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Spill-over effects between daily and air travel behavior: a panel analysis in the Netherlands

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Abstract
The existence of spill-over effects between pro-environmental behaviors has been well documented, but studies in the field of travel behavior are scarce. In this regard, individuals may behave consistent (daily and air travel behavior aligns) or inconsistent (daily and air travel behavior does not align), or spill-over effects between daily and air travel behavior may be non-existent. In this research, we explore the sign and directionality of spill-over effects between frequencies of daily mode use and air travel behavior. Using data from the Netherlands Mobility Panel, we employ a twofold approach to explore these spill-over effects both cross-sectionally and longitudinally. The results of the cross-sectional latent class analysis reveal that two out of three classes can be labeled as 'inconsistent'. For these travelers, the daily travel pattern is at the sustainable end of the spectrum (as observed in the sample), while the flying behavior is at the unsustainable end, as well as the other way around. The results of the panel analysis, however, indicate that the spill-over effects which are found cross-sectionally are not supported by the longitudinal approach. This suggests that the correlations are due to structural differences between people rather than psychological mechanisms (e.g. moral licensing) at the within person level.

Keywords Air travel · Daily travel · Spill-over effects · Latent class analysis · Panel analysis

Introduction

The nexus between individual mobility behavior and its implications for climate change mitigation is a pressing concern in ongoing transport planning and sustainable development. The challenges of traffic-related emissions in cities worldwide and the resulting surge in air travel emissions for longer trips make understanding the dynamics of mobility behaviors

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at the urban and interurban scales of importance. At the heart of this exploration lies the intriguing question: do sustainable daily travelers, who frequently use eco-friendly travel modes within their daily lives, extend this commitment to sustainability when embarking on long-distance journeys, indicating positive spill-over effects? Here, long-distance journeys are defined as those to destinations with a significant distance; more than 100 km is in Europe a generally accepted standard (e.g. Brög et al. 2003). Or do people, after performing a virtuous environmental action, feel they have "earned" the right to engage in less environmentally-friendly behaviors, yielding negative spillover effects?

The current study investigates the effects between sustainable daily travel behavior and flying behavior, aiming to uncover the existence, extent, and directionality of spillover effects in the context of mobility behavior. As the global community intensifies its efforts to curb carbon emissions and foster sustainable living, the findings of this study hold the promise of informing policy, urban planning, and individual decision-making in ways that contribute to a more environmentally conscious and sustainable future.

Sustainable urban mobility has received increasing attention in recent years, with cities worldwide striving to offer eco-friendly transportation options and reduce reliance on carbon-intensive modes of travel. Accordingly, some people have also been switching to sustainable urban mobility options. On the other hand, flight shaming is a growing social movement that criticizes and feels guilty about air travel's impact on the environment (Winter et al. 2021). This movement has gained momentum as more people become aware of the significant greenhouse gas emissions produced by the aviation industry, primarily due to the burning of fossil fuels in aircraft engines. Advocates of flight shaming argue that individuals and organizations should be more conscious of their carbon footprint and consider alternatives to flying when possible. The movement also encourages people to reduce air travel. In spite of this, the consequences of daily travel behavior and flying behavior on one another remain an area of investigation and debate. Understanding whether sustainable daily travelers, who may frequently use bicycles or public transport in their daily travel patterns, show consistent sustainability behavior when opting for air travel holds significant implications.

To explore the relation and dynamics between daily and air travel behavior, we adopt a twofold approach. The first is aimed at assessing -cross-sectionally- which combinations of frequencies of daily mode use and air travel behaviors are adopted by people. To this end, we use variables related to daily travel and air travel as indicators of a latent class model (Vermunt & Magidson 2004), thereby revealing to what extent there exist (in)consistencies among the daily travel and flying behaviors. Some classes will likely be consistent, e.g., a class with sustainable daily mode use and a low flight frequency, but some classes will likely also be inconsistent. The latent class analysis can reveal which groups/combinations exist and the relative sizes of these groups.

While this analysis can shed light on the question whether people have (in)consistent daily travel and flying behavior patterns, it does not give an answer to the question whether any observed (mis)alignment is due to causal relationships between daily travel and flying behavior. The second approach is aimed at assessing the reciprocal relationships between daily mode use and flying behavior *over time*. For this analysis, we specify and estimate a so-called Random Intercept Cross Lagged Panel Model (RI-CLPM) (Hamaker et al. 2015). This model is ideally suited to assess lagged 'within-person' effects between a set of dependent variables. This analysis will be able to reveal whether people who are using sustainable modes for their daily travel are also inclined to decrease or increase their flight frequency over time, as well as determine effects in the opposite direction (from flying behavior to daily mode use). This analysis can thus reveal whether indeed spill-over effects exist, in which direction and whether they are (predominantly) positive or negative.

To estimate the models, we use data from the Netherlands Mobility Panel (MPN), a large-on-going panel in the Netherlands that is representative of the Dutch population (Hoogendoorn et al. 2015). In total 1,549 individuals who have completed four surveys (four waves covering the period 2016–2019) are included in the analysis.

In the next section, we first provide a brief review of the literature with regard to behavioral spill-over effects, discussing the theoretical mechanisms that underlie them and empirical evidence from experimental and observational studies. We also briefly explore the literature concerning the role of environmental attitudes in explaining frequencies of daily mode use and air travel. This already provides a clue as to whether negative or positive spillover effects can be expected. After the literature section, we present our own empirical analysis including the estimated latent class analysis and RI-CLPM. We conclude by discussing the results and policy implications.

Literature background

Spill-over effects occur when engagement in one (environmental) behavior increases or reduces the propensity to engage in another (environmental) behavior. Spill-over effects may be positive or negative, or non-existent. Positive spill-over indicates that engagement in one behavior increases the likelihood of engaging in another, while negative spill-over indicates that engagement in one behavior diminishes the likelihood of the other (Truelove et al. 2014; Galizzi and Whitmarsh 2019). Spill-overs may also be non-existent, in cases when one behavior is determined by other factors than the other behavior.

Various mechanisms have been proposed that may underlie spill-over effects (Behn et al. 2025; Carrico 2021; Nilsson et al. 2017). Regarding positive spill-over, the explanations can broadly be categorized into two groups. The first relates to the notion of cognitive consistency. In line with cognitive dissonance theory (Festinger 1962), the reasoning behind this notion is that people strive for consistency between their attitudes and behaviors, as inconsistencies lead to undesirable feelings of tension. For example, a person engaging in a pro-environmental behavior may subsequently adjust his/her pro-environmental attitudes. In turn, these altered attitudes may inform other pro-environmental behaviors. Related to this explanation is Bem's self-perception theory and the concept of social identity (Bem 1972). This theory states that people infer their identities from their behaviors. Hence, a person engaging in a pro-environmental behavior, may infer that he/she cares for the environment, in turn, leading to other pro-environmental behaviors.

The second group of explanations revolves around the notions of learning and self-efficacy. By performing a pro-environmental behavior people may learn about its positive outcomes and subsequently engage in other pro-environmental behaviors (Carrico 2021; Behn et al. 2025). For example, a person who switches to LED lights is likely to increase his/her general knowledge regarding energy use in the household and, as a result, engage in other energy-saving behaviors like unplugging electronics or turning down the thermostat. In addition, by performing certain pro-environmental behaviors, people may gain more confidence in themselves and increase their self-efficacy beliefs. Strengthened by success people may engage in other behaviors that they believed were too difficult to perform previously.

Regarding negative spill-over effects (at least) two explanations can also be identified. The first is related to the notion of rebound effects, which occur when increased efficiency or reduced resource use leads to lower costs, encouraging people to use more of the resource (Nilsson et al. 2017). For example, people who switch to an electric car (being more energy efficient) may be inclined to drive more due to lower costs of driving (compared to a gasoline car) (Font Vivanco et al. 2014). Rebound effects may also be indirect, when efficiency gains in one domain free up resources that are then used elsewhere, leading to increased overall consumption. For instance, if energy-efficient appliances reduce electricity bills, consumers may spend the saved money on other energy-intensive goods or services.

A second explanation relates to the notion of 'moral licensing' (Tiefenbeck et al. 2013). This relates to the process whereby people who have engaged in a morally virtuous act -a certain pro-environmental behavior- may subsequently feel licensed or justified to engage in behaviors that are less environmentally friendly. In other words, people may believe that because they have acted in a morally responsible way in one domain, they have earned the right or moral permission to act less responsibly in another domain. This effect may also operate the other way around, which has been termed 'moral cleansing' (Brañas-Garza et al. 2013). This refers to the process wherein individuals seek to restore their moral self-image or alleviate guilt after engaging in environmentally harmful actions. This concept is related to the idea that people want to perceive themselves as morally upright, and when their actions conflict with this self-image, they may take steps to "cleanse" or restore their moral identity.

In addition to these mechanisms, it might also be that two pro-environmental behavior are correlated due to 'third' variables causing both behaviors, such as (social) identity (e.g. adopting behaviors that are line with the expectations of others). This should not be regarded as evidence of a spill-over effect (Carrico 2021). As such, it is important that spill-over effects are assessed using either an experimental approach, in which the manipulation is targeted at one behavior, or a panel data approach, whereby the behaviors are measured at multiple points in time (from the same individuals) and the statistical model assesses the effects between these behaviors over time.

Given the diversity of explanations that may underlie both positive and negative spill-over effects, it is not surprising that empirical research focused on spill-over effects has yielded mixed results. An extensive meta-analysis by Maki et al. (2019) of studies following a (quasi)-experimental design (observational studies were excluded for the reason state above), revealed that there was a small positive effect of engagement in one pro-environmental behavior on the intention to perform another pro-environmental behavior, but that the effect on actual behavior was negative, and even smaller. A three-level Bayesian meta-analysis by Geiger et al. (2021) revealed weak support for no spill-over effects on the intention to perform another pro-environmental behavior and strong support for no spill-over effects on the actual behavior. Interestingly, Greiger et al. (2021) conclude that, if any spill-over effects were to be present, it would most likely be small and positive for intentions. Given the mixed findings of empirical studies, research has focused on the question of which spill-over effects are likely to occur under which circumstances. In this regard, studies have shown that positive spill-over effects are more likely to occur when experimental manipulations are targeted at intrinsic motivation and when the two pro-environmental behaviors are more similar (Maki et al. 2019).

Several empirical studies have focused on spill-over effects between travel behavior and other (pro-) environmental behaviors. For example, in a longitudinal panel study, Thøgersen and Ölander (2003) found that recycling behavior at one point in time had a positive effect on the use of alternative modes of transport (public transport and cycling) at a later point in time. The size of the effect was significant but small. Mattioli and Scheiner (2024) conducted a panel analysis of changes in air travel behaviour in England, and found that those individuals that engage in pro-environmental behavior at home were less likely to increase their flying frequency than others. In contrast, based on a (cross-sectional) cluster analysis, Barr et al. (2010) found that home-based environmental behaviors did not transfer to (pro-environmental) tourism practices. While the majority of the sample was environmentally aware and engaged in home-based environmental behaviors, most were found to fly regularly for holiday purposes. The results of the qualitative part revealed that individuals with a heightened environmental awareness acknowledged the impact of air travel on climate change and were open to supporting taxes aimed at reducing air travel but were not inclined to make substantial reductions in their air travel behavior (Barr et al. 2010).

Focusing on Swiss night trains, Gerosa and Cellina (2024), revealed three heterogenous groups of night train users (greens, pragmatists, and dissonants) with different intentions of using night trains. Around 40% of the respondents were identified as *greens* who primarily used public transport and non-motorized modes for sustainable reasons, whereas almost 42% of the respondents were classified as *pragmatists* who primarily made their travel choices based on trip characteristics. Interestingly, 17% of the night train users in the sample were identified as *dissonants* who showed almost identical trip patterns and choices to the *greens* except for their preference towards long-distance trips. In this regard, the analysis revealed that these *dissonants* pay significant attention to the environmental impact of their choices, but still justify their plane choices for long-distance travel. Other research studied individuals' carbon emissions in relation to travel choices as well.

A recent study by Mattioli et al. (2023) focused on individuals' carbon emissions associated with the use of the car and air travel. They found that approximately 20% of the population exhibited 'inconsistent' emission patterns, with either high car emissions and low air travel emissions or vice versa. Individuals characterized by low car emissions coupled with high air travel emissions tended to be younger urban residents and belonged to higher-income groups. Still, it is important to note that emission estimates did not include business air travel and the type of seat as well as the vehicle occupancy, engine capacity and related engine characteristics (e.g. age, engine power). Besides Mattioli et al. (2023), Klein and Taconet (2024) studied the distribution of emissions from mobility in Germany among individuals (in particular: high emitters). The study reveals, among others, the top 10% of emitters account for around 80% of the emissions for long-distance travel. In addition, Klein and Taconet (2024) found that daily cycling was strongly associated with higher long-distance emissions.

Finally, studies have also provided some empirical insights on the theoretical mechanisms involved in the context of daily and air travel behavior. A consistent finding in this regard is that while environmental attitudes do correlate positively with the use of sustainable modes for daily travel (public transport and bicycle use), they do not correlate (negatively) with air travel behaviors (Alcock 2017; Kroesen 2013; Schubert et al. 2020).

In fact, the correlation may even be positive. For example, Magdolen et al. (2022), based on a latent class analysis, found one particular cluster of 'young travel-addicted urbanites', who, despite their environmentally conscious behavior in daily commuting and a greater inclination towards ecological norms compared to other groups, paradoxically recorded the highest frequency of leisure trips and the most frequent air travel. Hence, contrary to consistency theories, people do not necessarily strive to reach consistency between their pro-environmental attitudes and their flying behaviors.

While this empirical evidence points against consistency theory, there is some evidence in favor of the notion of moral licensing. For example, Kaklamanou et al. (2015) found that people who believe that the negative effects of unsustainable behaviors can be compensated for by engaging in sustainable behaviors, indeed engaged less in pro-environmental behavior (car use amongst others). The scale developed by these authors, referred to as Compensatory Green Beliefs (CGBs), can be viewed as a measure of the extent moral licensing indeed occurs. Besides compensatory beliefs as also studied by Capstick et al. (2019) and Nayum & Thøgersen (2022), other mechanisms underlying moral licensing are the self-perception of 'having done enough for the environment' (e.g. Urban et al. 2021) or a perceived obligation to reduce emissions (e.g. through meat consumption; Burger et al. 2022).

To synthesize, research has established various theoretical mechanisms through which pro-environmental behaviors may influence each other, yielding both negative and positive spill-over effects. With regard to the relationship between frequencies of daily mode use and flying behavior, both negative spill-over effects (indicative of moral licensing) and positive spill-over effects (indicative of consistency theory) may exist.

This study contributes to the existing literature in two ways. In line with the studies of Magdolen et al. and Mattioli et al. (2023), we first aim to identify -cross-sectionally- which consistent and inconsistent groups of travelers exist, having either aligned (or non-aligned) daily travel and air travel behaviors. Our second and more fundamental contribution is that we explore spill-over effects between daily mode use and flying behaviors longitudinally using a panel approach. Compared to cross-sectional studies, this will yield more rigorous empirical evidence regarding the direction and sign of the spill-over effects between these behaviors. In particular, by adopting a panel approach the (temporal) directionality of the effects can be empirically verified, typically regarded as one of the criteria for establishing causal effects (Kirk 2009).

Methods

Data

In this investigation, we employ panel data sourced from the Netherlands Mobility Panel (MPN) (Hoogendoorn et al. 2015). The MPN is an annual household panel initiated in 2013, comprising approximately 2000 households and 4500 individuals. Each year, members aged 12 and above within these households are invited to complete a 3-day travel diary (conducted in October/November) and each member is asked to respond to an extensive questionnaire encompassing diverse topics, such as occupational status, utilization of various transportation modes, and notable life events over the past year. For more in-depth details about the MPN, we refer to Hoogendoorn-Lanser et al. (2015). At the time of this research, data from nine waves (2013–2021) were available for analysis.

From 2016 onwards, the flying frequency was included in the survey distributed among household members. Given the exceptional circumstances in 2020 due to COVID-19, we excluded this year. Hence, for the present study, we use data from the period 2016–2019, thus including four years/waves. In total, 1,549 individuals participated in all waves and are included in the analysis. For the latent class model, we only use the data of the most recent year (2019), while for the RI-CLPM we use all available years (2016–2019). Table 1 presents the sample distributions of the most recent year (2019).

Table 1 Sample distributions of socio-demographic variables, income, level of urbanization and car ownership in wave 4 (2019, N = 1549)

Covariate	Categories	Sample
Gender (%)	Man	48
	Woman	52
Age (%)	18–29 years old	14
	30–39 years old	28
	40–49 years old	21
	50–59 years old	22
	60–69 years old	11
	70 years old and older	4
Level of education (%)	Vocational education	40
	College	44
	University	16
Level of urbanization (%)	Very highly urbanized (2500 or more inhabitants/km^2)	20
	Highly urbanized (1500 to 2500 inhabitants/km^2)	35
	Moderately urbanized (1000 to 1500 inhabitants/km^2)	18
	Low urbanization (500 to 1000 inhabitants/km^2)	19
	Non-urbanized area (Less than 500 inhabitants/km^2)	8
Household income (%)	Minimum (<€ 13,700)	1
	Below the national benchmark income (€ 13,700—<€ 28,600)	10
	National benchmark income (€ 28,600—<€ 42,400)	18
	1–2 × the national benchmark income (€ 42,400—<€ 71,000)	33
	2 × the national benchmark income (€ 71,000—<€ 84,700)	9
	More than 2 × the national benchmark income (>=€ 84,700)	14
	Do not know / do not want to say	15
Number of cars in the household (mean)		1.3
Origin	Native Dutch ethnic origin	94
	(Other) Europe	3
	Other world (not Europe)	3

Measures

In this research, we consider three variables related to frequencies of daily mode use and one variable related to flying frequencies. For frequencies of daily mode use, we consider the main modes in the Netherlands in terms of trip frequencies, i.e., the frequencies of car, the bicycle and train trips. These variables were measured on 6-point ordinal scales from (1) '(almost) never' to (6) '4 days a week or more'. For flying behavior, a single variable reflects the frequency of flying for private purposes in the past 12 months. Here, 4-point ordinal scales were used which were labelled as follows: (1) 'not', (2) '1–2 times', (3) '4–5 times' and (4) '6 times or more'. These four behavioral measures were measured in each wave (from 2016 to 2019). Table 3 (last column) presents the sample distributions of the frequencies of mode use in the last wave (2019).

For the latent class analysis, we considered several additional variables. Firstly, two attitudinal variables were included, the first relating to the extent of a person's worries about climate change, which is measured on a 5-point ordinal scale from (1) 'I am not worried at all' to (5) 'I am very worried', and the second relating to whether a person's takes the environment into account in one's travel behavior, measured on a dichotomous scale (no/yes). These items were only measured in the 2016 survey. Next to these attitudes, a set of seven variables related to behavioral responses to reducing the environmental impact of flying was included (e.g., travelling less by plane or whether a person engaged in carbon offsetting). These items were only measured in the 2019 survey. Finally, we included the personal characteristics presented in Table 1.

Latent class analysis

The latent class analysis is aimed at revealing whether and to what extent (in)consistencies exist among the variables related to frequencies of daily mode use and the flying behaviors. We chose to conduct a latent class analysis since such a clustering technique allows us to identify heterogeneity in daily and air travel patterns among individuals and to categorize groups of individuals based on their shared (personal) characteristics. Moreover, the latent class analysis is specifically useful when indicators are measured on an ordinal scale, which is a clear benefit over other clustering techniques such as K-Means clustering. Figure 1 presents the conceptualization that underlies the analysis. In the model, the behavioral indicators related to frequencies of daily mode use and private flying behavior are treated as indicators of the classes. The clustering is thus fully driven by the (shared) variance among these indicators. The determination of the optimal number of latent classes (discussed in a moment) is solely based on this part of the model, i.e., the measurement model. The indicators were specified as ordinal, which means that the links between the latent class variable and the indicators are captured by a series of ordinal regression models.

After the optimal number of classes is determined, we additionally profile the classes in terms of relevant socio-demographic variables (gender, age and education level), level of urbanization, income and car ownership (also taken from the 2019 survey) and origin. These variables may be assumed to influence latent class membership, and are thus included in the class membership function, the so-called structural part of the model.

Finally, the classes are additionally profiled in terms of the two attitudinal variables (measured in 2016) and as well as a set of seven variables related to behavioral responses

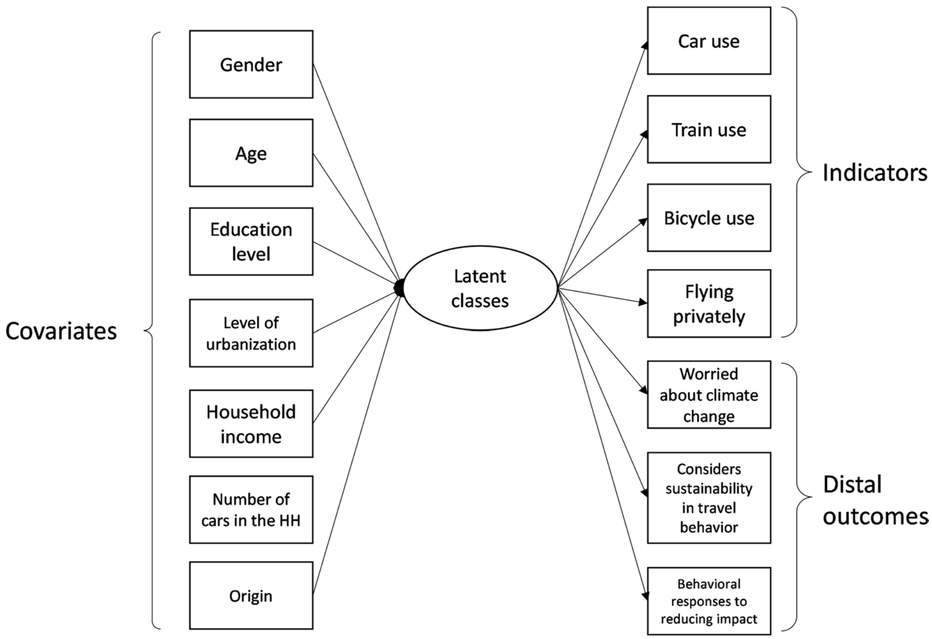

Fig. 1 Conceptualization of the latent class model

to reducing the environmental impact of flying (measured in 2019). By profiling the classes on these variables, the revealed (in)consistencies between the behavioral indicators can be placed into a richer context and therefore be better understood.

The attitudes and behavioral responses to reducing the environmental impact of flying are likely endogenous to the daily and air travel behavior, i.e., they may be assumed to influence the behavioral variables, but are likely (in turn) also influenced by them. To prevent these variables from having a strong (undue) impact on the clustering we therefore employed the 3-step approach and treated the variables as distal outcomes of the latent classes (Asparouhov and Muthén, 2012). This essentially means that separate regressions are estimated for each outcome, whereby the latent class variable forms the independent variable and the respective outcome the dependent. In these regressions, the measurement error present in the latent classes is taken into account (via the posterior membership probabilities). Latent Gold 5.1 was utilized to estimate the latent class model (Vermunt and Magidson 2013).

The primary goal of latent class analysis is to identify a model that strikes a balance between model fit and parsimony, aiming for the fewest latent classes that can explain the covariation among the indicators. To ascertain the optimal model, a series of models (with indicators only) was estimated with 1 through 10 latent classes. Table 2 displays the fit of these models, in terms of the Log-Likelihood and the Bayesian information criterion (BIC), a metric that considers both model fit and the number of parameters (Magidson & Vermunt 2004). While the BIC statistic indicates that the 5-class model has the lowest value and should be considered optimal, the BIC value only improves minorly when including more than 3 classes. Hence, the 3-class solution is considered optimal.

Table 2 Fit of the latent class models

No. of clusters	Npar	LL	BIC(LL)	L^2	df	p-value
1	18	−8165.7	16463.7	1303.6	845	0.00
2	23	−7973.8	16116.5	919.8	840	0.03
3	28	−7851.0	15907.6	674.1	835	1.00
4	33	−7823.2	15888.7	618.5	830	1.00
5	38	−7791.9	15862.9	555.9	825	1.00
6	43	−7776.4	15868.7	525.0	820	1.00
7	48	−7766.1	15884.7	504.3	815	1.00
8	53	−7760.9	15911.1	494.0	810	1.00
9	58	−7755.8	15937.5	483.7	805	1.00
10	63	−7750.7	15964.1	473.6	800	1.00

Npar, number of parameters; LL, log-likelihood; BIC, Bayesian information criterion

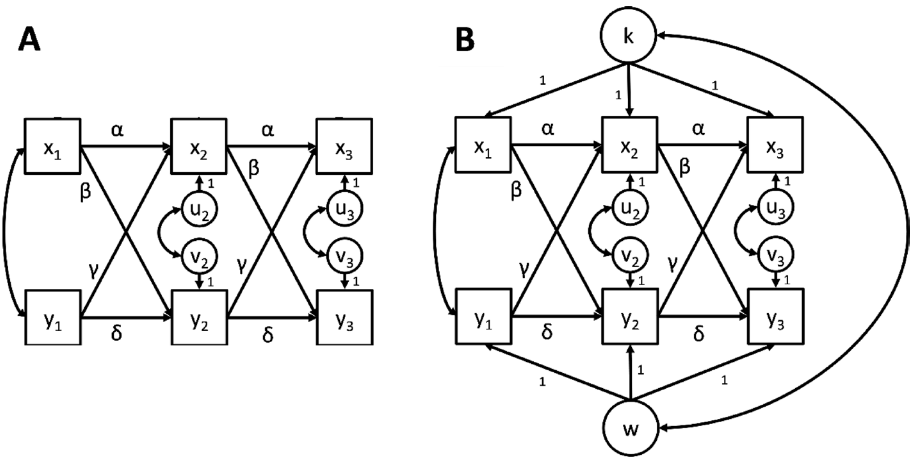

Fig. 2 Structure of a 2-variable 3-waveCLPM (**A**) and RI-CLPM (**B**) (Hamaker et al. 2015). Note: To account for structural/period effects the observed values for *x* and *y* are typically mean-centered around the respective mean of each wave

Random intercept cross lagged panel model

To examine the reciprocal (bidirectional) relationships between daily travel behavior (car, train and bicycle use frequencies) and flying behavior (for private purposes), we employed a Random-Intercept Cross-lagged Panel Model (RI-CLPM). The RI-CLPM is a structural equation model using longitudinal rather than cross-sectional data, allowing us to explore the direction of causality between two or more constructs. We provide a brief introduction to the model here; for a comprehensive description, we refer to Hamaker et al. (2015).

Figure 2a presents an exemplary CLPM for three measurement occasions and two variables. Note that in the present study this structure is expanded to 5 variables (3 relating to frequencies of daily mode use and 2 to flying behaviors) and 4 waves (covering the period 2016–2019). Basically, the CLPM allows the researcher to assess whether variation in a certain variable (e.g. x_1) can explain variation in another variable at a later point in time

(y_2) (via coefficient β), while controlling for prior values of that variable (y_1) (through the stability coefficient (δ) and the correlation between x_1 and y_1), and similarly the other way around. The correlations between the error terms of the endogenous variables (u and v) capture the influences of unobserved (time varying) variables and/or possible synchronous effects between x and y (i.e. effects with a shorter time lag than the period between the measurement occasions). The significance and strength of the 'cross-lagged' parameters β and γ are informative as to which of the two variables, x or y, is the strongest temporal predictor (or whether both variables influence each other).

The RI-CLPM (Fig. 2b) additionally includes random intercepts for each dependent variable, respectively denoted as ω and k, which are both assumed to have a time-constant influence on the observed scores at each point in time. As a result, the factor loadings of the random intercept are fixed at 1, underscoring that between-person differences are invariant over time. By 'factoring-out' these stable individual differences, the model controls for time-constant variables and the cross-lagged parameters (subsequently) only capture within-person carry-over effects from one occasion to the next (Hamaker et al. 2015). The correlation r between ω and k reveals to what extent both variables are associated at the between-person level. Note that in the present application there are four dependent variables and so 4 random intercepts, which results in the estimation of 6 correlations.

To assess whether the random intercepts indeed capture stable between-person variation, we compare the fit of the RI-CLPM with the fit of the conventional CLPM, which does not include the random intercepts ω and k. A significant improvement in model fit indicates that this is indeed the case. Fit indices used to assess the improvement in model fit are the Chi-square difference test and differences in Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean squared Residual (SRMR). While the Chi-square difference test is a common method to assess fit improvement, the Chi-square values are somewhat sensitive to sample sizes (Hu and Bentler 1999). Therefore, additional (common) fit indices are used to complement the Chi-square difference test. In addition to the model fit improvements, we also analyze the (significance and magnitude of) variances of the random intercepts. These variances indicate the extent individuals differ from one another in their stable traits.

To sufficiently account for possible confounding effects by personal characteristics, such characteristics measured in the survey (see Table 1) have been included as exogenous variables of the random intercepts. The models are estimated using Mplus 8.6.

Results

Bivariate correlations

To get an initial grasp of the relationship between frequencies of daily mode use and flying behavior, we computed the bivariate (Spearman rank) correlations between the behavioral variables, including the two environmental attitudes as well. Table 3 presents the resulting correlation matrix.

The correlations related to the daily travel behaviors are intuitively plausible; car use is negatively associated with bicycle and train use, indicating these modes substitute for one another, while train and bicycle use are positively associated, indicating these modes are

Table 3 Bivariate Spearman's rank correlations for wave 4 (2019)

	Car use	Bicycle use	Train use	Flying privately	Worried about climate	Considers environment in TB
Frequency of car use (as driver or passenger)	1.00					
Frequency of bicycle use	−0.35**	1.00				
Frequency of train use	−0.35**	0.27**	1.00			
Frequency of flying privately	−0.02	0.13**	0.20**	1.00		
To what extent are you worried about climate change?	−0.12**	0.16**	0.16**	0.04	1.00	
Do you take the environment into account in your travel behavior (TB)?	−0.23**	0.17**	0.13**	-0.02	0.36**	1.00

*Significant at 5% level

**Significant at 1% level

complementary (in the Netherlands the bicycle is often used as access/egress mode for the train). The frequency of flying for private purposes is not significantly associated with car use, but is positively associated with bicycle and train use. Hence, people who use more sustainable travel modes in their daily lives tend to fly more frequently. Finally, in line with expectations, the two environmental attitudes are negatively associated with car use and positively with bicycle and train use. However, the attitudes are not significantly correlated with the flying behavior. Overall, the pattern of correlations is well aligned with the results of previous studies that indicate that environmental attitudes do influence daily travel decisions but not holiday practices (Barr et al. 2010; Mattioli et al. 2023; Magdolen et al. 2022).

Results of the latent class model

Table 4 presents the class profiles in terms of the behavioral and attitudinal variables and Table 5 further profiles the classes with regard to several socio-demographic variables, the level of urbanization and car ownership. Overall, the classes are well interpretable.

Class 1—car and bike users with a high flying frequency. Individuals in the first class (49% of the sample) travel by car most of the time, but also use the bicycle and train occasionally. Members of this class have a relatively high frequency of flying privately. A large share (47%) travels 1–2 times per year for private reasons. Hence, both the daily travel and the flying behavior of members of this class can be classified as relatively unsustainable. The level of environmental concern is in between the other two classes. Looking at the demographic profile, the members of this class are relatively old, with high income and the highest level of car ownership.

Class 2—car users with low flying frequency. The second class (39% of the sample) consists of travelers who predominantly use the car in their daily travel, and have the lowest flight frequency. Hence, while their daily travel behavior can be classified as unsustainable, their flying behavior is most sustainable relative to the other classes. Members of this class are worried about climate change, but least compared to the other classes, and generally do not consider the environment in their travel behavior. Hence, the low flying frequency does not seem to originate from concern for the environment, but rather from a low desire to fly.

Table 4 Class profiles

	Class	1	2	3	Sample
	Class size (%)	49	39	12	100
Indicator (daily travel)	Categories				
Frequency of car use (%)	(Almost) never	0	0	25	3
	1–5 days per year	0	0	11	1
	6–11 days per year	1	0	18	3
	1–3 days per month	10	2	25	9
	1–3 days per week	40	24	17	31
	4 or more days per week	48	74	4	53
Frequency of bicycle use (%)	(Almost) never	16	36	6	22
	1–5 days per year	5	8	2	5
	6–11 days per year	5	7	3	6
	1–3 days per month	14	13	12	14
	1–3 days per week	27	19	29	24
	4 or more days per week	33	17	48	29
Frequency of train use (%)	(almost) never	16	77	4	38
	1–5 days per year	39	22	16	29
	6–11 days per year	20	1	15	12
	1–3 days per month	14	0	21	9
	1–3 days per week	6	0	17	5
	4 or more days per week	5	0	27	6
Indicator (flying behavior)					
Frequency of flying privately (%)	Not	41	65	39	50
	1–2 times	47	32	48	41
	3–5 times	10	3	11	7
	6 times or more	1	0	2	1
Dital outcomes (inactive covariates)					
Worried about climate change (%)	I am not worried at all	3	4	5	4
	I am not worried	7	12	7	9
	Neutral	25	36	24	29
	I am worried	49	39	43	45
	I am very worried	15	9	20	13
Takes environment into account in travel behavior (%)	Yes	38	26	48	35
	No	61	74	51	65
Because of sustainability reasons					
I travel more often with the train or bus instead of the plane (% yes)		2	0	12	3
I go on holiday less often (% yes)		5	3	6	5
I went to holiday destinations that are closer by (% yes)		10	6	12	9
I travel less with the plane within Europe (% yes)		8	4	10	7
I went on holiday outside Europe less often (% yes)		7	3	8	5
I went on holiday within the Netherlands more often instead of abroad (% yes)		9	7	9	8
I paid to compensate for the CO_2-emissions (% yes)		6	3	11	5

Table 5 Covariate distributions of the classes

Covariate	Categories	Class 1	Class 2	Class 3	Sample
Gender (%) (Wald = 19.2, $p < 0.000$)	Man	40	58	47	48
	Woman	60	42	54	52
Age (%) (Wald = 9.7, $p = 0.009$)	18–29 years old	15	11	23	14
	30–39 years old	26	28	39	28
	40–49 years old	19	25	15	21
	50–59 years old	24	23	9	22
	60–69 years old	10	11	10	11
	70 years old and older	6	2	4	5
Level of education (%) (Wald = 43.8, $p < 0.000$)	Vocational education	39	69	44	40
	College	40	26	27	44
	University	21	5	29	16
Level of urbanization (%) (Wald = 19.6, $p = 0.033$)	Very highly urbanized (2500 or more inhabitants/km^2)	23	8	48	20
	Highly urbanized (1500 to 2500 inhabitants/km^2)	41	30	33	35
	Moderately urbanized (1000 to 1500 inhabitants/km^2)	18	20	11	18
	Low urbanization (500 to 1000 inhabitants/km^2)	14	30	7	19
	Non-urbanized area (Less than 500 inhabitants/km^2)	4	12	2	7
Household income (%) (Wald = 49.3, $p < 0.000$)	minimum (<€ 13,700)	1	1	4	1
	below the national benchmark income (€ 13,700 − <€ 28,600)	7	9	29	10
	national benchmark income (€ 28,600 − <€ 42,400)	17	17	22	18
	1–2 × the national benchmark income (€ 42,400 − <€ 71,000)	33	36	20	33
	2 × the national benchmark income (€ 71,000 − <€ 84,700)	10	10	5	9
	more than 2 × the national benchmark income (>=€ 84,700)	18	10	12	14
	Do not know / do not want to say	14	18	9	15
Number of cars in the household (mean)		1.7	1.3	1.6	0.3
Origin (%) (Wald = 6.1, $p < 0.41$)	Native Dutch ethnic origin	93	96	92	94
	(Other) Europe	3	3	6	3
	Other world (not Europe)	4	1	2	3

Table 5 reveals that individuals in this class are more often male, lower educated and living in rural areas compared to the sample as a whole.

Class 3—Bicycle and train users with a high flying frequency. Members of this class (13% of the sample) travel most sustainably in their daily travel, using a combination of the bicycle and train. The frequency of car use and car ownership are lowest compared to the other classes. The flying frequency, on the other hand, is highest compared to the other classes. Given that the environmental concern is very high, members of this class arguably experience quite some inconsistency. While efforts are reported to reduce the environmental impact of flying (e.g., traveling by train, choosing destinations closer by, traveling less by plane and offsetting carbon emissions), the members of this class do not actually succeed in traveling less by plane. Compared to the sample, the members of this class are relatively young, highly educated and living in highly urbanized areas.

Classes two and three can be identified as 'inconsistent', in the sense that the daily travel pattern is on the unsustainable end of the spectrum (as observed in the sample), while the flying behavior is on the sustainable end (class 2) or the other way around (class 3). Class 1 takes a middle position on both dimensions. Overall, in line with the correlations presented in Table 3, the results show that the sustainable behavior in daily travel is inversely related to sustainable behavior in terms of flying frequency. The question is whether the correlations/patterns have come about due to spillover effects, e.g. people who cycle and/or travel by train feel morally licensed to travel more by plane, or whether they have come about due to possible 'third' variables. The longitudinal analysis in the next section will answer this question.

Results of the RI-CLPM

Table 6 displays the model fit statistics for both the CLPM and the RI-CLPM. The Chi-square difference test is significant, indicating a substantial enhancement in model fit. Other fit indices improved as well. Overall, this signifies that the random intercepts effectively account for stable individual differences between people. The RI-CLPM demonstrates good fit according to commonly employed relative fit indices as well (Hu and Bentler 1999).

In addition to the model fit, the estimated variances of the random intercepts can be useful to assess whether the random intercepts indeed capture between-person stable variations. These variances (see Table 7) highlight the extent to which individuals differ from one another in their stable traits. All variances are significant and large, indicating substantial between-person differences which are captured with the random intercepts, which is in line with the model fit improvements.

Table 8 presents the standardized parameter estimates of the RI-CLPM. We focus first on the autoregressive effects, which represent the within-person carry-over effects from a vari-

Table 6 Model fit of CLPM and RI-CLPM

Model	χ^2	df	*p*-value	RMSEA[a]	CFI[b]	SRMR[c]
CLPM	991.8	120	0.000	0.068	0.932	0.052
RI-CLPM	408.4	126	0.000	0.038	0.979	0.037
Difference	583.4	6	0.000	0.030	0.047	0.015

[a]Root mean square error of approximation (<0.06 indicates a good fit, Hu and Bentler (1999))

[b]Comparative fit index (>0.95 indicates a good fit, Hu and Bentler (1999))

[c]Standardized root mean squared residual (<0.08 indicates a good fit, Hu and Bentler (1999))

Table 7 Estimated variances and *p*-values of random intercepts

Random intercept	Est	*p*-value
Car	0.645	0.000
Bike	0.666	0.000
Train	0.759	0.000
Flying privately	0.859	0.000

Table 8 Standardized parameter estimates of the RI-CLPM[a]

Effect	Autoregressive effects (α and δ)	
	Est	*p*-value
Car use (t−1)→car use (t)	0.320	0.000
Bicycle use (t−1)→Bicycle use (t)	0.734	0.000
Train use (t−1)→train use (t)	0.306	0.000
Flying privately (t-1)→Flying privately (t)	0.195	0.000

Effect	Cross-lagged effects (within-person) (β and γ)		Correlations random intercepts (between-person)	
	Est	*p*-value	Est	*p*-value
Car use (t−1)→Bicycle use (t)	−0.010	0.520	**−0.545**	0.010
Bicycle use (t−1)→Car use (t)	−0.039	0.267		
Car use (t−1)→Train use (t)	**−0.108**	0.002	**−0.358**	0.000
Train use (t−1)→Car use (t)	−0.056	0.069		
Car use (t−1)→Flying privately (t)	0.035	0.231	−0.058	0.249
Flying privately (t-1)→Car use (t)	0.002	0.927		
Bicycle use (t−1)→Train use (t)	−0.026	0.576	**0.403**	0.022
Train use (t−1)→Bicycle use (t)	−0.025	0.231		
Bicycle use (t−1)→Flying privately (t)	0.032	0.323	−0.020	0.886
Flying privately (t−1)→Bicycle use (t)	0.022	0.122		
Train use (t−1)→Flying privately (t)	0.005	0.872	**0.231**	0.000
Flying privately (t−1)→Train use (t)	−0.001	0.974		

[a]The provided autoregressive and cross-lagged effects at the within person show the average values of the standardized estimates over all time periods. The unstandardized effects remain constant across all waves, however, the standardized estimated exhibit slight variations from one wave to another due to the changing variances of the variables over time. Estimates in bold are significant at the 0.05 level.

able to its future counterpart. The findings show that at t−1, bicycle use has the strongest impact on its corresponding counterpart at t (0.734), followed by car use (0.320), train use (0.306), and flying privately (0.195). The presence and significance of these effects suggest that there are internal processes within an individual that facilitate these positive carry-over effects. Especially for cycling these carry-over effects are strong, indicating that the performance of this behavior leads people to keep performing this behavior. This might be the result of positive experiences or due to the role of habits or personal and/or social norms which may be strengthened by performing the behavior.

The cross-lagged effects, which are of primary concern, reveal the degree to which the variables exert influences on each other over time. Like the autoregressive effects, these estimates can be understood as carry-over effects within individuals from one instance to the next, but in this case, they pertain to the relationships between different variables. Surprisingly, the results reveal that only one effect (out of 12) is significant at the 5% level, namely from car use to train use. The effects related to the relationships between car use and train use are negative in both directions, while only the effect from frequencies of car use to train use is significant at the 5% level. This indicates that these modes act as substitutes for one another; higher use of the car leads to lower use of the train. The cross-lagged effects between daily and air travel behavior indicate the extent to which spill-over effects between the two are present. Overall, the results indicate that spill-over effects at the within-person level between daily travel and flying behavior are non-existent since they do not reach statistical significance.

Finally, the findings show that the correlations between the random intercepts of daily mode frequencies are significant. More specifically, we find large negative correlations between car use on the one hand and train (−0.358) and bicycle use (−0.545) on the other hand. These results suggest that, at the between-person level, car users tend to use the train and bike less frequently, and vice versa. In contrast, the correlation between train and bicycle use is large and positive (0.403), indicating that train and bike users -on average- tend to use both. Regarding the correlations between the random intercepts, only the correlation between flying privately and the frequency of train use is positive and significant (0.231). Hence, at the between-person level higher train use is still associated with higher flying frequency, while controlling for the effects of the sociodemographic characteristics.

Conclusion and discussion

Using data from the Netherlands Mobility Panel, we employed a twofold approach to explore spill-over effects between frequencies of daily mode use and flying behavior both cross-sectionally and longitudinally. Using a cross-sectional latent class analysis, we find three clusters of individuals with heterogeneous daily and air travel patterns. In general, the results of this cross-sectional analysis corroborate the findings of earlier studies, in that people who travel more sustainably for their daily travel tend to fly more often (and vice versa) (Mattioli et al. 2023). While this may be taken as evidence that moral licensing occurs (i.e. people who travel much with sustainable modes in their daily lives feel morally licensed to fly more often) the longitudinal analysis reveals that these (cross-sectional) associations are *not* due to effects at the within-person level. None of the cross-lagged effects between daily mode use and flying frequency are significant. Hence, the observed positive correlations between train/bicycle use and the frequencies of flying privately, have come about due to structural differences between people, and not because of psychological mechanisms operating at the within-person level. This is an important finding in relation to previous cross-sectional research that has primarily relied on (between-person) correlations between behaviors.

In line with other studies, we found that environmental attitudes were correlated positively with the use of sustainable modes for daily travel, but not significantly correlated with flying behaviors (Alcock et al. 2017). Several explanations have been offered for this pattern of correlations. Alcock et al. (2017) mention the role of habits as a possible reason. While daily travel decisions form routine/repetitive decisions, the decision to fly is typically infrequent. Consequently, informed by pro-environmental attitude habits may be formed that influence daily travel behavior, while this may not be the case for flight behavior. In fact, flight behavior for private (holiday) purposes is typically seen as a break from the routine, which allows the suspension of norms (Cohen et al. 2013). This explanation is also supported in the study of Kroesen (2013) who found that people regard the holiday as an event that explicitly allows for indulgence. This indulgence may become a habit itself, enforcing earlier (less sustainable) behavior. (Rev #3, comment #26) From this perspective, the observed lack of correlation between pro-environmental attitudes and flying behavior is not surprising.

It is worthwhile to highlight several limitations of this study. One important limitation lies in the measurements of frequencies of daily mode use and flying behavior, which both consisted of ordinal scales and, as such, do not necessarily accurately reflect the associated environmental impacts. Ideally, these behavioral variables should be captured by measuring the distances traveled by the various modes, although this is quite complex and typically also involves making some assumptions (see e.g., Mattioli et al. 2023). It should be noted in this regard, that our research was not focused on estimating the environment effects per se, but on exploring whether spill-over effects exist between these behaviors. Secondly, while the panel model can provide empirical evidence regarding the direction of effects (unlike cross-sectional studies), this model is also based on certain assumptions, for example concerning the assumed duration of the causal lags between the variables, in our study assumed to be equal to the time between surveys (one year). In future research, other time lags (synchronous effects or 2-year lagged effects) can also be explored, although research has shown that empirically determining which lag better fits the data is difficult (Muthén and Asparouhov 2023).

To conclude, the results have important policy implications. Apparently, trying to influence environmental attitudes to induce pro-environmental behavior may work well for daily travel, but (up till now) not for flying behavior. In a way, this also shows the limits of 'voluntary behavioral change' as a paradigm to substantially reduce carbon emissions; people who are highly environmentally aware and knowledgeable about the impact of aviation on the climate still choose to fly regularly. Of course, it may be that norms with respect to flying will also change on a larger scale in the future (e.g., considering the flight shame movement), but this has not happened to date. Instead of raising awareness it might be better to focus efforts on providing alternatives. The study of Schubert et al. (2020) is interesting in this regard, which showed that people who prefer to have enjoyable daily free-time can find satisfaction without needing to travel far by air.

Author contributions Maarten Kroesen: writing, model conceptualization, data-analysis. Milad Mehdizadeh: writing, review and editing. Milan Moleman: writing, review and editing.

Data availability No datasets were generated or analysed during the current study.

Declarations

Conflict of interest The authors declare no conflict of interest.

References

Alcock, I., White, M.P., Taylor, T., Coldwell, D.F., Gribble, M.O., Evans, K.L., Corner, A., Vardoulakis, S., Fleming, L.E.: 'Green' on the ground but not in the air: pro-environmental attitudes are related to household behaviours but not discretionary air travel. Glob. Environ. Change. **42**, 136–147 (2017)

Asparouhov, T., Muthén, B.: Auxiliary variables in mixture modeling: a 3-step approach using Mplus. Mplus Web Notes **15**, 1–51 (2012)

Barr, S., Shaw, G., Coles, T., Prillwitz, J.: 'A holiday is a holiday': practicing sustainability, home and away. J. Transp. Geogr. **18**(3), 474–481 (2010)

Behn, O., Wichmann, J., Leyer, M., Schilling, A.: Spillover effects in environmental behaviors: a scoping review about its antecedents, behaviors, and consequences. Curr. Psychol. **44**(5), 3665–3689 (2025)

Bem, D. J.: Self-perception theory. In: Advances in experimental social psychology vol. 6, pp. 1–62. Academic Press 1972

Brañas-Garza, P., Bucheli, M., Espinosa, M.P., García-Muñoz, T.: Moral cleansing and moral licenses: experimental evidence. Econ. Philos. **29**(2), 199–212 (2013)

Brög, W., Erl, E., Sammer, G., and Schulze, B.: Dateline-design and application of a travel survey for long-distance trips based on an international network of expertise-concept and methodology. In: 10th International Conference on Travel Behaviour Research. Lucerne (2003)

Burger, A.M., Schuler, J., Eberling, E.: Guilty pleasures: moral licensing in climate-related behavior. Glob. Environ. Change. **72**, 102415 (2022)

Capstick, S., Whitmarsh, L., Nash, N., Haggar, P., Lord, J.: Compensatory and catalyzing beliefs: their relationship to pro-environmental behavior and behavioral spillover in seven countries. Front. Psychol. **10**, 963 (2019)

Carrico, A.R.: Climate change, behavior, and the possibility of spillover effects: recent advances and future directions. Curr. Opin. Behav. Sci. **42**, 76–82 (2021)

Cohen, S.A., Higham, J.E., Reis, A.C.: Sociological barriers to developing sustainable discretionary air travel behaviour. J. Sustain. Tour. **21**(7), 982–998 (2013)

Festinger, L.: Cognitive dissonance. Sci. Am. **207**(4), 93–106 (1962)

Font Vivanco, D., Freire-González, J., Kemp, R., van der Voet, E.: The remarkable environmental rebound effect of electric cars: a microeconomic approach. Environ. Sci. Technol. **48**(20), 12063–12072 (2014)

Galizzi, M.M., Whitmarsh, L.: How to measure behavioral spillovers: a methodological review and checklist. Front. Psychol. **10**, 342 (2019)

Geiger, S.J., Brick, C., Nalborczyk, L., Bosshard, A., Jostmann, N.B.: More green than gray? Toward a sustainable overview of environmental spillover effects: a Bayesian meta-analysis. J. Environ. Psychol. **78**, 101694 (2021)

Gerosa, T., Cellina, F.: Who uses night trains and why? A mixed-method study profiling night train users in Switzerland. Travel Behav. Soc. **37**, 100854 (2024)

Hamaker, E.L., Kuiper, R.M., Grasman, R.P.P.: A critique of the cross-lagged panel model. Psychol. Methods **20**(1), 102 (2015)

Hoogendoorn-Lanser, S., Schaap, N.T., OldeKalter, M.J.: The Netherlands Mobility Panel: an innovative design approach for web-based longitudinal travel data collection. Transp. Res. Proc **11**, 311–329 (2015)

Hu, L.T., Bentler, P.M.: Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives. Struct. Equ. Model. **6**(1), 1–55 (1999)

Kaklamanou, D., Jones, C.R., Webb, T.L., Walker, S.R.: Using public transport can make up for flying abroad on holiday: compensatory green beliefs and environmentally significant behavior. Environ. Behav. **47**(2), 184–204 (2015)

Kirk, R. E.: Experimental design. In: Sage Handbook of Quantitative Methods in Psychology, pp. 23–45. (2009).

Klein, F., Taconet, N.: Unequal 'drivers': on the inequality of mobility emissions in Germany. Energy Econ. **136**, 107630 (2024)

Kroesen, M.: Exploring people's viewpoints on air travel and climate change: understanding inconsistencies. J. Sustain. Tour. **21**(2), 271–290 (2013)

Kroesen, M., Le, H.T., De Vos, J., Ton, D., de Bruyn, M.: Revealing latent trajectories of (intended) train travel during and after COVID-19. Transp. Res. D Transp. Environ. **124**, 103952 (2023)

Magdolen, M., von Behren, S., Chlond, B., Vortisch, P.: Long-distance travel in tension with everyday mobility of urbanites–a classification of leisure travellers. Travel Behav. Soc. **26**, 290–300 (2022)

Magidson, J., and Vermunt, J. K.: Latent class models. In: The Sage Handbook of Quantitative Methodology for the Social Sciences, pp. 175–198. (2004).

Maki, A., Carrico, A.R., Raimi, K.T., Truelove, H.B., Araujo, B., Yeung, K.L.: Meta-analysis of pro-environmental behavior spillover. Nat. Sustain. **2**(4), 307–315 (2019)

Mattioli, G., Scheiner, J.: A panel analysis of change in personal air travel behaviour in England between 2012 and 2019. Transportation (2024). https://doi.org/10.1007/s11116-024-10571-9

Mattioli, G., Büchs, M., Scheiner, J.: Who flies but never drives? Highlighting diversity among high emitters for passenger transport in England. Energy Res. Soc. Sci. **99**, 103057 (2023)

Muthén, B. and Asparouhov, T.: Can cross-lagged panel modeling be relied on to establish cross-lagged effects? The case of contemporaneous and reciprocal effects. Under review. (2023). Available at: https://www.statmodel.com/download/ReciprocalV3.pdf

Nayum, A., Thøgersen, J.: I did my bit! The impact of electric vehicle adoption on compensatory beliefs and norms in Norway. Energy Res. Soc. Sci. **89**, 102541 (2022)

Nilsson, A., Bergquist, M., Schultz, W.P.: Spillover effects in environmental behaviors, across time and context: a review and research agenda. Environ. Educ. Res. **23**(4), 573–589 (2017)

Schubert, I., Sohre, A., Ströbel, M.: The role of lifestyle, quality of life preferences and geographical context in personal air travel. J. Sustain. Tour. **28**(10), 1519–1550 (2020)

Thøgersen, J.: Spillover processes in the development of a sustainable consumption pattern. J. Econ. Psychol. **20**(1), 53–81 (1999)

Thøgersen, J., Ölander, F.: Spillover of environment-friendly consumer behaviour. J. Environ. Psychol. **23**(3), 225–236 (2003)

Tiefenbeck, V., Staake, T., Roth, K., Sachs, O.: For better or for worse? Empirical evidence of moral licensing in a behavioral energy conservation campaign. Energy Policy **57**, 160–171 (2013)

Truelove, H.B., Carrico, A.R., Weber, E.U., Raimi, K.T., Vandenbergh, M.P.: Positive and negative spillover of pro-environmental behavior: an integrative review and theoretical framework. Glob. Environ. Change **29**, 127–138 (2014)

Urban, J., Braun Kohlová, M., Bahník, Š: No evidence of within-domain moral licensing in the environmental domain. Environ. Behav. **53**(10), 1070–1094 (2021)

Van der Werff, E., Steg, L., Keizer, K.: I am what I am, by looking past the present: the influence of biospheric values and past behavior on environmental self-identity. Environ. Behav. **46**(5), 626–657 (2014)

Vermunt, J.K., Magidson, J.: Latent class analysis. In: The Sage Encyclopedia of Social Sciences Research Methods, vol. 2, pp. 549–553. (2004)

Winter, S.R., Lamb, T.L., Wallace, R.J., Anderson, C.L.: Flight shaming consumers into aviation sustainability: which factors moderate? Int. J. Sustain. Aviat. **7**(1), 21–45 (2021)

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