Follow the e-riders: Exploring behaviour change processes among e-bike adopters through a mixed-methods approach

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SHORT SUMMARY

Promotion and assessment of sustainable and active mobility are increasingly widespread. Recent studies explore the role of electric-assisted bicycles (e-bikes) in travel behaviour, identifying motivation, substitution effects in other transport modes and changes at the individual level. However, evidence from longitudinal methods has been limited, and the use of either quantitative or qualitative approaches creates a gap between statistical generalisation and contextual understanding. This study employs a mixed-method approach to understanding the individual behaviour change process of e-bike adopters. Analyses are based on data from four waves of an online panel survey, semi-structured interviews conducted before and after with individuals who reported intention and then either adopted or did not adopt an e-bike, and approximately 9 months of mobility diaries from a mobile app. The study provides a comprehensive understanding of how, why, and under what conditions new technology adoption, such as e-bikes, can support modal shifts.

Keywords: electric bikes, technology adoption, cycling behaviour, travel behaviour, longitudinal mixed-method approach.

1. INTRODUCTION

Promoting the use of sustainable and active transport modes is a widely recognised policy goal in urban areas. Electric-assisted bicycles (e-bikes) have emerged as a promising technology innovation in the transport sector. This micro-mobility alternative allows for retaining many of the health and environmental benefits of cycling while reducing physical effort and maintaining physical activity levels. A growing number of studies and meta-reviews suggest that e-bikes can extend feasible cycling distances, enabling cycling among older individuals and those with physical impairments (e.g., see Van Cauwenberg et al., 2019), and substitute other transport modes (e.g., see Rérat et al., 2025). In this way, when the e-bike replaces car trips, there is evidence of additional benefits in terms of greenhouse gas emissions reductions (McQueen et al., 2020). Moreover, e-bike adoption can induce travel trips that would not have occurred without the adoption and can promote well-being and personal growth at the individual or household level (Azzouz et al., 2026). As such, e-bikes are likely to be relevant for reducing car dependency and supporting individual modal shifts, especially when longer trips are needed and public transport access is limited (Chevance et al., 2025). Despite recent insights into the motivations for adoption, the literature remains unclear about how and for whom the motivation to adopt an e-bike influences the identified behavioural change (de Haas et al., 2022).

Qualitative studies provide rich insights into the psychological processes related to e-bike use and adoption, highlighting conflicts between identity and attitudes and behaviours, as well as changes in perceptions of distance and effort (Mayer, 2020). Nevertheless, such studies are often conducted in isolation from quantitative analyses, limiting their capacity to inform generalisable conclusions. Recent studies demonstrate the value of integrating behavioural metrics with qualitative

reflection, yet these approaches are typically short-term and focus on discrete interventions rather than long-term adoption trajectories (Wilson & Whitmarsh, 2025).

A critical limitation of many existing quantitative studies is their reliance on cross-sectional or short-term pre-post research designs. Longitudinal data are needed to analyse within-person dynamics over time, supporting more robust inference about behavioural change processes, including behavioural adaptation and habit formation, as well as the role of psychological variables as moderators of transport choices. Existing longitudinal panel studies remain comparatively rare, yet they consistently show more nuanced and heterogeneous effects. For instance, longitudinal analyses from the Netherlands, a country that worldwide reports higher cycling rates, reveal that e-bike uptake does not uniformly substitute car travel but instead interacts with prior travel habits, trip purposes, and user profiles (de Haas et al., 2022). These findings underline the risk of overestimating behavioural impacts when temporal dynamics and within-person change are not explicitly accounted for.

Existing research on e-bike adoption and longitudinal behaviour change has mainly explored the effects of using e-bikes either in the context of shared e-bike programs relying on operator usage data (e.g., Wilson & Whitmarsh, 2025) or through controlled interventions where behaviour is tracked over time (e.g., see Bjørnaå et al., 2019). These studies identify limitations in their findings, such as the risk of differential effects between ownership and sharing e-bikes and the uncertainty that individuals adopt stable routines when they own e-bikes for longer periods. There is a gap in the literature regarding the role of e-bike ownership and its effects on long-term behavioural choices, using more granular measures of behaviour that do not rely solely on self-reported data.

The aim of this study is to understand the individual change process of e-bike adopters and to identify how adoption (or non-adoption) relates to short-term and long-term behavioural choices in the transport domain. Using a longitudinal mixed-method design and triangulating repeated measures of travel behaviour, the study seeks to bridge the gap between statistical generalisation and contextual understanding. In doing so, it offers a more comprehensive understanding of how, why, and under what conditions e-bikes can support modal shifts.

2. METHODOLOGY

This study adopts a mixed-methods approach to investigate the behaviour change process and the development of mobility patterns following e-bike adoption. We rely on three primary data sources, integrated through four complementary analyses (see Figure 1). ***Analysis 1*** examines the role of adoption motivation in behavioural outcomes using a before–and–after design (n = 1,295 intenders and 272 adopters). ***Analysis 2*** explores the stability of long-term behavioural choices regarding trip purposes and substitution effects (n ≈ 900 longitudinal observations from regular e-bike users). ***Analysis 3*** examines changes in high-resolution measures of travel behaviour among e-bike adopters (n ≈ 18 users with up to nine months of daily tracking data). Finally, ***Analysis 4*** investigates the psychological mechanisms and narrative changes associated with adoption or non-adoption among intenders of e-bikes who either adopted (n=5) or did not (n=4) after the end of the tracking period.

We use a longitudinal survey conducted in Denmark, comprising four biannual panel waves from November 2023 to May 2025. These data support Analysis 1 and 2. To obtain more detailed behavioural and psychological insights, individuals who reported concrete plans to adopt an

e-bike in earlier survey waves (November 2023 or May 2024) were invited to participate in a case study. These participants provided data for the other two data sources: approximately 9 months of mobility tracking via a mobile app and 2 semi-structured interviews. The mobility app retrieves information on daily trips (mode, duration, distance, purpose, speed, weather, etc.) and routine activities around the expected period of e-bike adoption to support Analysis 3. Furthermore, the approximately one-hour interview provided rich qualitative data for Analysis 4, before and after the intended e-bike adoption.

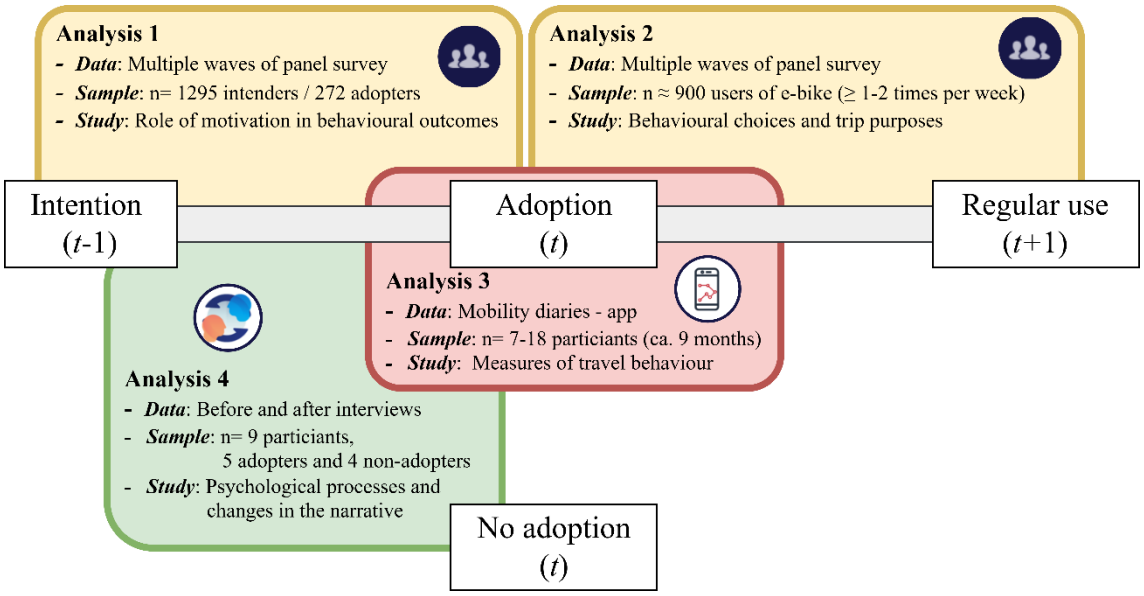


Figure 1. Mixed-method approach, data sources, samples and aims of the study

Each analysis includes its own analytical approach, which is briefly introduced in the next section, followed by preliminary results. By integrating the results of the four analyses, we aim to gain a more comprehensive understanding of the behaviour change process underlying e-bike adoption, while balancing the strengths and limitations of qualitative and quantitative methods. Parts of the results and discussion from our four complementary analyses are summarised in the following section.

3. RESULTS AND DISCUSSION

In the first analysis, we examine the role of motivation for e-bike adoption in behavioural outcomes (e.g., monthly frequency of transport modes used, e-bike modal share across trip purposes, and number of household cars) and psychological variables (e.g., cycling identity, perceived autonomy when cycling, and cycling resistance towards weather conditions). A before-and-after design is used, and statistically significant differences between pre- and post-observations are identified using the Wilcoxon signed-rank test. The aspects included in this analysis show a statistically significant difference between the observations before and after. The motivation for adoption is measured on a 5-point importance scale using 7 psychological items that capture the importance of adopting an e-bike. To account for heterogeneity in motivational profiles and their relationship with post-adoption outcomes, a three-step Latent Class Cluster Model (LCCM) is estimated in Latent Gold 6.1, allowing for missing data in distal outcomes through full-information maximum likelihood estimation.

In the first step, the latent class measurement model is estimated, and the optimal number of classes is selected based on the Bayesian Information Criterion, maximum bivariate residual, and classification error, resulting in a five-class solution (BIC = 25,582; max. BVR = 3.51; classification error = 0.17). In the second step, posterior class membership probabilities are computed. In the third step, class membership is related to individual covariates (gender, age, residential area, presence of children in the household, and occupation) and to distal outcomes, including a proportional correction to account for classification uncertainty while keeping the latent class measurement model fixed. The final model reports, for each latent class, statistically significant ($p < 0.05$) indicators, covariates, and distal outcomes. Figure 2 presents the model-based class-specific averages of the motivation items used in the class formation.

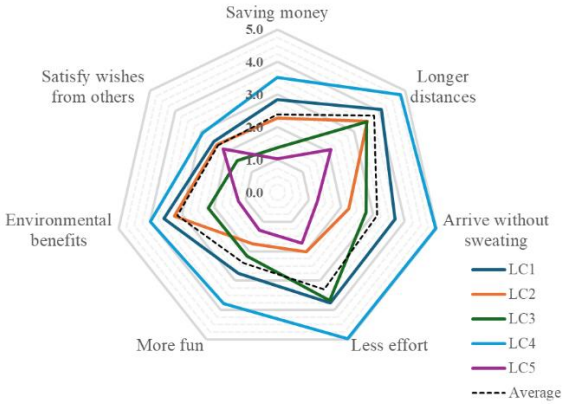


Figure 2. Latent class profiles in the class indicators related to the motivation for adoption.

The largest segment of the sample is characterised by a ***convenience-oriented and practical*** motivation (LC1, 41%). In terms of behavioural change, this group does not show significant differences in e-bike usage time, cycling behaviour, or car use compared with the overall sample. No significant effects are observed for psychosocial cycling indicators or car ownership. This class is over-represented by students and individuals in younger age groups, and individuals with underage kids in the household are more likely to belong to this group.

The second-largest segment (LC2, 24%) comprises individuals ***who care only about distance, with overall low motivation*** for the other items. This class is overrepresented by individuals with kids in the household and full-time homemakers. This class does not significantly differ from the overall sample with respect to changes in e-bike usage, cycling behaviour, or car use. Psychological cycling indicators also do not differ significantly. The probability of adoption after the observation period does not significantly differ from the average.

The third-largest group (LC3, 19%) shows a motivation more oriented towards the ***comfort of the cycling experience, both for longer distances and with less effort***. This class show a tendency toward younger and middle-aged respondents, with marginal under-representation of the youngest age group (18–34). This class exhibits significantly higher car use over time and a significant decline in e-bike use for work trips. Car ownership also increases significantly. This profile suggests a modal reinforcement of car use rather than a shift toward cycling or e-bikes.

The fourth group (LC4, 8%) includes the ***highly motivated and enthusiastic towards all the motivations***. This group is strongly associated with younger respondents with kids in the household, while the older age group is significantly under-represented. Despite strong demographic distinctiveness, Class 4 shows no statistically significant behavioural change in e-bike use, cycling, or

car use. Adoption probability is higher in magnitude but not statistically significant. This class appears to represent an exploratory group with heterogeneous and unstable mobility trajectories.

The latest group (LC5, 6%) reflects a trend toward ***lower goals, mainly as rejecters or not strongly motivated***. Males are significantly over-represented, and those aged between 55 and 64 are more likely to belong to this class. Unemployed individuals are significantly over-represented. Behaviourally, Class 5 shows the strongest and most consistent decline in e-bike engagement. The frequency of using e-bikes significantly decreases, as does e-bike use for work trips. Adoption likelihood after the period is lower in magnitude but not statistically significant.

In the second analysis, we explore how stable behavioural choices regarding substitution effects are in the long term (see Figure 3). We use a sample of individuals who regularly used their e-bikes (more than 1-2 times per week) and participated in at least 3 survey waves (n=933). We examine how stable transport mode substitution is across existing owners before the first wave (n=724) and new adopters in some survey waves (n=209). This analysis provides insights into how strong behavioural choices and habits disruption can be near the technology adoption period. In our preliminary results, we find a negative correlation between changes in e-bike and car use frequency, and this effect is stronger among new adopters than among prior owners. In the longer term, we identify that new adopters have higher monthly use of regular bikes and public transport than habitual e-bike users.

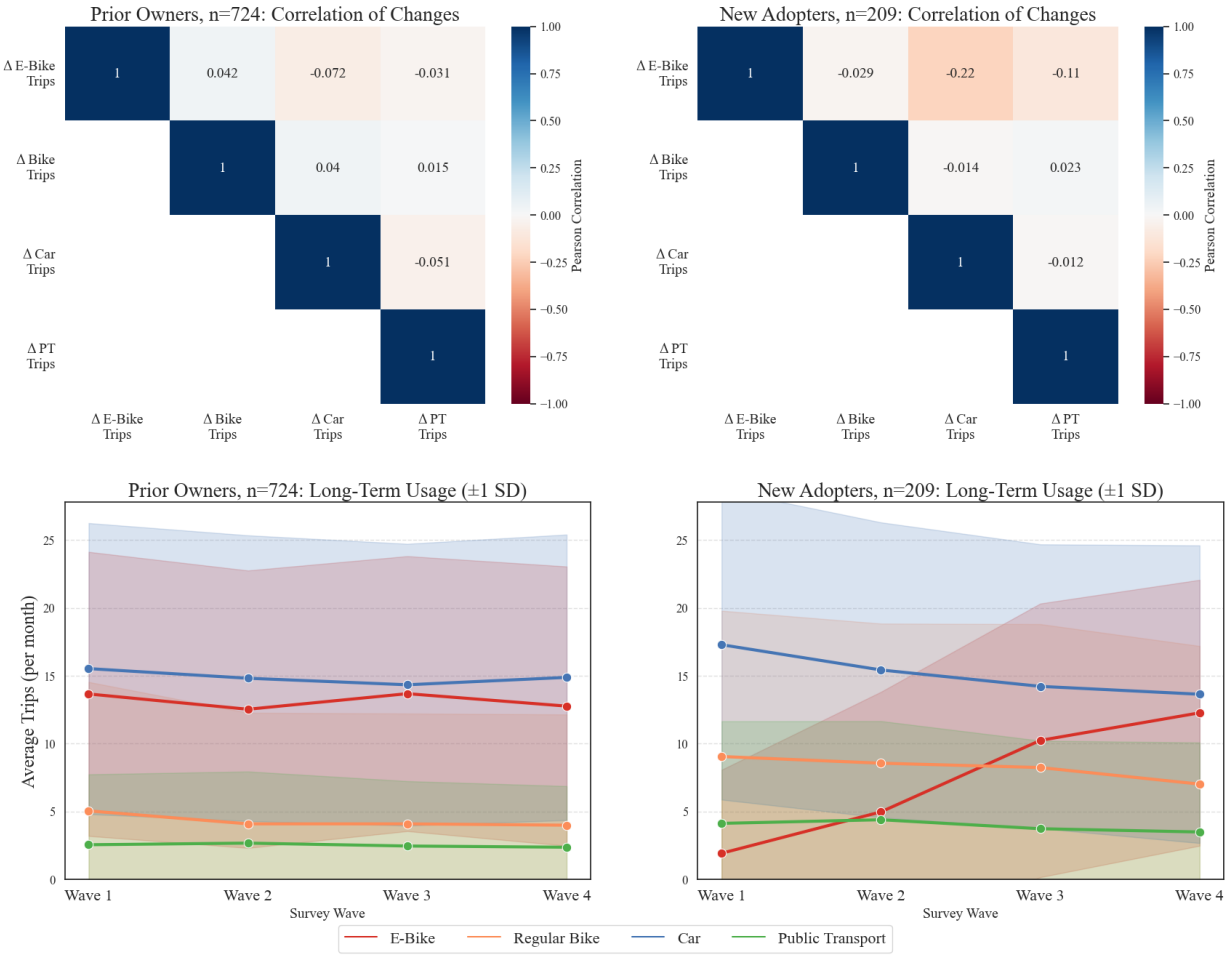


Figure 3. Longitudinal stability of frequencies using transport modes among the existing owners and new adopters of e-bikes.

In the third analysis, we identified the changes in high-resolution measures of travel behaviour among e-bike adopters. This analysis allows us to identify differences between self-reported travel behaviour measures in the survey and the app-detected averages. Figure 4 shows the average distribution of time spent in different transport modes during the observation period for one participant who adopted an electric bike. As indicated in the figure, before the adoption (23rd of July 2024), typical working days had a high car duration. However, after adoption, the share of time spent on the e-bike increased, and car use was limited to short periods in the coming days. Next steps will explore changes in time- and activity-based behaviour across the e-bike user sample and the comparison group.

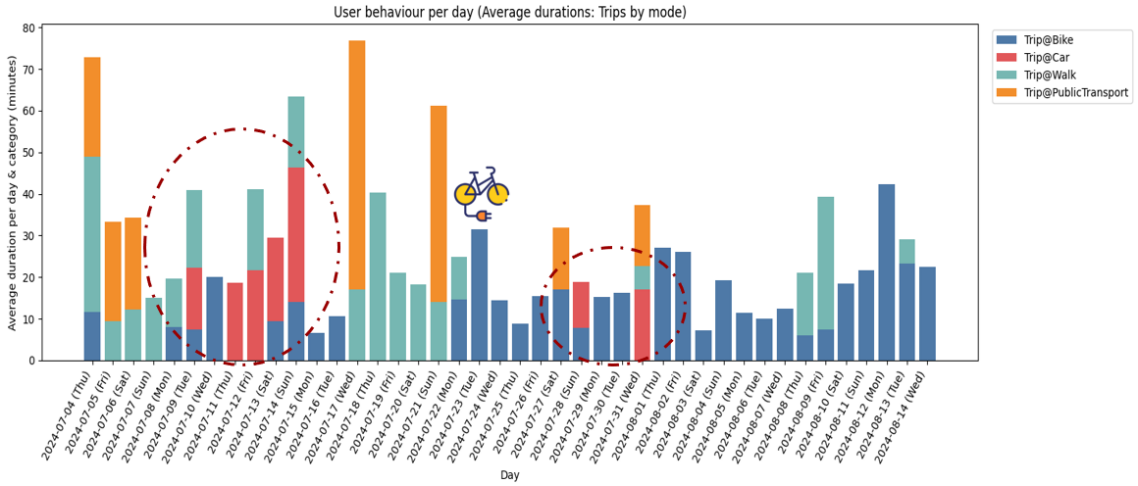


Figure 4. Individual travel behaviour (average trip duration) around e-bike adoption.

In our fourth analysis, we identify the psychological mechanisms behind the individuals who participated in our qualitative interviews. Results show that e-bikes can facilitate life transitions (e.g., childbirth, residential relocation, job routines) while avoiding the purchase of a car. Before adoption, participants carefully evaluated attributes including brand, country of manufacture, utility, and model. After selecting the e-bike, participants anticipate challenges they will need to overcome. For example, the riding experience. "*(...) So you can go a little bit faster, but if I'm going to have my kids in front, I'm not sure I'm going to ride that fast because I'm always scared of having an accident (...). So yeah, but in the city centre, definitely I will try to go slow, and I also check the people around (...)*" (ID21_before).

After adoption, individuals may reflect on the new symbolism of e-bikes and how they are now playing in the household dynamics regarding mobility. This new vehicle can be described as a "new" member of the household, for example, in the weekly scheduling exercise: "*(...) So, yeah, as I said, we bring it into the weekly schedule for who is going to use it, which days. But you know, you could say that... we had the need, and it was very much solved when we got it (...)*" (ID15_after).

However, e-bike adoption is not always a priority in household dynamics. Even if individuals realise that there is a strong need to make their transport choices easier, this adoption takes a secondary role and is postponed if other household needs arise: "*(...) Now we have a very practical challenge, where to park (...) What I could say may have changed is that now there is a priority to have at least a good-quality cargo bike. But we have had some issues with a water problem in the house (...). So let's first determine how much this is going to cost before we can invest in a good cargo bike (...)*" (ID13_after).

4. CONCLUSIONS

Longitudinal data provides the opportunity to explore changes at the individual level. This study explored the individual change process and how adopting an electric bike can be reflected in behavioural changes in transport, using a multi-method longitudinal approach. In our survey data, we identify five population segments and predict behavioural changes in the use of different transport modes. In addition, our longitudinal survey data reveal how stable the substitution effects can be and how new adopters are more likely to replace car use during a technology-adoption period. However, in the long run, these substitution effects can decrease, as individuals tend to increase their car use frequency for specific trip purposes. The tracking diaries help identify how minor changes can be hidden using self-reported instruments, and at a daily granularity level, we identify how the adaptation process unfolds in specific adopters. Moreover, e-bike adoption often does not translate into practice, and through qualitative analysis, we identify how narratives associated with e-bikes differ between adopters and non-adopters. This abstract summarises our current work. In the next step, the analyses will be completed and integrated to achieve a more comprehensive understanding of the behaviour change process underlying e-bike adoption.

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REFERENCES

Azzouz, L., Brand, C., Cass, N., & Philips, I. (2026). Miles with smiles: The role of e-cargo bikes in facilitating new personal and family-oriented travel and relevant beyond-utility motivations. *Travel Behaviour and Society*, *43*, 101217. https://doi.org/10.1016/j.tbs.2025.101217

Bjørnarå, H. B., Berntsen, S., Velde, S. J. te, Fyhri, A., Deforche, B., Andersen, L. B., & Bere, E. (2019). From cars to bikes – The effect of an intervention providing access to different bike types: A randomized controlled trial. *PLOS ONE*, *14*(7), e0219304. https://doi.org/10.1371/journal.pone.0219304

Chevance, G., Bourne, J., Foley, L., Green, J., Sundfør, H. B., Fyhri, A., & 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

Mayer, A. (2020). Motivations and barriers to electric bike use in the U.S.: Views from online forum participants. *International Journal of Urban Sustainable Development*, *12*(2), 160–168. https://doi.org/10.1080/19463138.2019.1672696

McQueen, M., MacArthur, J., & Cherry, C. (2020). The E-Bike Potential: Estimating regional e-bike impacts on greenhouse gas emissions. *Transportation Research Part D: Transport and Environment*, *87*, 102482. https://doi.org/10.1016/j.trd.2020.102482

Rérat, P., Marincek, D., & Ravalet, E. (2025). How do e-bikes compete with the other modes of transport? Investigating multiple dimensions of a modal shift. *Applied Mobilities*, *10*(1), 85–98. https://doi.org/10.1080/23800127.2024.2332006

Van Cauwenberg, J., De Bourdeaudhuij, I., Clarys, P., de Geus, B., & Deforche, B. (2019). E-bikes among older adults: Benefits, disadvantages, usage and crash characteristics. *Transportation*, *46*(6), 2151–2172. https://doi.org/10.1007/s11116-018-9919-y

Wilson, M., & Whitmarsh, L. (2025). Behavior change interventions to promote adoption of e-bike shared mobility in a rural area: Evidence from a mixed-method field trial. *Frontiers in Psychology*, *16*. https://doi.org/10.3389/fpsyg.2025.1569176