The impacts of e-bike adoption on attitudes and travel behaviour – a longitudinal investigation using the Swiss Mobility Panel

Jérôme Laviolette*[1], Eva Heinen[2]

[1] Postdoctoral Researcher, Department of Civil, Environmental and Geomatic Engineering, ETH Zürich, Switzerland

[2] Full Professor, Department of Civil, Environmental and Geomatic Engineering, ETH Zürich, Switzerland

SHORT SUMMARY

As e-bike ownership and use grow in Europe and beyond, mass adoption could represent a substantial shift in how people travel and how they perceive cycling. While much of the research on e-bikes has focused on substitution effects with other modes, notably the car, this paper investigates how adoption affects cycling practices. Using three waves of the Swiss Mobility Panel from 2020 to 2025, we apply a random-intercept cross-lagged panel model (RI-CLPM) to estimate the effects of switching from a conventional bike to an e-bike on cycling frequency and cycling attitudes. Because the RI-CLPM disentangles between-person and within-person effects, the results confirm that those who adopt e-bikes increase their cycling frequency and develop more positive cycling attitudes. Furthermore, these effects grow stronger over time. These findings suggest that even among current cyclists, e-bikes can further expand cycling practices.

Keywords: attitudes, cycling behavior, e-bike, longitudinal, RI-CLPM

1. INTRODUCTION

E-bike ownership and use are rising across Europe. E-bikes can increase active travel among diverse populations by overcoming many barriers associated with traditional bicycles, including long distances, hilly terrain, physical effort, poor health, and the need to carry cargo or children (Rérat, 2021). Their potential contribution to a low-carbon mobility transition and healthier cities depends on the extent to which e-bike trips replace car trips. Recent reviews have concluded that substitution does occur, with levels varying by local and individual context as well as baseline travel behaviour (Chevance et al., 2025). For example, in a high-cycling country such as the Netherlands, multi-wave longitudinal evidence using a Random-Intercept Cross-Lagged Panel Model (RI-CLPM) suggests that e-bikes primarily replace regular bicycle trips overall, and that replacement of car trips is significant only when focusing on commuting purposes (de Haas et al., 2022).

Large-scale societal changes in the way we travel require a deep understanding of mechanisms of change at the individual level. The rapid pace of e-bike adoption provides an opportunity to examine the psychological processes of behaviour change when an important mobility tool is adopted. For example, do people acquire an e-bike because they value cycling but are dissatisfied with aspects of cycling on a regular bicycle? Once they begin using that newly acquired e-bike, either for leisure or for travel, do their perceptions of cycling change? Do they become more positive? Among cyclists, qualitative evidence using a mobility biography approach suggests that e-bike adoption can lead to a resilient trajectory (allowing one to continue cycling despite changing spatial or personal contexts) or a restorative trajectory (allowing someone who had stopped

cycling to resume the practice) (Marincek & Rérat, 2021). Beyond the implications for cycling and e-cycling, answering these questions can provide insights into the complex relationship between travel behaviour and attitudes over time, a topic that has received increasing attention in travel behaviour research over the last decade (De Vos, 2022).

While some prior studies suggest that perceptions of e-bikes become more positive following e-cycling trials (Bourne et al., 2020), to the best of our knowledge no study has used exogenous longitudinal data to empirically examine the direction of causality between e-bike adoption, bicycle use, and cycling attitudes over time. This study therefore investigates these effects by estimating a random intercept cross-lagged panel model (RI-CLPM) using three waves of the Swiss Mobility Panel collected in 2020, 2022, and 2025.

2. METHODOLOGY

Conceptual model

In this study, we focus on the relationship between cycling behaviour, cycling attitudes, and the switch from a regular bicycle to an E-bike. We therefore exclude respondents who switch from *no bicycle* to an *E-bike*. We make this distinction because we believe the psychological and behaviour change processes, as well as the impact of acquiring an e-bike, differ meaningfully between non-cyclists and cyclists. We decompose our main objective into three research questions:

1. For regular bicycle owners, does switching to an E-bike as the main bicycle lead to an increase in cycling frequency?
2. For regular bicycle owners, does switching to an E-bike as the main bicycle lead to a change in cycling attitudes?
3. Is the impact of the e-bike switch on behaviour and attitudes sustained over time?

We hypothesize that the answers to 1 and 2 are yes, but that the effect will diminish over time.
To investigate these questions, we use three non-consecutive waves of the Swiss Mobility Panel to estimate a *random-intercept cross-lagged panel* (RI-CLPM). The conceptual model is presented in Figure 1.

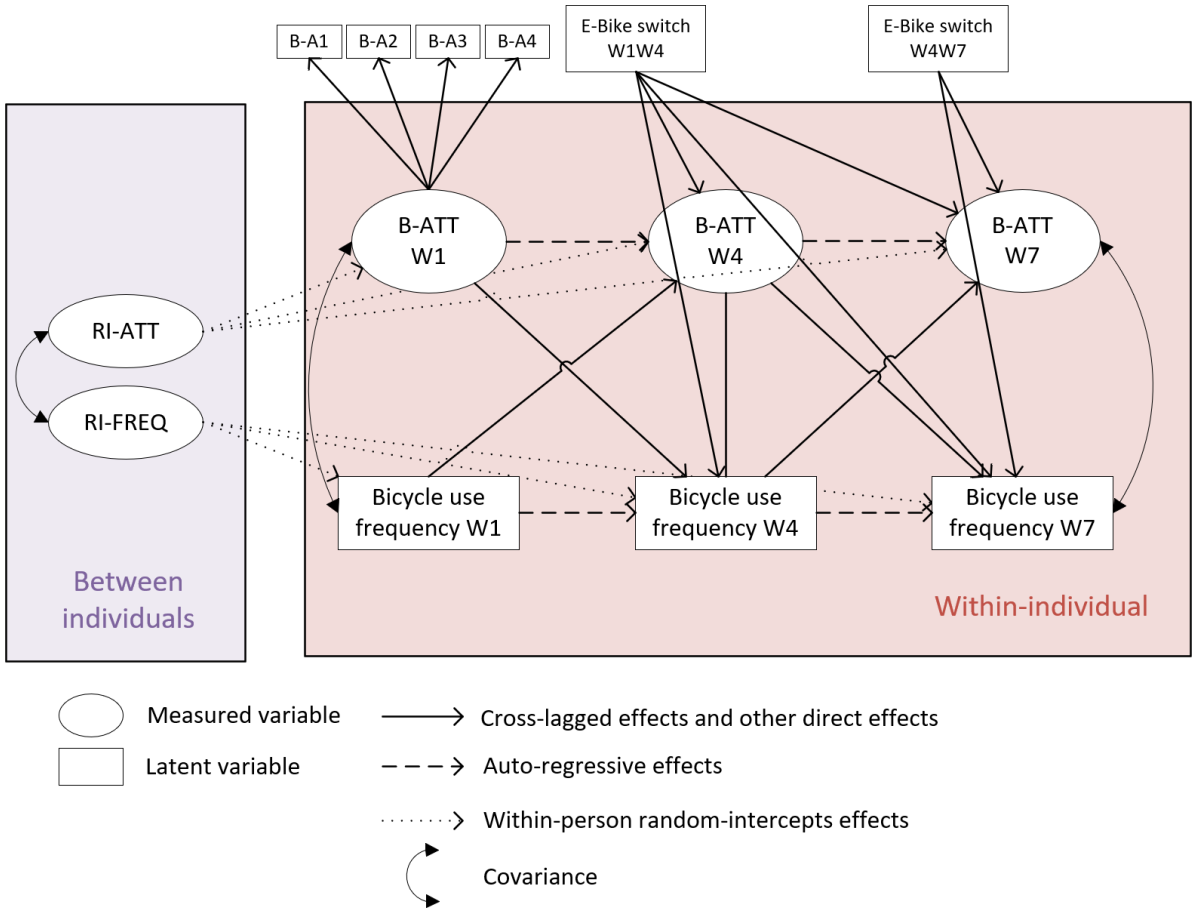


Figure 1: Conceptual model of cycling attitudes, cycling frequency and E-Bike switch estimated with the RI-CLPM.

Data

The Swiss Mobility Panel (SMP) was initiated in 2020 by researchers at ETH Zürich to investigate the dynamics of travel behaviour, preferences, and attitudes, as well as public opinion about transport-related policies. It is a longitudinal survey designed to be representative of the Swiss resident population aged 18 to 80. Initial recruitment is conducted by mail using the address list provided by the Swiss Federal Statistical Office (FSO). Recruitment for subsequent waves is conducted by both email and mail. New respondents are added every third wave (baseline waves) to balance attrition and maintain sample representativeness. For the current study, we use three available baseline waves — W1 (12.2020), W4 (12.2020), and W7 (06.2025) — in which bicycle ownership, mode use frequency, and mode-specific attitudes were measured (n = 3276). While W1 and W4 were collected in early December, W7 was collected in June. Although questions are asked in general terms to minimize seasonal influence, there is likely a seasonal trend in cycling frequency between winter (W4) and summer (W7), and, to a lesser extent, in cycling attitudes. We explain how we account for this in the model description below.

Variables and data preparation

The bicycle ownership question asked whether respondents owned a bicycle and, if so, which type they used most often. The choices were (1) *No*, (2) *Yes, a standard bicycle*, and (3) *Yes, an*

electric-assist bicycle (e-bike). This means that *technically*, for bicycle owners, we do not know whether they acquired an e-bike between waves or simply shifted which bicycle they used more often. For this reason, we use the terms 'adoption' or 'switch' instead of 'acquisition' or 'purchase' throughout the paper. We computed a bicycle switch variable between each wave (W1 → W4; W4 → W7), which is used as an exogenous variable for W4 and W7 frequency and attitudes. This is equivalent to treating Bike → E-Bike as the treatment group and Bike → Bike as the control group.

General cycling frequency ("How often do you ride a bicycle?") was measured using a 6-point frequency scale ranging from *Never* to *Daily*, coded 0 to 5. For cycling attitudes, five items were measured on a 5-point Likert scale (Disagree Strongly to Strongly Agree): (A1) *I ride my bike even in bad weather*, (A2) *When I sit on the bike, I feel independent and free*, (A3) *Cycling is a practical way for me to get around*, (A4) *Cycling is a good way for me to stay fit*, and (A5) *It is dangerous to ride a bicycle on shared roads.* Respondents could also select "I don't know" for these items. Selecting "I don't know" is not random, and those without a bicycle are more likely to choose it. However, since our sample is restricted to bicycle owners, the proportion for any given item across all three waves is at most 1.3% (n=21) of our final sample. As this is marginal, we imputed a value of 3 without inflating the neutral category. Exploratory factor analysis suggested a 1-factor, 4-item solution (A1, A2, A3, A4), with Cronbach's $\alpha = 0.80$, dropping A5. Loadings are presented in the results section.

Descriptive statistics

Table 1 shows bicycle ownership types across waves for respondents who answered all three waves. Overall, we observed a trend across Switzerland: regular bicycle ownership decreases over time, E-bike ownership increases substantially, and the share of adults without a bicycle also increases, despite the rise in e-bikes.

Table 1: Bicycle ownership across waves of the Swiss Mobility Panel (unweighted)

	W1 (2020)		**W4 (2022)**		**W7 (2025)**		Δ
Type	N	%	N	%	N	%	W1-W7
Bicycle	1890	58%	1656	51%	1423	43%	-25%
E-Bike	623	19%	796	24%	969	30%	56%
None	763	23%	824	25%	884	27%	16%
Total	3276	100%	3276	100%	3276	100%	-

However, because our objective is to specifically investigate the relationship between cycling frequency, changes in cycling attitudes over time, and the impact of switching to an e-bike, we further restrict our sample to respondents who had a bicycle at W1 (n=1890), continued to have a bicycle at W4 and W7 (our "control group"), or switched to an e-bike at W4 ("Core treatment") or at W7 ("Secondary treatment: late switchers"), thus retaining 1,600 respondents.

Modelling framework

Random-Intercept Cross-Lagged Panel model

The RI-CLPM is an extension of the traditional Cross-Lagged Panel Model proposed by Hamaker et al. (2015). Unlike the traditional model, it explicitly distinguishes within-person effects over time from between-person variance by including random-intercept parameters that capture trait-like characteristics influencing the outcome variables. In other words, the RI-CLPM allows us to

investigate within-person dynamics over time, strengthening causal inference. To be estimated adequately, it requires a minimum of three waves of data.

Assessing measurement invariance (MI)
When using repeated measures of psychometric latent variables (or constructs) over time, it is essential to validate measurement invariance, that is, to test whether the LVs are equivalent across time points and not changing due to drift in item interpretation. Following the method ofMulder and Hamaker (2021), we tested measurement invariance for the cycling attitude latent variable. Results supported scalar invariance (same intercepts), which implies configural invariance (same factor structure) and metric invariance (same factor loadings) across all three waves ($\Delta CFI \leq .003$, $\Delta RMSEA \leq .001$).

Final model estimation
To estimate the RI-CLPM we use the R package *lavaan* (Rosseel, 2012). From the 3-wave respondents, we further remove those having missing values attitudinal items values, dropping our sample to n = 1585. However, because of question conditions in W4 and W7, a subset of respondents who have a bicycle, but never use it were not asked the attitudinal questions. As the issue is not too severe representing less than 5% in W4 and W7, the missing values are handled through *lavaan*'s Full information maximum likelihood (FIML).

As MI tests confirmed metric and scalar invariance across waves, we constrain the intercepts and the loadings of the cycling attitude items (B-ATT) to be equal across waves. We allow the random intercept for frequency and attitudes (RI_FREQ and RI_ATT) to covary. This is theoretically justified as between-person differences in attitudes and frequency are highly correlated. We also allow attitudes and frequency at W1 (i.e., within-person deviation from their expected mean) to covary for the same reason. By specifying do not assume any dominant direction of causality within waves.

Furthermore, while we fix the RI_ATT mean to 0, we allow the RI_FREQ mean to be freely estimated to accommodate a wave-level upward shift in frequency from winter (W4) to summer (W7). Additionally, unlike de Haas et al. (2022), we do not constrain autoregressive and cross-lagged effect to be equal across waves also to accommodate seasonal variations. The model is estimated using Robust maximum-likelihood (MLR) with robust standard errors to handle missing data and non-normal distribution of cycling frequency values and attitudinal indicators.

3. RESULTS AND DISCUSSION

The RI-CLPM results are presented in Table 2. The model offers a reasonable fit to the data considering its complexity. All fit indices are within the acceptable thresholds or very close (Robust CFI > .95, Robust TLI ~= .95, Robust RMSEA ~= .06, SRMR < .08). The measurement part of the model presents the latent cycling attitude factor structure, with standardized factor loadings for W1 ranging from .58 to .74, indicating acceptable to good indicator reliability.

Table 2: RI-CLPM of cycling frequency, cycling attitudes and the effect of shifting to e-bike

Measurement model	W1: B-ATT LV	
	Std. loadings	(SE)
B-ATT1: Weather	.653	(0.000)
B-ATT2: Freedom	.645	(0.040)
B-ATT3: Practicality	.739	(0.037)

B-ATT4: Fitness	.58	(0.035)		
Structural model	B	(SE)	*β*	*p*
Autoregressive effects				
B-ATT W1 --> B-ATT W4	**0.214**	**(0.038)**	**0.203**	**< .001**
B-ATT W4 --> B-ATT W7	**0.250**	**(0.039)**	**0.243**	**< .001**
B-FREQ W1 --> B-FREQ W4	**-0.040**	**(0.008)**	**-0.040**	**< .001**
B-FREQ W4 --> B-FREQ W7	0.005	(0.010)	0.005	0.637
Cross-lagged effects				
B-FREQ W1 --> B-ATT W4	**-0.040**	**(0.007)**	**-0.062**	**< .001**
B-FREQ W4 --> B-ATT W7	**-0.073**	**(0.007)**	**-0.110**	**< .001**
B-ATT W1 --> B-FREQ W4	**0.179**	**(0.033)**	**0.109**	**< .001**
B-ATT W4 --> B-FREQ W7	0.013	(0.033)	0.008	0.695
E-Bike switch effects				
W1/W4 Early switch --> B-ATT W4	**0.260**	**(0.065)**	**0.080**	**< .001**
W1/W4 Early switch --> B-ATT W7	**0.351**	**(0.067)**	**0.105**	**< .001**
W1/W4 Early switch --> B-FREQ W4	**0.475**	**(0.089)**	**0.094**	**< .001**
W1/W4 Early switch --> B-FREQ W7	**0.639**	**(0.089)**	**0.129**	**< .001**
W4/W7 Late switch --> B-ATT W7	**0.324**	**(0.051)**	**0.101**	**< .001**
W4/W7 Late switch --> B-FREQ W7	**0.614**	**(0.068)**	**0.130**	**< .001**
Between-person structure				
RI_ATT	**0.610**	**(0.069)**	**-**	**< .001**
RI_FREQ	**1.601**	**(0.059)**	**-**	**< .001**
RI_ATT ~~ RI_FREQ	**0.901**	**(0.061)**	**0.912**	**< .001**

Notes: B, SE and *p* = unstandardized, β = Std.all fully standardized.
Model fit: χ^2 (106) = 641.03, p < .001 (Yuan-Bentler scaled, correction factor = 1.174), Robust CFI = .959, Robust TLI = .948, Robust RMSEA = .062, SRMR = .053.

The **autoregressive effects** for attitudes (B-ATT) show moderate within-person stability between waves. Effects are very similar from W1 (winter) to W4 (winter) and W4 (winter) to W7 (summer), suggesting consistent cycling attitudes dynamics over time, even between different seasons. For cycling frequency, the results are a bit more surprising. W1 to W4 effects indicate that someone with a higher-than-expected cycling frequency at W1 will have a lower-than-expected cycling frequency at W4. However, the effect is small (β = -0.04). As for W4 to W7, the autoregressive term is positive but not significant. This suggests that individuals' deviation from their own baseline frequency are not strongly associated with their past frequency.

The **cross-lagged effects** indicate that higher cycling frequency at W_{t-1} predicts lower than expected cycling attitudes at W_t, with the effect being stronger from W4 to W7. This seems counterintuitive and might be explained by a ceiling effect where those with high cycling frequency already have high cycling attitudes and those attitudes can then only go down, with no room in the measurement instruments to further increase. The CL effects from attitudes to frequency are positive from W1 to W4, suggesting that higher attitudes predict higher frequency at the next wave. However, this is not sustained from W4 to W7 where the effect is not significant. As W4→W7 is a winter-summer interval, is it possible that natural seasonal change in cycling behaviour dominates the decisions, irrespective of attitudes at the previous wave (i.e., even people with lower cycling attitudes would increase their cycling frequency from winter to summer).

Finally, the **e-bike switch effects** are all positive, suggesting that adopting the e-bike as main cycling modes leads to a within-person increase in both cycling frequency and attitudes. The standardized coefficients suggest these effects are slightly stronger for frequency than attitudes. Furthermore, the effect of switching to an e-bike between W1 and W4 on both attitudes and frequency are getting stronger over time, with larger coefficients observed for W7 than W4. The effects are also observed for late switchers (W4-W7 switch). The immediate post-switch effects are not significantly different between early and late switchers: $\chi^2(2) = 1.60$, $p = .448$.

4. CONCLUSION

In this study we estimate a Random-intercept cross-lagged panel using three 3 waves of the Swiss Mobility Panel to investigate the impact of e-bike adoption on cycling frequency and cycling attitudes among cyclists. First, results confirm that both cycling behaviour and cycling attitudes are not fixed and can be changed over time following the adoption of a mobility tool and, second, this happens gradually over several years. The implications are particularly important for attitudes as these tend to be considered constant over time. This would suggest a restorative cycling trajectory (Marincek & Rérat, 2021), confirming that e-bikes can expand cycling practice and attitudes for those previously owning a conventional bicycle, but who might have been disenchanted with its use. Future research should use similar causal method to determine if the increased in cycling is associated with a reduction in other mode frequency as empirical longitudinal evidence on this matter remains scarce.

ACKNOWLEDGEMENTS

The authors would like to thank Dr. Florian Maurus Lichtin from ETH Zürich for his help in understanding the structure of the Swiss Mobility Panel.

REFERENCES

Bourne, J. E., Cooper, A. R., Kelly, P., Kinnear, F. J., England, C., Leary, S., & Page, A. (2020). The impact of e-cycling on travel behaviour: A scoping review. *Journal of Transport & Health*, *19*, 100910. https://doi.org/https://doi.org/10.1016/j.jth.2020.100910

Chevance, G., Jessica, B., Louise, F., James, G., Beate, S. H., Aslak, F., & and Bernard, P. (2025). E-bikes and travel behaviour change: systematic review of experimental studies with meta-analyses. *Transport Reviews*, *45*(3), 433–454. https://doi.org/10.1080/01441647.2025.2474556

de Haas, M., Kroesen, M., Chorus, C., Hoogendoorn-Lanser, S., & Hoogendoorn, S. (2022). E-bike user groups and substitution effects: evidence from longitudinal travel data in the Netherlands. *Transportation*, *49*(3), 815–840. https://doi.org/10.1007/s11116-021-10195-3

De Vos, J. (2022). The shifting role of attitudes in travel behaviour research. *Transport Reviews*, *42*(5), 573–579. https://doi.org/10.1080/01441647.2022.2078537

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

Marincek, D., & Rérat, P. (2021). From conventional to electrically-assisted cycling. A biographical approach to the adoption of the e-bike. *International Journal of*

Sustainable Transportation, *15*(10), 768–777. https://doi.org/10.1080/15568318.2020.1799119

Mulder, J. D., & Hamaker, E. L. (2021). Three Extensions of the Random Intercept Cross-Lagged Panel Model. *Structural Equation Modeling: A Multidisciplinary Journal*, *28*(4), 638–648. https://doi.org/10.1080/10705511.2020.1784738

Rérat, P. (2021). The rise of the e-bike: Towards an extension of the practice of cycling? *Mobilities*, *16*(3), 423–439. https://doi.org/https://doi.org/10.1080/17450101.2021.1897236

Rosseel, Y. (2012). lavaan: an R package for Structural Equation Modelling. *Journal of Statistical Software*, *48*(2), 1–36.