, these processes are interrelated. For example, a person who learns that cycling is good for health, may then start cycling and then experience that cycling is fun. In turn, this affective outcome may reinforce the behaviour and/or the cognitive belief. This argument has also recently been confirmed empirically by Kroesen and Chorus (2020) who show that cognitive and affective attitudes and behaviours influence each other in dynamic psychological networks.

Capitalizing on the circumstances presented by the ongoing COVID-19 pandemic, this research empirically follows up on the model proposed by Van Wee et al. (2019) and explores how the fear of COVID-19 infection and (the attitude towards) working-from-home influence train use as well as train use attitudes. The fear of infection can be seen as an entirely new element that has entered the 'attitude-behaviour domain' of train travel. As such, by studying its effects, a better understanding of the (general) processes of attitude-behaviour dynamics may arise. For example, it may be expected that people with stronger fears of getting infected will directly reduce their travel by train to reduce infection risks, but they may also revise their attitude toward travelling by train accordingly (i.e. they start disliking travel by train because of the fear). In addition, reverse effects may also exist. For example, if a person has a favourable travel experience by train (during the pandemic), e.g. because the train was not perceived as (too) crowded, the person may adjust his/her fear of infection downwards (or upwards, if the experience was bad). Furthermore, the attitude may also affect the fear of infection. For example, a person who really likes to travel by train may suppress and/or downplay his/her fears. By assessing which of these effects actually occur, new theoretical insights on how the fear of infection as a new disposition would inform the dynamics in this particular attitude-behaviour domain.

In addition to the fear of infection, working from home (WFH) and the attitude towards this behaviour also present new elements that may influence train use and/or the attitude towards train use. While WFH has been around before COVID-19, it has received a strong boost, partly due to the travel restrictions imposed by national governments (e.g., Mohammadian et al., 2022; Ton et al., 2022a; Wang et al., 2022). Here, it may be expected that the extent to which a person works from home directly functions as a substitute for travel by train. In addition, also the attitude toward WFH may play a role. As shown by Rubin et al. (2020) and Beck et al. (2020), experiences with WFH differ greatly among people and these may also determine the current and future use of the train (Ton et al., 2022a). Finally, reverse effects are also plausible for these relationships. For example, people who continue to travel by train or (still) like to travel by train may choose to work less from home and/or reduce their (positive) evaluation of it.

The objective of this study is to analyse how the fear of infection and (attitude towards) WFH influence the use of the train and the attitude toward the use of this mode. In addition to the theoretical contributions mentioned above, knowledge of these effects arguably has relevant practical implications. For example, should the fear of infection only influence the behaviour and not the attitude, it may be expected that travel behaviours, such as train use, will resume faster to pre-COVID-19 levels when the pandemic is over, or under control. However, should the fear of infection also influence the attitude towards train use, the current decline in train use will likely last longer.

To assess how the fear of infection and (attitude towards) WFH influence train use and the attitude towards train use as well as possible reverse effects, we estimate (two) random-intercept cross-lagged panel models (RI-CLPM) (Hamaker et al., 2015). This model is ideally suited to assess 'within-person' reciprocal effects between multiple variables over time. Data to estimate the model come from a large panel of train travellers in the Netherlands. In this panel a survey was administrated at four time points after the onset of the COVID-19 pandemic.

The structure of this paper is as follows. We will first briefly review the growing body of literature on attitude change in travel behaviour research and several empirical studies that have explored attitude changes in response to the COVID-19 crisis. Next, we will present the results of two models, one for the full sample to explore relationships between the (perceived) risk of infection, train use and train use attitude, and another model for the subsample of people who were able to work from home to additionally explore relationships with WFH and the attitude toward this behaviour. In discussing the results, we provide possible explanations for observed effects. The conclusion summarises the main findings and discusses implications for policy.

2. Background

2.1. Attitude change: Theory

Van Wee et al. (2019) recently presented a conceptual model of attitude change, in which attitude change is assumed to originate from three interrelated processes, namely cognitive, affective and behavioural processes. In turn, these processes may be activated by external triggers, which are categorized into personal, social and environmental triggers. According to Van Wee et al. (2019), personal triggers relate to an actor's own information and experiences, social triggers to influences from the actor's network (e.g. family, friends or colleagues) and environmental triggers to all other possible triggers from the surrounding environment, for example, changes in the residential environment or in the transport system. Similar to the three mechanisms of attitude change, the triggers may also be interrelated. For example, the birth of a child can be seen as both a personal and a social trigger, as it affects the actor directly, but also indirectly through his or her network.

Within the model of Van Wee et al. (2019), the COVID-19 pandemic can clearly be identified as an environmental trigger, which may have led to attitude changes in various ways. Because train travel implies being in physical proximity to other people, the fear of infection (as a new disposition) represents one such way. This new disposition may trigger cognitive, affective and behavioural processes leading to attitude change. On a cognitive level, people who are fearful of getting infected likely take this new information into account when deciding to ride public transport modes vis-à-vis private travel modes (e.g. car and bicycle) or not travelling at all (e.g. by WFH). On an affective level, the fear of getting infected may negatively influence a person's preference toward travelling by public transport modes and/or positively influence preferences toward travelling by private modes or WFH. And on a behavioural level, the actual decision to travel with modes other than those previously used (before COVID-19) or to WFH may have led to new experiences and thereby attitude change.

Although most social-psychological theories such as the Theory of Planned Behaviour (Ajzen, 1991), and the Theory of Interpersonal Behaviour (Triandis, 1977) suggest that attitudes are important predictors of behavioural intention, some also indicate that behaviour may affect attitudes. The relatively old Theory of Cognitive Dissonance (Festinger, 1957) and Balance Theory (Heider, 1958) indicate that attitudes may change, especially to reduce inconsistency between attitudes and behaviour. In case of such an inconsistency (or dissonance) people may either change their behaviour, or (in case changing behaviour is perceived impossible) change their attitudes. In terms of travel, this would mean that people who (are forced to) travel with an undesired travel mode will try to change their behaviour (i.e., use another mode) or justify their choice by improving their attitude toward the chosen mode (Kroesen et al., 2017; De Vos & Singleton, 2020).

Some travel behaviour studies have found bidirectional relationships between travel attitudes and travel behaviour (e.g., Dobson et al., 1978; Tardiff, 1977), while some of them even indicate that people are more likely to change their travel attitudes than their travel behaviour (e.g., Golob, 2001; Kroesen et al., 2017; McCarthy et al., 2021), indicating that travel behaviour may often be hard to change and that some travellers may be captive travellers (e.g., captive public transport users). Recently, De Vos et al. (2021) have introduced the travel mode choice cycle indicating that attitudes can influence behaviour through desires and intentions, but that behaviour can also affect attitudes, through satisfaction. The former effects have been found by some studies testing social-psychological theories (such as the Theory of Planned Behaviour) in a travel behaviour context (e.g., Bamberg et al., 2003). The latter effects have, for instance, been found by Fujii and Kitamura (2003), who observed that attitudes toward bus use improved after a switch from car use to bus use, partly because people started appreciating the positive aspects of public transport after using it.

2.2. Empirical studies of behavioural and attitudinal changes in response to COVID-19

Various empirical studies have examined the effects of the COVID-19 pandemic on travel preferences and behaviour. Empirical research has found substantial changes in travel frequency and trip purpose during the pandemic (Capasso da Silva et al., 2021, de Haas et al., 2020; Kar et al., 2021; Salon et al., 2021). Specifically, trip frequency and distances travelled decreased, mostly due to travel restrictions such as lockdown and stay-at-home orders in most countries. As most commuting halts due to COVID-19, WFH has become popular, as well as recreation and leisure trips such as visiting parks and exercise loop trips (e.g., running around the neighbourhood) (de Haas et al., 2020; Hook et al., 2021; Galleguillos-Torres et al., 2022; Kar et al., 2021; Salon et al., 2021).

In addition to changes in trip frequency and distances travelled, mode switch is also common. Many studies have found a significant drop in public transport ridership and an increase in private automobile and active transport mode use (Abdullah et al., 2021; de Haas et al., 2020; Salon et al., 2021; Shamshiripour et al., 2020), where sometimes a car is purchased especially to replace public transport trips (van Hagen et al., 2021). Unlike changes in travel distance, trip frequency, and trip purpose which are likely introduced by travel restrictions (e.g., lockdown), a mode switch and increased WFH levels are likely due to health concerns and fears of infection as sharing space with other people can be perceived as unsafe during this time (Capasso da Silva et al., 2021).

A few stated-preference studies also examine the possibility that concerns around COVID-19 and on-going changes in travel will persist after the pandemic is over (Mirtich et al., 2021; Salon et al., 2021; Shamshiripour et al., 2020). It is implied that attitude toward travel and WFH is fairly stable for up to a year (Mirtich et al., 2021), suggesting that travel adjustments during the pandemic may not be long-lasting. Salon et al. (2021) found that shifting to active transport and shifting away from public transport are likely to stick post-COVID-19, while Mohammadian et al. (2022) – using a 4-wave panel – mainly indicates that public transport will struggle to attract passengers post-COVID-19. It is noteworthy that these studies used US-based samples, which may be different from other cities/countries in the world.

2.3. Synthesis and research focus

To summarise, the COVID-19 pandemic can be considered an environmental trigger that has resulted in attitude and behaviour changes in various ways. In this study we focus in particular on how the fear of infection and (the attitude toward) WFH influence the (attitude toward the) use of the train. The fear of infection is an entirely new element that can trigger affective, cognitive and behavioural processes that influence (the attitude toward) train travel. In addition, WFH has received a strong boost due to travel restrictions and thus may influence the (attitude toward) train travel, especially considering that relatively many train travellers are highly educated and often have the ability to WFH. Finally, in line with recent theorising and empirical research in the field of travel behaviour we assume that the fear of infection and (the attitude toward) WFH may vice-versa be influenced by the (attitude toward) train use. Hence, all possible bidirectional effects will be explored.

3. Method

3.1. Data collection

To gain insights into passenger behaviour during and after the pandemic, a longitudinal survey is organised by NS (Dutch Railways) and Delft University of Technology with the goal to capture behaviour, attitudes and intentions regarding travel behaviour in general and train use in particular. The participants of the survey are part of the existing panel of NS. This panel represents all train travellers in the Netherlands and participation is voluntary. The total panel encompasses more than 80,000 members and members can receive invitations for a variety of research initiatives related to train travel. Since it was expected that behaviour, attitudes and intentions would change during the pandemic, multiple surveys were planned and held. Beforehand it was unknown how many surveys would be distributed in total. The argument was that when drastic changes in the measures happened, it would possibly lead to behavioural changes, therefore a new survey would be distributed.

The first survey was distributed among all panel members and about 46,000 respondents completed the survey (roughly 57 % response rate). This survey aimed at capturing respondents' behaviour in April 2020 during the "intelligent lockdown". In this period, train travelling was only allowed for people working in essential sectors. 96 % of the respondents agreed to participate in a longitudinal study to monitor trends and changes. In this survey, the pre-COVID-19 situation was also captured by asking about the travel behaviour in February 2020. In June 2020 (end of lockdown, but still many limitations), September 2020 (more working allowed in the office), December 2020 (second COVID-19 wave and news about a vaccine), April 2021 (restrictions are relaxed), September 2021 (restrictions are relaxed further), and April 2022 (no restrictions), follow-up surveys were held. In addition, more in-depth questions were asked to focus on specific topics, for instance WFH (see Ton et al., 2022a), vehicle purchase behaviour and home relocation behaviour. Every survey was filled in by at least 18,000 respondents, but a decline in response can be seen over time.

To check for bias and self-selection among the internal NS panel, an external panel was approached in parallel, where a sample representative for the Dutch train traveling population was invited (1,500 respondents) to verify the behaviour, attitudes and intentions of the internal panel members. Furthermore, each of the waves of data collected on the internal panel, is weighted against the Dutch train traveling population. These two panels showed similar behaviour, attitudes and intentions; hence, we conclude that the internal panel can be considered representative of the train traveling population (Ton et al., 2022b).

3.2. Data description

For this study the first four waves of data are used (April, June, September, and December 2020). As the goal is to capture the within-person changes over time, it is essential that each individual has participated in all waves. This also means that the resulting dataset is not weighted against the Dutch train traveling population and is therefore not necessarily representative. A total of 14,760 respondents participated in each wave and are used in the analysis. Of those respondents, 3,587 could work from home. Table 1 shows the socio-demographic characteristics of both samples (full and WFH sample).

Table 1
Sample distributions of socio-demographic characteristics of the full sample and WFH sample.

Variable	Categories	Full sample (%)	WFH Sample (%)
Gender	Male	48.1	55.3
	Female	49.7	42.2
	Other / missing	2.1	2.6
Age	18–34 years	5.1	8.8
	35–44 years	5.2	11.6
	45–54 years	10.5	21.8
	55–64 years	24.9	38.9
	65–74 years	38.8	12.4
	75 years and older	10.8	1.7
	Missing	4.6	4.8
Level of education	Intermediate secondary education	9.8	1.6
	Higher secondary education	10	6.6
	Intermediate vocational education	12.4	5.6
	Higher vocational education (college)	33.7	30.6
	University	29.0	50.7
	Missing or other	5.2	4.7
Occupational status	Paid employment	35.9	73.4
	Freelancer or self-employed	4.4	11.6
	Attends school or is studying	2.2	2.3
	Takes care of the housekeeping	1.8	0.0
	Pensioner	46.1	6.7
	Missing or other	9.5	6.0
Household composition	Alone	34.0	27.2
	With partner	49.2	40.3
	With partner and child(ren)	10.3	23.8
	Missing or other	6.5	8.7

There are quite some differences between the full sample and the WFH sample, most of these are attributed to the large share of pensioners (46.1 %) in the full sample, who no longer perform paid work. This affects age distributions and household composition. Furthermore, the share of highly educated respondents in the WFH sample is much larger compared to the full sample (50.7 % versus 29 %). This is mostly because highly educated respondents often hold white-collar office jobs that facilitate WFH (Ton et al., 2022a). In addition, there are fewer women in the WFH sample (compared to the general population). This is in part due to the lower employment rate among women in the Netherlands. In Q2 of 2022, 76 % of the (Dutch) men were employed compared to 68 % of the women (Statistics Netherlands, 2022a). In addition, the average commuting distance of women (19.1 km) is lower than that of men (24.8 km) (Statistics Netherlands, 2022b). Given that the train only becomes popular for longer commute distances (>30 km) it seems plausible that men are overrepresented among the population of employed people travelling by train.

For this study, the questions related to train use frequency, WFH frequency, attitude toward train use, attitude toward WFH, and fear of infection are most relevant. These questions were included in each wave, with the first survey also reflecting the pre-COVID-19 situation (only travel behaviour). As no information was available before the pandemic, this information serves as the reference point for changes occurring during the pandemic. To ensure good quality of the information on travel behaviour, the respondents were asked about their travel behaviour in the past week. Regarding train use, the respondents were asked how often they used the train in the past week (0–7 days). For WFH, an ordinal scale was used, ranging from *none* (1), *1 day* (2), *2–3 days* (3) and *4 or more days* (3). For the attitudes toward train use (“*I enjoy travelling by train*”) and WFH (*“I enjoy working from home”*) 5-point Likert scales were used with answer categories ranging from *strongly disagree* (1) to *strongly agree* (5). The fear of infection was captured using the following statement: “*I am afraid to become infected by the coronavirus*”. This was also measured on a 5-point Likert scale from *strongly disagree* (1) to *strongly agree* (5).

Table 2 shows the means and standard deviations of the train use, train attitude and fear of infection variables for the full sample. The results show that train use decreased significantly during the pandemic and has not yet reached its reference point. Furthermore, both the attitude toward train use and the fear of infection vary slightly over time and are seemingly correlated with the number of positive COVID-19 cases and the strictness of the measures imposed by the government.

Table 3 shows the means and standard deviations of all the relevant variables for the WFH sample. Also here, several differences can be seen compared to the full sample. Train use before COVID-19 is higher for the WFH sample. These respondents were mostly commuting by train to work, hence their weekly train use is higher compared to the full sample where many incidental social and recreational trips are also made. Furthermore, the attitude toward the train is slightly lower for the WFH sample, and fear of infection is also slightly lower. The attitude toward WFH is generally very positive among the WFH sample and the frequency is high. In addition, it is also interesting to see that the attitude towards WFH has become more positive over time.

3.3. Statistical model

To test the bidirectional relationships between train use, the attitude toward train use, the fear of infection, and (the attitude toward) WFH, two Random-Intercept Cross-lagged Panel Models (RI-CLPM) were specified. In the following, the first model will be briefly introduced (for a full description of the RI-CLPM we refer to Hamaker et al. (2015)).

Fig. 1 presents the structure of the first RI-CLPM that was specified and estimated in this study. For each observed variable (in rectangles) a respective latent variable is specified. The paths linking these latent variables to the observed ones are set to 1. In addition, temporal means are included for each respective point in time. As such, the latent variables effectively capture respondents' temporal deviations from the time-varying group means, thereby accounting for population-wide structural change in the variables of interest. Note that such structural changes are indeed present (see Tables 2 and 3).

Next, it is assumed that the (mean-centred) latent variables influence their future counterparts (autoregressive effects) as well as each of the other variables (cross-lagged effects) over time. The cross-lagged effects are of main interest as they indicate to which extent causal effects exist and in which directions.

Finally, the error terms of the latent variables on each occasion are allowed to correlate (not shown) as well as exogenous latent variables at wave 1. These (dynamic) correlations account for possible synchronous effects between both variables as well as the effects of (unmodelled) time-varying factors between the three variables.

So far, the above description captures the traditional CLPM. An important limitation of this model, as argued by Hamaker et al. (2015), is that, while the CLPM is able to capture temporal stability, it does not account for stable individual differences that endure over time (at least for the periods typically considered in panel studies). Indeed, this is a problematic assumption, since behavioural and attitudinal variables are generally characterized by stable individual differences (Hamaker et al., 2015), e.g. due to the presence of habits.

These stable differences may be accounted for by introducing three additional latent variables, the so-called random intercepts. To capture the notion that they have a constant (time-independent) ‘trait-like’ influence on the observed outcomes, the paths linking these variables to the observed variables are set to 1. Essentially, since the random intercepts capture variation between persons, stable ‘between-person’ variation is factored out. This has two benefits, namely (1) the stability/cross-lagged relations now capture ‘within-person’ carry-over effects from one occasion to the next, i.e. the level at which the causal processes are assumed to operate, and (2) all time-constant variables that may influence the three dependent variables are controlled for. This also means that it is not vital to include socio-demographic variables, which are generally (very) inert, as confounders in the model. Finally, the three random intercepts are allowed to correlate. These correlations indicate the extent to which the variables of interest are correlated at the ‘between-person’ level due to other factors than the assumed causal effects that operate between the three variables at the ‘within-person’ level.

To estimate model 1, data from the full sample are used. The second model (model 2) is specified as similar to model 1, but

Table 2
Means and standard deviations of the dependent variables (full sample).

Wave	Train use (days/week) Mean	SD	Attitude toward train use (1–5) Mean	SD	Fear of infection (1–5) Mean	SD
0 (pre-COVID-19)	1.3	1.7				
1 (April - lockdown)	0.2	0.7	2.8	1.5	3.3	1.1
2 (June – end of lock down, with restrictions)	0.4	0.9	3.1	1.3	3.0	1.0
3 (September – some office working allowed)	0.7	1.2	3.3	1.2	3.2	1.0
4 (December – second wave of COVID-19)	0.5	1.0	3.1	1.3	3.4	1.1

Table 3
Means and standard deviations of the dependent variables (WFH sample).

Wave	Train use (days/week) Mean	SD	Attitude toward train use (1–5) Mean	SD	Fear of infection (1–5) Mean	SD	WFH (1–4) Mean	SD	Attitude toward WFH (1–5) Mean	SD
0 (pre-COVID-19)	2.4	1.9					2.8	1.3		
1 (April 2020)	0.1	0.5	2.7	1.5	3.1	1.1	3.7	0.5	3.5	1.0
2 (June 2020)	0.4	0.8	3.0	1.3	2.9	1.0	3.6	0.6	3.7	1.0
3 (September 2020)	0.7	1.1	3.2	1.2	3.1	1.0	3.4	0.7	3.7	1.0
4 (December 2020)	0.4	0.8	3.0	1.3	3.2	1.1	3.6	0.6	3.8	1.0

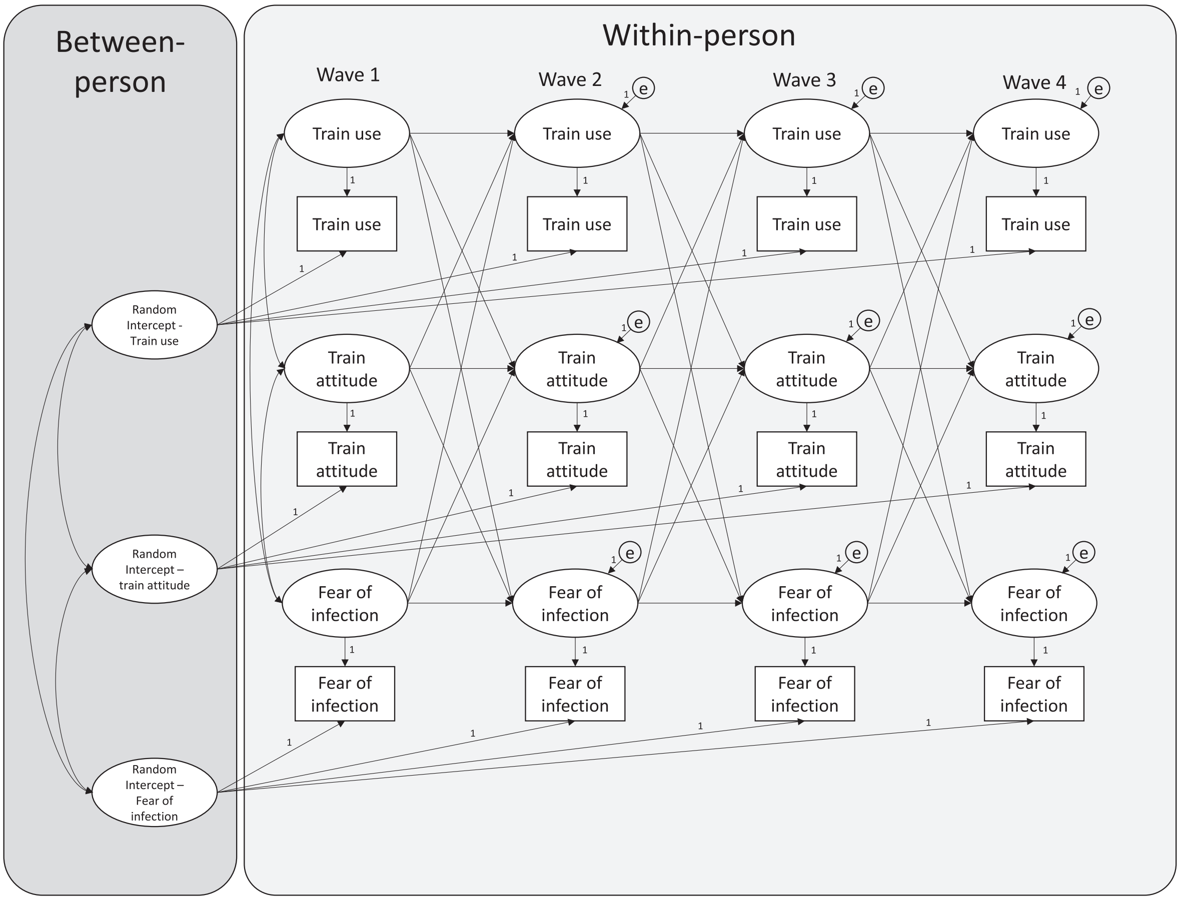

Fig. 1. A 4-wave 3-variable Random Intercept Cross-Lagged Panel Model (Model 1).

considers two additional variables, namely WFH and the attitude toward WFH. This model thus includes five autoregressive effects and twenty (5x4) cross-lagged relationships. This model is estimated using data from the WFH sample. For both models, it is assumed that the effects are stable over time, hence equality constraints are imposed on the same effects across each wave-pair.

4. Results

The models were estimated using Mplus applying the robust maximum likelihood estimator to account for the fact that the data are not normally distributed. Table 4 presents the model fit of the CLPM (a) and the RI-CLPM (b) of models 1 and 2. For both models a large improvement in model fit can be observed indicating that the random intercepts indeed capture stable between-person individual differences. The RI-CLPMs fit well in terms of conventionally used relative fit indices (Hu and Bentler, 1999).Table 5 presents the (standardized) parameter estimates of model 1 (the full sample).[1] Turning first to the autoregressive effects, which can be interpreted as 'within-person' carry-over effects of the same variable from one wave to the next, the results indicate that train use at t-1 has the largest effect on its respective counterpart at t (0.328), followed by the fear of infection (0.144) and the attitude toward train use (0.117). This means that, on top of the overall stability in - for example - the use of the train, if a person has a higher (or lower) use of the train than his/her expected score in a certain wave (following from the random intercept for train use), he or she will also have a 'higher (lower) than expected' score in the subsequent wave. The presence and significance of these effects thus indicate that there are 'within-person' processes at work that enable these intrapersonal carryover effects. For example, for train use, it may be speculated that the experience of using the train leads a person to use the train again (in the next wave).

The cross-lagged effects, which are of main interest, indicate the extent to which the variables influence each other over time. Similar to the autoregressive effects, the estimates can be interpreted as within-person carry-over effects from one occasion to the next, but now from one variable to the other. With respect to the relation between train use and the attitude toward train use, the results indicate that the effect of behaviour on attitude is approximately twice as large (0.108) as vice versa (0.058), though both effects are statistically significant. This result is consistent with findings of previous panel studies, which have consistently shown that the effect of behaviour on later attitudes is stronger than the other way around (Kroesen et al., 2017; Olde Kalter et al., 2021). Significant bidirectional effects also exist between train use and the fear of infection: those with stronger fears of infection in one wave tend to use the train less in a subsequent wave (-0.048). Meanwhile, the use of the train reduces the fear of infection over time (-0.071). Here, in line with the expectation formulated in the introduction, it seems that people's experiences of travelling by train generally lead them to become less fearful of being infected. Finally, with regards to the relation between the fear of infection and the attitude toward travel by train, both effects are also negative but not statistically significant. Hence, while the fear of infection does lead people to travel less by train, it does not directly alter people's attitude toward travelling by train (although the attitude is indirectly affected via the reduced use of the train).

Finally, the correlations between the random intercepts capture the associations between the stable individual factors that are assumed to exist for each variable in the model. For the relationships between train use and the attitude toward the train, as well as between train use and the fear of infection, these correlations (0.264 and −0.186, respectively) have the same signs and (relative) sizes as the within-person effects. Hence, at the between-person level, people who use the train more often have more positive attitudes toward train travel and lower fears of infection. It is likely that a part of these between-persons correlations has resulted from the (accumulation of) within-person effects. But the correlations may also (partly) be the result of other stable individual differences. For example, older people may generally use the train less and be more fearful of infection.

Interestingly, while the within-person effects were not significant between the attitude toward train use and the fear of infection, at the between-person level, the respective individual factors are strongly correlated (-0.377). As the within-person effects are insignificant here, this correlation should be entirely attributed to stable between-person differences. It may be speculated that certain stable personality traits inform both the fear of infection as well as the attitude toward train travel. For example, a general dislike of being in physical proximity to other people may be responsible. The fact that for this relationship the between-person correlation is large (in fact the largest of all three pairs) whereas the within-person effects are non-significant also illustrates the importance of discriminating these effects in the first place. Based on the (cross-sectional) correlation (Table 4) one might conclude that the fear of infection leads to a dislike of travelling by train (or vice versa) at the within-person level. The present results, however, disconfirm this conclusion and indicate that the association is entirely due to other stable differences across people.

Table 6 shows the estimates of model 2, in which two additional concepts have been added, namely WFH and the attitude toward WFH, yielding five autoregressive effects, twenty cross-lagged effects and ten correlations between the (five) random intercepts. The estimates associated with (the attitude toward) train use and the fear of infection are overall similar to those in model 1, indicating that being employed and being able to WFH, does not moderate these effects.

The autoregressive effects of WFH and the attitude toward WFH are positive and similar in size as those of the fear of infection and the attitude toward train use. Again, it may be speculated that the experiences gained during WFH lead people to continue this behaviour at the next point in time (in addition to an overall stable habitual effect as captured by the random intercept).

[1] Note that the model 1 effects are not (yet) controlled for working from home (which model 2 does). To assess whether the differences in the effects between model 1 and 2 are due to this correction for confounding or due to the difference in sample composition, we estimated model 1 (with the 3 variables) using the data from model 2, i.e. the subsample of employed people who can work from home. The estimated effects remain close to the estimated coefficients of model 2, indicating that the differences in the estimates between model 1 and 2 are primarily due to the difference in sample composition (rather than the presence of WFH as additional control variable).

Table 4
Model fit.

Model	χ^2	df	p-value	RMSEA[a]	CFI[b]	SRMR[c]
Model 1a (CLPM)	10437.8	46	0.000	0.124	0.781	0.124
Model 1b (RI-CLPM)	1690.4	40	0.000	0.053	0.965	0.041
Model 2a (CLPM)	3170.4	120	0.000	0.084	0.870	0.068
Model 2b (RI-CLPM)	709.4	105	0.000	0.040	0.974	0.039

[a] Root Mean Square Error of Approximation (<0.06 indicates good fit. Hu and Bentler (1999)).
[b] Comparative Fit Index (>0.95 indicates good fit. Hu and Bentler (1999)).
[c] Standardized Root Mean squared Residual (<0.08 indicates good fit. Hu and Bentler (1999)).

Table 5
Standardized parameter estimates of model 1 (full sample).[a]

	Autoregressive effects			
Effect	Est.	p-value		
Train use (t-1) → train use (t)	0.328	0.000		
Attitude toward train use (t-1) → Attitude toward train use (t)	0.117	0.000		
Fear of infection (t-1) → Fear of infection (t)	0.144	0.000		
	Cross-lagged effects (within-person)		**Correlation RIs (between-person)**	
Effect	**Est.**	**p-value**	**Est.**	**p-value**
Train use (t-1) → Attitude toward train use (t)	0.108	0.000	0.264	0.000
Attitude toward train use (t-1) → Train use (t)	0.058	0.000		
Train use (t-1) → Fear of infection (t)	−0.071	0.000	−0.186	0.000
Fear of infection (t-1) → Train use (t)	−0.048	0.000		
Attitude toward train use (t-1) → Fear of infection (t)	−0.013	0.073	−0.377	0.000
Fear of infection (t-1) → Attitude toward train use (t)	−0.013	0.109		

[a] The presented values in the table show the means of the standardized estimates across all waves. Note that, while the unstandardized estimates are equal across all waves, the standardized estimates differ slightly from wave to wave due to the time-varying variances of the variables.

Train use negatively influences both WFH frequency (-0.062) and the attitude toward WFH (-0.059), and these variables in turn also influence train use negatively (respectively −0.035 and −0.058). Regarding the relationship between WFH and train use, these negative reciprocal influences can be interpreted as substitution effects, where an increase in one results in a decline in the other (and vice versa). It is interesting to see that train use not only affects WFH but also the attitude toward WFH. Hence, people who (continue to) travel by train - over time - develop more negative attitudes toward WFH. Since frequently travelling by train results in lower WFH frequencies, people may develop more negative WFH attitudes in order to justify the choice to travel, in line with the cognitive dissonance theory. This pattern does not exist for the relationship between WFH and the attitude toward train use; no significant effects are found in either direction. At the level of attitudes, however, again significant bidirectional effects exist: the attitude toward train use negatively affects the attitude toward WFH (-0.052) and vice versa (-0.045).

The fear of infection positively influences WFH frequency (0.038), and those who work from home also become more fearful of infection over time (0.043). This pattern is consistent with the negative reciprocal effects between train use and the fear of infection. It seems the fear of infection is strengthened when people are not exposed to other people and reduced when people are. Overall, these findings support cognitive dissonance theory: people align their attitudes and behaviours to avoid contradictions between attitudes and behaviours (over time). For example, travelling by train and being (very) fearful of infection is a combination that would lead to a strong psychological tension, which can be reduced by either travelling less or becoming less fearful of infection. Similarly, people who WFH can 'allow' themselves to become (very) fearful of infection, as they are not exposed to actual risks. In this case, a position of being fearful does not lead to tensions with actual behaviour.

Finally, it is interesting to see that WFH and the attitude toward WFH do not strongly influence each other; the effects are not significant in either direction. This is surprising given that attitudes directed toward specific behaviours generally correlate quite strongly with the behaviour in question, and contradicts existing COVID-19 studies (e.g., Lee & De Vos, 2022). A plausible explanation is that WFH is often involuntary. Due to the restrictions imposed by the government, many people who do not like WFH were forced to do so. Similarly, there may be many people who want to work from home but their job does not allow it. Having these groups forced into these respective combinations suppresses the correlation between WFH and the attitude toward WFH. In this case, the 'inconsistent' combinations arguably do not result in a psychological tension, since the inconsistency (between attitude and behaviour) is not due to an individual choice but due to restrictions imposed by the government. Hence, there is no strong need to either adjust the behaviour or the attitude, which may have given rise to the small (insignificant) effects.

The correlations between the random intercepts again provide some interesting additional insights. For example, a large negative correlation exists between train use and WFH (-0.387). This means that in addition to the negative within-person reciprocal effects,

Table 6
Standardized parameter estimates of model 2 (WFH sample).[a]

Effect	Autoregressive effects Est.	p-value
Train use (t-1) -> train use (t)	0.271	0.000
Attitude toward train use (t-1) -> Attitude toward train use (t)	0.153	0.000
Fear of infection (t-1) -> Fear of infection (t)	0.139	0.000
WFH (t-1) -> WFH (t)	0.155	0.000
Attitude toward WFH (t-1) -> Attitude toward WFH (t)	0.121	0.000

	Cross-lagged effects (within-person)		Correlation RIs (between-person)	
Effect	Est.	p-value	Est.	p-value
Train use (t-1) -> Attitude toward train use (t)	0.160	0.000	0.247	0.000
Attitude toward train use (t-1) -> Train use (t)	0.100	0.000		
Train use (t-1) -> Fear of infection (t)	−0.055	0.000	−0.187	0.000
Fear of infection (t-1) -> Train use (t)	−0.046	0.001		
Attitude toward train use (t-1) -> Fear of infection (t)	−0.006	0.722	−0.392	0.000
Fear of infection (t-1) -> Attitude toward train use (t)	−0.025	0.102		
Train use (t-1) -> WFH (t)	−0.062	0.000	−0.387	0.000
WFH (t-1) -> Train use (t)	−0.035	0.006		
Train use (t-1) -> Attitude toward WFH (t)	−0.059	0.000	−0.120	0.000
Attitude toward WFH (t-1) -> Train use (t)	−0.058	0.000		
Attitude toward train use (t-1) -> WFH (t)	0.003	0.843	−0.146	0.000
WFH (t-1) -> Attitude toward train use (t)	0.015	0.277		
Attitude toward train use (t-1) -> Attitude toward WFH (t)	−0.052	0.003	−0.049	0.118
Attitude toward WFH (t-1) -> Attitude toward train use (t)	−0.045	0.003		
Fear of infection (t-1) -> WFH (t)	0.038	0.015	0.010	0.675
WFH (t-1) -> Fear of infection (t)	0.043	0.004		
Fear of infection (t-1) -> Attitude toward WFH (t)	0.045	0.004	0.158	0.000
Attitude toward WFH (t-1) -> Fear of infection (t)	0.017	0.271		
WFH (t-1) -> Attitude toward WFH (t)	0.031	0.064	0.192	0.000
Attitude toward WFH -> WFH (t)	0.012	0.491		

[a] The presented values show the means of the standardized estimates across all waves. Note that, while the unstandardized estimates are equal across all waves, the standardized estimates differ slightly from wave to wave due to the time-varying variances of the variables.

there is a correlation across people in the general tendency to work from home and the general tendency to travel by train. This signifies that there are different groups that either tend to work from home or travel by train, this is also found by Ton et al. (2022a). Also a substantial correlation exists (0.192) between the attitude toward WFH and WFH frequency, even though the within-person effects were insignificant for this relationship. Again, this correlation has likely arisen due to other factors at the between-person level.

5. Conclusion and discussion

This study examined the effects of fear of infection with COVID-19 and WFH on the attitude toward train use and train use itself during the COVID-19 pandemic in the Netherlands by using a longitudinal dataset collected among train travellers during four periods during the pandemic (April 2020, June 2020, September 2020, and December 2020). This study contributes to the understanding of travel behaviour during COVID-19 and its implications for public transport planning beyond the pandemic. Our study provides a unique perspective and evidence for the attitude-behaviour dynamics, both within- and between-person levels, during an unprecedented social and public health disruption. We found that, at the within-person level, the attitude toward train travel was not affected by the fear of infection, but was negatively affected by the reduced train travel. At the between-person level, however, the fear of infection and attitude toward the train are strongly correlated. It seems plausible that similar psychological traits inform both, such as the dislike of being in physical proximity to other people. We also found that WFH clearly substitutes travel by train and vice versa. People who (continue) to travel by train become less fearful of infection while people who WFH become more fearful of infection.

Overall, our study confirms cognitive dissonance theory, i.e. people mutually adjust their attitudes and behaviors over time. This finding invalidates theories that assume that attitudes act as (stable) precedents of behavior and favors theories that do account for reciprocal effects, such as the travel mode choice cycle introduced by De Vos et al. (2021) or theoretical framework of Van Wee et al. (2019). In addition, whereas previous studies examined bidirectional effects between attitudes and behaviors with respect to the same mode (see e.g. Kroesen et al., 2017; Olde Kalter et al., 2021), the present study shows that people align their attitudes and behaviors across multiple domains. For example, people who travel less by train become more fearful of infection, or: people who travel more by train develop a more negative attitude towards WFH. Hence, the tendency to reach/maintain cognitive consistency is not confined to (same) attitude-behavior pairs. At the level of behaviors, our findings also provide evidence of substitution between train travel and WFH. Such substitution effects thus operate in tandem with tendencies to reach cognitive consistency, adding to the complexity of attitude-behavior dynamics.

This study offers several implications for urban planning and transportation practice. First, the plunge in train ridership during COVID-19 might be temporary and may recover after the pandemic. While the fear of infection is found to negatively affect train use, we found no evidence that the fear of infection alters the attitude toward train travel. This indicates that people may resume train travel again when the pandemic and the fear of infection are over. Furthermore, as train use has a strong negative effect on the fear of infection, current train users are consequently likely to continue train use after the pandemic.

Second, our results imply that the fear of infection might have driven some people to WFH. It is therefore important to nudge these people to travel by train again and disincentivise them from switching to car use when commuting resumes after the pandemic. Since using the train negatively affects fear, giving people temporal incentives to travel by train (e.g., a one-month free public transport pass) may reduce their fear, resulting in more train use in the future. Doing so may also improve train attitudes, which can then become stronger than feelings of fear. Previous studies have found that temporary incentives for using public transport can increase public transport ridership, but also improve attitudes and satisfaction levels (e.g., Abou-Zeid & Ben-Akiva, 2012; Fujii & Kitamura, 2003).

Third, it is unclear whether WFH will continue to affect train ridership post-pandemic. Insofar as a long-term negative effect on the attitude towards train use indeed exists, our results suggest this is due to the reduction in train travel and not due to the fear of infection. The fact that WFH does not affect the attitude toward WFH and vice versa may be attributed to the partly involuntary nature of WFH during COVID-19. Specifically, some people who WFH actually prefer not to do so, while some people who cannot WFH would actually want to do so. Also the insignificant bidirectional links between WFH and train attitudes suggest that some people may be forced to WFH, which is likely the case during the pandemic. In case WFH would be a free choice, it could be expected that those who WFH are those with especially negative attitudes towards train travel. Since train commutes often have relatively long commute durations, WFH may result in a considerable gain of time, which especially is of interest for those disliking the time on a train. Finally, the attitude toward WFH has become more positive over time, not so much due to the increased WFH, but due to reduced train travel. Due to this positive attitude, it is likely that a considerable portion of people will continue to work from home.

On a more general note, this study revealed that WFH and train travel act as clear substitutes for one another. Both are typically identified as ‘desirable’ behaviours from a policy perspective as they are associated with less environmental impacts compared to car use (typically the dominant alternative). Our results suggest that policy makers seeking to stimulate travel by train or WFH may inadvertently also discourage the other desirable behaviour (i.e. WFH or travel by train). Knowledge of such side-effects is crucial when trying to optimise the transport system as a whole.

This study has several limitations pertaining to data collection and measurement. First, our study relies on a set of single measures for train use, attitude toward train use, WFH, and fear of COVID-19 infection, therefore measurement errors are not accounted for in the analysis. However, the presented results are likely on the conservative side because, if we controlled for measurement errors (i.e. if multiple items were available), the estimates would have been larger than reported presently, as (random) measurement errors in the dependent variable typically attenuate estimates downwards. In addition, standard errors would have become smaller, leading to more significant effects. Nonetheless, future studies should employ multi-item measurement and account for measurement errors to have a better estimate of the true effects.

Secondly, the data for this study was collected during the COVID-19 pandemic, a period with an unusually high level of WFH and fear of infection. Although of course the pandemic was one of the reasons for analysing links between train use, WFH and fear of infection, performing similar analyses with data from a non-pandemic time (e.g., post-COVID-19), or a combination of stated and revealed preference data would be of interest. Doing so may better indicate, for instance, how attitudes toward train use influence WFH (attitudes) and whether the current travel adjustments would linger beyond the pandemic. In addition, once WHF becomes completely voluntary, it can be expected that the effects between WFH and the attitude towards WFH would also become stronger. These research directions may be explored when new waves of the panel become available (at the time of writing this article, the panel consists of 7 waves, but even in the last wave restrictions existed).

Thirdly, the current study focuses only on train travel while dismissing other travel modes. Future studies should include multiple travel modes to explore a full range of effects of COVID-19 on mode shift, public transport ridership, and travel rebound effects of WFH. Specifically, the fear of infection may actually have increased car use and the use of active modes, and attitudes toward these modes. In a post-pandemic world, it is also possible that WFH may not only result in fewer commute trips, but also in more frequent leisure and shopping trips due to the saved time of not commuting (i.e., rebound effect). These leisure/shopping trips are often shorter than commute trips (which are often covered by train) and may be taken by active modes or car.

Fourthly, even though the present study has established significant (within-person) effects between various concepts, i.e. the fear of infection, (the attitude towards) travel by train, and (the attitude towards) WFH, a qualitative research approach would be required to uncover the causal mechanisms and processes behind the specific observed effects. Such an approach would be better suited to empirically validate the model of attitude change as proposed by Van Wee et al. (2019) and assess which particular mechanism (affective, cognitive, behavioural or combination) indeed underlies the observed effects.

Finally, it would be worthwhile to consider other statistical models to explore the panel dataset. In this regard, a specific direction would be to estimate a latent class trajectory model (Muthén and Muthén, 2000). Such a model would be able to reveal the various latent trajectories in the dependent variables (WFH, train use and the attitudinal variables) over the considered time period. The trajectories thus revealed would show to what extent initial reactions echo through in later waves, and whether there are groups that (quickly or slowly) revert to per-COVID-19 behavioural/attitudinal patterns or groups that have durably changed their behaviour/attitudes.

To conclude, there is much scope to increase our understanding of attitude-behavior dynamics. A main challenge will be to connect (new) dynamic theories of travel behaviour (change) with suitable modelling frameworks. We look forward to addressing this challenge and welcome other researchers to join us in this effort.

CRediT authorship contribution statement

Maarten Kroesen: Conceptualization, Methodology, Formal analysis, Writing – original draft. **Jonas De Vos:** Writing – original draft, Writing – review & editing. **Huyen T.K. Le:** Writing – original draft, Writing – review & editing. **Danique Ton:** Writing – original draft, Writing – review & editing, Investigation, Data curation.

Declaration of Competing Interest

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

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