How do electric bikes affect the route choice of cyclists? A case study of Greater Helsinki

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Short summary

Cycling as a clean, green, and environmentally friendly mode of transportation plays a crucial role in society by fostering physical activity and a healthy lifestyle, reducing traffic congestion, and improving mobility. To create more efficient strategies for promoting cycling, there is a need to gain a better understanding of the influential factors on cyclists' route choice behaviour. Electric bikes (e-bikes) are an emerging technology that appeared to assist cycling by using battery-powered motors. Researchers consider e-bikes as an emerging technology with its most certain effect being easing up cycling. Hence, investigating individual route choice behaviour with respect to their bike type can unveil new insights for cycling promotion. To this end, we used data collected via a stated preference (SP) survey in Finland not only to investigate the factors affecting cyclists' route choice behaviour but also to compare the behaviour of e-bikers with regular bike users (r-bikers) in order to identify the changes that may happen by easing the pedalling fatigue due to the pedal-assist feature of e-bikes. Our results indicate that low interaction with traffic, fewer intersections, and separated bike facilities are the main factors unchanged to promote cycling among r-bikers and e-bikers. Furthermore, we compare the outputs of simple Logit models (SLMs) and random parameter Logit models (RPLMs) for r-bikers' and e-bikers' route choices to address the impact of error correlation among observations in SP data. Our findings imply that the SP data is well-designed to capture the preferences of the individuals accurately, so the observations are not severely correlated, i.e., the IID assumption is held. This suggests that using SLMs can lead to similar outputs with RPLMs, without increasing the complexity of the estimation process.
Keywords: Cycling, E-bike, Route choice, Discrete choice modelling.

1 Introduction

Motivation

Promoting active modes of travel provides many advantages, from decreasing air pollution to declining obesity cases and related diseases (Sałabun et al., 2019; Anderson et al., 2022). One popular active mode is cycling, which can be used for almost all purposes, including with kids and for the elderly. With advancements in technology, there are solutions available that are believed to decrease the physical strain of cycling. Pedal-assisted electric bikes (in short *e-bikes*) can help the cyclist while pedalling, especially on routes with hills. It is proven to be effective on obese people evidencing that the physical and mental status of overweight people in Australia has improved after 12 weeks of e-bike cycling (Anderson et al., 2022).

It is worth noting that easing up the cycling pedalling is not enough to promote an active mode to the rest of the currently passive transport users unless planned properly. Although bicycle usage is promoted in many European countries, different patterns regarding cycling have been observed. For instance, France, Italy, and Germany have witnessed a more than 10% increase in cycling demand, in 2020, compared to 2019, while Finland and Ireland lost more than 10% of their weekday cyclist in the same period (Counter, 2021). One method to promote cycling in cities is believed to be planning the infrastructures for absorbing cyclists. Therefore, planners must know what measures affect cycling more (Broach et al., 2012; Huber et al., 2021).

A key cycling decision associated with transportation infrastructure is route choice. Researchers usually employ route-choice modelling for active modes (e.g., bicycles) to assess the infrastructure characteristics' impacts on the mode users (Segadilha & Sanches, 2014; Bernardi et al., 2018).

Studies using these models conclude that length, maximum steepness, and the type of road significantly affect cyclists' route choice. It can be concluded that safety and pedalling fatigue are the main concerns reducing the cycling demand when the infrastructure, traffic laws, and affordability of bikes are in place (Hull & O'Holleran, 2014).

Background

The literature on bicycle route choice is pretty rich and comprehensive reviews of influential factors on the cyclists' route choice behaviour can be found in previous studies (e.g., see Hull & O'Holleran (2014), Tarkkala (2022), Huber et al. (2021), and Tarkkala et al. (2023)). Studies dedicated to route choice of e-bikers or the change in the attitude of cyclists using e-bikes are limited but provide interesting insights. Chavis & Martinez (2021) found that e-bikes increase the length that cyclists ride, while they also reported shorter travel times for e-bikers than regular bike users (in short r-bikers), which means a significant increase in speed is observed. Moreover, with the increase in e-bike numbers, major roads were more frequently selected by cyclists than minor roads.
Rérat (2021) surveyed more than 2000 e-bikers and almost 11000 r-bikers, revealing an increased usage of e-bikes by females (50% of e-bikers vs 40% of r-bikers), as well as an increase in average age in the e-bikers. Regarding the season of cycling, it was observed that the e-bikers were almost abandoning their bikes in winter, switching to public transport or other motorised modes, probably due to the fact that e-bikes are used more frequently for longer trips than r-bikes.
Dane et al. (2020) provided mixed Logit models for r-bikers and e-bikers that show different factors affecting their route choices. However, their study results in favour of longer trips for both e-biker and r-bikers which is not in line with previous literature on the bike route choice models. They have used the interaction of different variables with length to account for differences in length for different groups of people which may have caused the positive sign of the length variable, however, no clear effect was found. They stated that the positive sign may be caused by the alternative generation algorithm they employed to generate the shortest paths. However, their findings regarding differences in route choice of r-bikers and e-bikers refer to variables that cannot be affected by specific policies (e.g., they found that daylight and weekday play major roles in r-bikes and e-bikes usage.

Research Contributions

According to the background section, little attention has been paid to the e-bike's effect on the route choice of cyclists. Although general studies are available, they have not assessed the change due to electrification and did not compare their results with route choice models with r-bikes. Simply put, studies regarding changes due to e-bike usage have not comprehensively resulted in the main variables responsible for r-bike and e-bike promotion. Hence, this research addresses this gap in the body of literature that, to the best of the authors' knowledge, has not been explored before.
Accordingly, in this research, the effects of e-bikes on the route choice decision of cyclists are investigated. We evaluate e-bikes' effects on different aspects of cycling and route choice using separate discrete choice models developed for cyclists with r-bikes and e-bikes. We evaluate the effects of various factors on cyclists' route choice while the pedalling is eased up by e-bikes. This may cause some factors to have a decreased importance in the route choice. In fact, a contribution of this research is to test the hypothesis that e-bikes change the important factors affecting cyclists' route choice decisions that may be used in infrastructure planning.
The above-mentioned contribution is obtained by comparing bikers' and e-bikers' route choice models, estimated using one source of data. The data used for this research is obtained through a stated preference (SP) survey that provides us with the chance to analyze the findings regarding route choice model specifications. The model specification may interfere with factors' effects on route choice. Two different types of models, i.e., simple Logit model (SLM) and random parameter Logit model (RPLM), are estimated for each type of bike. Comparing the models including different variables' significance depicts the impacts of model specification on our main findings. Using an SLM requires the errors to be independently and identically distributed (IID). On the other hand, the error term in the RPLM is not bounded to these assumptions. As in this research, each choice situation presented to respondents is considered an observation, the error terms of discrete choice models may not be IID (Axhausen et al., 2006). Moreover, similar types of models are used in (Meister et al., 2022) and for many other studies that are looking for the model specification effects in their results (Brownstone et al., 2000).
Thus, the contribution of this research to the literature is threefold:

1. investigating factors affecting route choice of e-bikers;
2. comparing r-bikers and e-bikers to identify the main affecting factors of cycling promotion with less pedalling fatigue; and
3. analyzing the impacts of model specification on research findings.

The remainder of this paper presents the data and method we employ to investigate the route choice behaviour of cyclists in Section 2; the outputs of the estimated models and the results' interpretations in Section 3; Finally, conclusions are drawn in Section 4.

2 Methodology

Data Collection

To analyze the route choice of bikers concerning the technology of their bikes, and bicycle route choice data, this study uses the SP data collected in Greater Helsinki, Finland. The study area is a collaborative region of 14 municipalities and the Siuntio Municipality which has around 1.53 million population with 1.20 million living in the capital area. More details about the data can be found in Tarkkala (2022). The data is gathered using a survey assessing the following general factors: the presence or type of a bike facility, the road type, the vehicle traffic, the presence of controlled intersections along the route, the route gradients, and its length. The survey was offered online for one month during September 2021 and 1029 respondents filled out the questionnaire. Figure 1 depicts one of the hypothetical choice situations used in the survey.

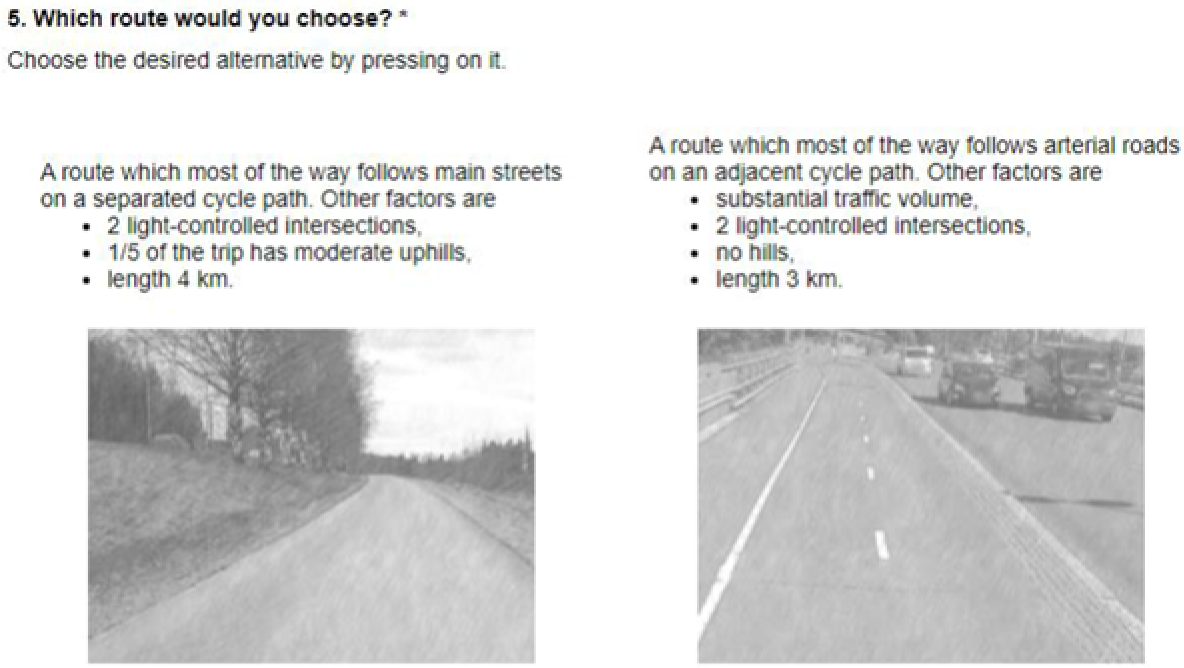

Figure 1: An example of a choice situation used in the survey

The characteristics of the sample population including trip purposes, age groups, their experience in riding a bike, and the time of year they bike, are depicted in charts of Figure 2. The e-bikers share of the respondents is almost 9.6% which is similar to the reported share from the market, i.e., 9% (Kuva, 2020). Moreover, the share of female respondents from the filled questionnaire is 49.3% which is a fair share regarding the target society composition.

Method and Models

One of the common approaches to identify factors affecting route choice decisions is implementing the discrete choice models. In this research, as said before, two different types of discrete choice models are implemented: SLM and RPLM, which enables to investigate the model specification impacts by comparing the models' results.

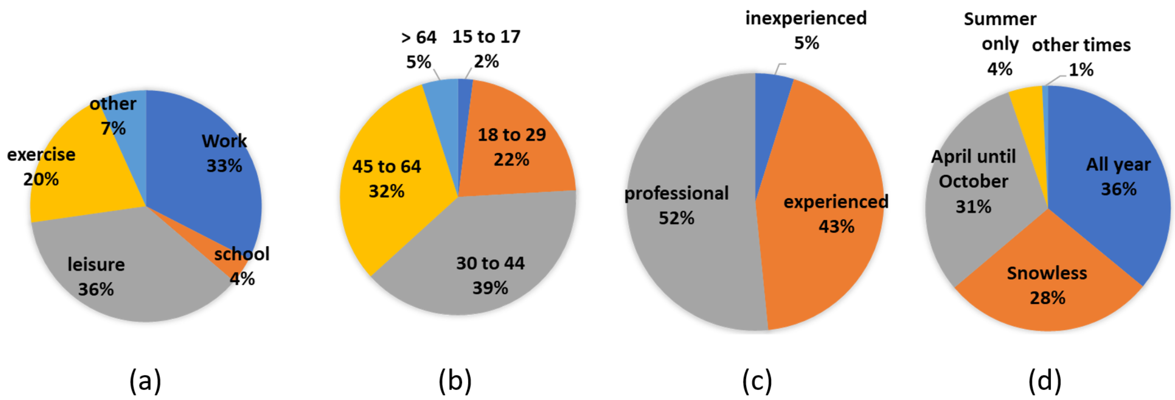

Figure 2: Understudy population characteristics; (a) Trip purpose, (b) Age, (c) Cycling experience, and (d) Time of the year cycling

SLM estimates the probability of choosing each route based on a linear combination of factors forming a utility value, as shown in Eq. (1). Since it is impossible to capture completely the utility value; a utility function composed of two parts is employed: the deterministic part, V_{in}, and the random/error part, ϵ_{in}, where i and n refer to alternative and individual, respectively. The deterministic part of the utility is a linear combination of effective factors in which β_{ik} is the coefficient related to k^{th} variable representing individual or alternative characteristics, X_{ink}. Then, the probability of each alternative selection is derived using Eq. (2).

$$U_{in} = V_{in} + \epsilon_{in} = \beta_i + \beta_{i1}X_{in1} + \beta_{i2}X_{in2} + ... + \epsilon_{in} \tag{1}$$

$$P_{in} = \frac{\exp(V_{in})}{\sum\limits_{j}\exp(V_{jn})} \tag{2}$$

The RPLM relaxes the IID assumption by introducing a random term, which eventually changes the error term to $\delta_{i1}X_{in1} + \epsilon_{in}$, as shown in Eq. (3). Different assumptions regarding the distribution of δ_{i1} is possible, with the most common to be a normal distribution.

$$U_{in} = V_{in} + \epsilon_{in} = \beta_i + \beta_{i1}X_{in1} + \delta_{i1}X_{in1} + \beta_{i2}X_{in2} + ... + \epsilon_{in} \tag{3}$$

This change in error term distribution would be addressed through simulation and the expected probability of each alternative selection is derived by approximately estimating the result of Eq. (4) (Train, 2009).

$$P_{in} = \int_{-\infty}^{\infty} \frac{\exp(V_{in})}{\sum\limits_{j}\exp(V_{jn})} f(\delta_{i1})d\delta_{i1} \tag{4}$$

We estimate both models for r-bikers and e-bikers separately. The maximum likelihood method, which is used for model calibration, estimates the covariance matrix of coefficients as well. The results obtained through all four models are then compared to show the differences between r-bikers and e-bikers as well as the significance of the impact of error correlation among observations.

3 Results and Discussion

Two sets of models (SLM and RPLM) are calibrated using Stata 17 (StataCorp, 2021) for r-bike and e-bike route choices, and their results are presented in Table 1. For each type of model, two models are presented for e-bikes' route choice. The first one includes the same variables as the r-bike model while the second one is without the variables found to be insignificant in the first model. In RPLMs, the random parameter is the coefficient of the route's length variable with the normal distribution.

Then, Logit models of r-bikers and e-bikers are compared to identify the prominent factors affecting the route choice of individuals, while the pedalling fatigue of cycling is removed due to the electrification of bikes. Another comparison is made between SLMs and RPLMs for regular bikes and e-bikes to evaluate the effect of error correlation on the effective route choice factors.

Table 1: SLMs and RPLMs for e-bikers' and r-bikers' route choice

Row	Variables	SLM			RPLM		
		R-Bikers	E-bikers (1)	E-bikers (2)	R-Bike	E-bike (1)	E-bike (2)
1	Route consists of main streets	0.102** (2.22)	-0.01 (-0.07)	-	0.411*** (6.80)	0.103 (0.60)	-
2	Route consists of arterial streets	0.253*** (4.04)	0.024 (0.14)	-	0.366*** (6.16)	-0.084 (-0.48)	-
3	Route is mixed with vehicular traffic	-0.846*** (-12.36)	-0.731*** (-3.78)	-0.873*** (-6.35)	-1.089*** (-12.31)	-0.848*** (-3.30)	-1.010*** (-4.21)
4	Route is on a bike lane	-0.221*** (-3.15)	0.234 (1.18)	0.293** (2.15)	-0.161* (-1.80)	0.447* (1.64)	0.481*** (1.80)
5	Route is on a separated adjacent path	-0.203*** (-3.75)	0.024 (0.15)	-	-	-	-
6	Moderate traffic near bike facility	-	-	-	-0.501*** (-7.52)	-0.500** (-2.37)	-0.485** (-2.28)
7	Heavy traffic near bike facility	-0.749*** (-10.85)	-0.663*** (-3.38)	-0.791*** (-5.27)	-1.678*** (-17.55)	-1.542*** (-5.46)	-1.639*** (-7.15)
8	Substantial traffic near bike facility	-0.699*** (-8.98)	-0.703*** (-3.18)	-0.787*** (-4.79)	-1.195*** (-15.40)	-1.161*** (-5.21)	-1.139*** (-5.33)
9	Route has controlled intersections	-0.322*** (-15.14)	-0.332*** (-5.44)	-0.316*** (-5.56)	-0.308*** (-11.09)	-0.415*** (-5.25)	-0.434*** (-5.42)
10	Route has hills	-0.661*** (-17.45)	-0.439*** (-3.85)	-0.433*** (-3.81)	-1.103*** (-15.17)	-0.802*** (-4.14)	-0.832*** (-5.38)
11	2^{nd} variable and being female	-0.246*** (-2.91)	-0.479* (-1.80)	-0.587*** (-2.94)	-0.561*** (-6.00)	-0.520* (-1.65)	-0.485** (-2.16)
12	3^{rd} variable and being female	-0.430*** (-5.08)	-0.217 (-0.77)	-	-	-	-
13	4^{th} variable and being female	0.153* (1.77)	0.110 (0.38)	-	-	-	-
14	7^{th} variable and being female	-0.236** (-2.53)	-0.458 (-1.46)	-	-0.477*** (-4.26)	-0.500 (-1.30)	-
15	8^{th} variable and being female	-0.200** (-2.04)	-0.230 (-0.77)	-	-	-	-
16	9^{th} variable and being female	0.120*** (4.76)	0.199** (2.45)	0.148** (2.34)	0.132*** (3.53)	0.241** (2.05)	0.236** (2.06)
17	10^{th} variable and being female	-	-	-	-0.140 (-1.47)	-0.164 (-0.56)	-
18	3^{rd} variable and being older than 65	-0.611*** (-2.96)	-0.451 (-0.97)	-	-	-	-
19	4^{th} variable and being older than 65	-0.490** (-2.37)	0.497 (1.17)	-	-	-	-
20	7^{th} variable and being older than 65	-	-	-	-0.717** (-2.33)	0.250 (0.45)	-
21	9^{th} variable and being older than 65	0.129** (2.16)	0.017 (0.14)	-	-	-	-
22	10^{th} variable and being older than 65	-	-	-	-0.356 (-1.40)	0.226 (0.52)	-
23	Route length	-0.311*** (-22.48)	-0.269*** (-6.28)	-0.267*** (-6.39)	-1.000*** (-25.65)	-0.929*** (-7.48)	-0.942*** (-7.56)
24	Standard deviation of the route length	-	-	-	0.599***	0.700***	0.701***
25	Constant	2.850*** (31.33)	2.359*** (8.63)	2.379*** (9.03)	-0.101** (-2.48)	0.119 (0.02)	-0.270** (-2.29)

*: 90%, **: 95%, ***: 99%

R-bikers vs. E-bikers

Both sets of models verify the previous findings in the literature regarding the route choice behaviour of r-bikers. These findings consist of the negative influence of length and steepness on the selection probability of a route. Moreover, less interaction with traffic through low adjacent traffic and the provision of completely separated bike facilities are the main factors that remained effective in r-bikers' and e-bikers' route choices. Some new insights are also observed for r-bikers. Female cyclists are avoiding vehicular traffic and prefer controlled intersections in their routes more than men. A similar attitude is observed for r-bikers older than 65 years.
On the other hand, e-bikes provide ease and a sense of confidence for cyclists that changes vehicle avoidance preferences. The changes are clearly observable in previously cautious and maybe vulnerable cyclists like females and old people. Since the e-bike route choice models can make no distinction based on gender and age among e-bikers. For instance, we observed that r-bikers older than 65 years find the traffic disturbing more than other r-bikers while e-bikers older than 65 years do not get bothered by heavy traffic. A similar attitude towards traffic situations is observed in female cyclists. Some other differences e-bikes make in cyclist route choice behaviour can be concluded as:

- The male cyclists' preference towards main streets mitigates due to e-bikes while the corresponding coefficient for females stays the same (negative) as r-bikers.
- The 65 years old and older cyclists riding e-bikes are not affected by the presence of hills anymore.
- Although the length of the trip and hills are significant factors for both r-bikers and e-bikers, yet, as expected, the impacts of these variables are much milder for e-bikers.
- E-bikers prefer bike lanes, which is not the case for r-bikers.
- Female r-bikers have significant preferences for traffic avoidance, compared to men, while all e-bikers do not like heavy and mixed traffic almost similarly.

Furthermore, the results of the random parameter of the RPLMs indicate that the taste variation is significantly present in both r-bikers and e-bikers' route choices, due to the large value of the standard deviation coefficient. However, the confidence interval for e-bikers ([-2.31, 0.43]) shows more dispersion than the r-bikers ([-2.17,0.17]), implying that the e-bike increases the variation of people's opinions toward the length of cycling.

SLM vs. RPLM

In general, the outputs of the two types of models are quite aligned, especially for e-bikers, and RPLMs results verify the findings from SLMs. In comparison to the RPLMs, more variables are found significant in the SLM for the r-bikers' route choice model (e.g., variables in rows 5, 12, 13, 15, 18, 19, and 21). Besides, there are a few significant variables in the RPLMs that are not found significant in the SLM for r-bikers (e.g., variables in rows 6 and 20). These differences lead to the following conclusions:

- The effect of substantial traffic on route choice is significant for female r-bikers with SLM, whereas it is not significant using the RPLM.
- Controlled intersections are favourable for r-bikers older than 65 based on SLM which is not significant using RPLM.
- Female and elderly r-bikers, based on SLM, are reluctant to cycle in routes with mixed traffic, while RPLM does not confirm the significance of these interactive variables.
- Interestingly, no significant difference is observed between the two types of models for e-bikers.

It should be noted that no significant difference is found between the coefficients' signs of the two types of models. These findings demonstrate that the SP survey is designed properly to capture the preferences of the individuals so that the errors in the responses are not severely correlated. This is why there are no substantial differences between the two models' outputs.

4 Conclusions

The differences in route choice behaviour between r-bikers and e-bikers are investigated in this research. Two sets of models, SLM and RPLM, are estimated based on data gathered through a stated preference survey. Both sets of models verify the previous findings in the literature regarding the negative influence of length and steepness on the selection probability of a route by r-bikers. Riding an e-bike, on the other hand, reduces the importance of the length of the trip and steepness, and e-bikers care less about the type of facility, i.e., major or minor streets, that they are cycling along.

From the transportation planners' point of view, providing dedicated routes with no interruptions from vehicular traffic can be introduced as the main effective factor in bike promotion. We observed that women like to cycle in a completely dedicated path with signalized intersections that minimizes the probability of colliding with other vehicles. Therefore, there is a trade-off between vehicles and bike volumes.

Regarding the model specification, we realized that there is no substantial difference between SLMs and RPLMs for e-bikers, in our case. This implies that the errors in the responses are not severely correlated and can be assumed to possess the IID character. If the IID assumption holds, it is considered to be a desirable property of the SP data, meaning that despite the hypothetical situations and panel effect, respondents' preferences do not affect the error terms. Hence, the SLMs without increasing the complexity in the estimation process can lead to similar outputs with RPLMs.

A major limitation of this research (shared with previous literature as well) is that respondents are already cyclists; hence, the results cannot be simply used for addressing non-bikers about their preferences and obstacles towards biking. However, focusing on cyclists is needed in this research due to the fact that we were looking for the differences created by e-bike implementation.

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References

Anderson, C. C., Clarkson, D. E., Howie, V. A., Withyman, C. J., & Vandelanotte, C. (2022). Health and well-being benefits of e-bike commuting for inactive, overweight people living in regional australia. *Health promotion journal of Australia: official journal of Australian Association of Health Promotion Professionals*, *33*(S1), 349–357.

Axhausen, K. W., Hess, S., König, A., Abay, G., Bates, J., & Bierlaire, M. (2006). State of the art estimates of the Swiss value of travel time savings. *Arbeitsberichte Verkehrs-und Raumplanung*, *383*.

Bernardi, S., Geurs, K., & Puello, L. L. P. (2018, oct). Modelling route choice of Dutch cyclists using smartphone data. *Journal of Transport and Land Use*, *11*(1), 883–900. Retrieved from `https://www.jtlu.org/index.php/jtlu/article/view/1143` doi: 10.5198/JTLU.2018.1143

Broach, J., Dill, J., & Gilebe, J. (2012, dec). Where do cyclists ride? A route choice model developed with revealed preference GPS data. *Transportation Research Part A: Policy and Practice*, *46*(10), 1730–1740. doi: 10.1016/J.TRA.2012.07.005

Brownstone, D., Bunch, D. S., & Train, K. (2000). Joint mixed logit models of stated and revealed preferences for alternative-fuel vehicles. *Transportation Research Part B: Methodological*, *34*(5), 315–338.

Chavis, C., & Martinez, V. (2021). *E-Bikes' Effect on Mode and Route Choice: A Case Study of Richmond, VA Bike Share* (Tech. Rep.). Urban Mobility Equity Center, Morgan State University.

Counter, E. (2021). *Bike count dashboard: tracking the growth of cycling by country.* Retrieved from https://www.eco-counter.com/cycling-data-tracker/

Dane, G., Feng, T., Luub, F., & Arentze, T. (2020). Route choice decisions of E-bike users: Analysis of GPS tracking data in the Netherlands. *Lecture Notes in Geoinformation and Cartography*, 109–124. Retrieved from https://link.springer.com/chapter/10.1007/978-3-030-14745-7_7 doi: 10.1007/978-3-030-14745-7_7/COVER

Huber, S., Lißner, S., Lindemann, P., Muthmann, K., Schnabel, A., & Friedl, J. (2021, jun). Modelling bicycle route choice in German cities using open data, MNL and the bikeSim web-app. *2021 7th International Conference on Models and Technologies for Intelligent Transportation Systems, MT-ITS 2021*. doi: 10.1109/MT-ITS49943.2021.9529273

Hull, A., & O'Holleran, C. (2014, jan). Bicycle infrastructure: can good design encourage cycling? *Urban, Planning and Transport Research*, *2*(1), 369–406. Retrieved from https://www.tandfonline.com/doi/abs/10.1080/21650020.2014.955210 doi: 10.1080/21650020.2014.955210

Kuva, H. (2020). *Smaller volumes but same e-bike trend in Finland.* Retrieved 2023-01-20, from https://digimagazine.bike-eu.com/market_reports/finland

Meister, A., Axhausen, K. W., Felder, M., & Schmid, B. (2022). Route choice modelling for cyclists on dense urban networks. *Available at SSRN 4267767*.

Rérat, P. (2021). The rise of the e-bike: Towards an extension of the practice of cycling? *Mobilities*. Retrieved from https://www.tandfonline.com/doi/abs/10.1080/17450101.2021.1897236 doi: 10.1080/17450101.2021.1897236

Sałabun, W., Palczewski, K., & Wątróbski, J. (2019). Multicriteria approach to sustainable transport evaluation under incomplete knowledge: Electric bikes case study. *Sustainability*, *11*(12), 3314.

Segadilha, A. B. P., & Sanches, S. d. P. (2014, dec). Identification of Factors that Influence Cyclistś Route Choice. *Procedia - Social and Behavioral Sciences*, *160*, 372–380. doi: 10.1016/J.SBSPRO.2014.12.149

StataCorp. (2021). *Stata Statistical Software: Release 17.*

Tarkkala, K. (2022). *Application of cyclists' route choice preferences in travel demand modelling.* Finland.

Tarkkala, K., Vosough, S., West, J., & Roncoli, C. (2023). Implementing cyclists' route choice models into travel demand modelling: A case study of greater helsinki. *Under review*.

Train, K. E. (2009). *Discrete Choice Methods with Simulation* (2nd ed.). Cambridge: Cambridge University Press. Retrieved from https://www.cambridge.org/core/books/discrete-choice-methods-with-simulation/49CABD00F3DDDA088A8FBFAAAD7E9546 doi: DOI:10.1017/CBO9780511805271