Discrete choice analysis of travel behaviour in Austria

Saumya Sadhu[1]

[1] University of Graz, Merangasse 18, 8010 Graz, Austria
Corresponding author. saumya.sadhu@uni-graz.at

ABSTRACT

The transport sector significantly contributes to environmental impacts, making its decarbonisation essential for meeting Europe’s 1.5°C climate goal. This requires both technological improvements and shifts in travel behaviour. To support the latter, understanding current determinants of mode choice is crucial. This study uses a nested logit model calibrated with data from Austria’s national mobility survey “Österreich Unterwegs” to examine how socio-demographic and infrastructure-related factors influence the likelihood of choosing public transport, cycling, or walking over car use. Results show that proximity to public transport and household income are key predictors. The findings also underscore car dependency in rural areas and reveal the inelasticity of car use with respect to travel time, suggesting strong behavioural lock-in.

1. INTRODUCTION

This study aims to analyse travel behaviour in Austria using a nested multinomial logit (MNL) model and find factors which help determine travel mode choice between walking, cycling, driving or taking public transportation. Such an endeavour can help with guiding transport planning towards a more sustainable path and assist the government’s efforts to decarbonize this sector (BMK, 2021). The transport sector is one of the leading emitters in the world. It accounts for almost 21% of all GHG emissions and 24% of CO2 emissions worldwide (Ritchie & Roser, 2023). Within Austria, the transport sector accounts for the highest CO2 emissions out of all sectors at 37% and has contributed the most to the overall increase in emissions since 2015 (IEA, 2022). Not only is this sector's impact on the environment tremendous but there is

https://doi.org/10.25364/978-3-903374-48-5_42

also harsh inequity in emissions versus exposure, as poor households relying more on walking or public transportation bear the brunt of vehicular emissions higher than affluent households (Breffle et al., 2015). Therefore, there is a strong need for sustainable transport systems and decarbonisation. In its Mobility Master Plan, Austria signifies the importance of decarbonizing the transport sector to meet its carbon neutrality goals by 2040 (BMK, 2021). The country aims to utilize the Avoid-Shift-Improve Strategy, targeting I) mobility behaviour from the usage of private vehicles to using more public transportation and active mobility, II) elimination of combustion engine transport technology by ensuring that all cars and two-wheelers are electric, and III) a shift from commercial vehicles to carbon-neutrality via electrification and eliminate fuel export by 2040. Changing mobility behaviour alone can help reduce at least 3 million tonnes of CO2 equivalent emissions in the country (BMK, 2021). This means there is a dire need to analyse people's mobility behaviours and identify factors which shape them in order to shape policies that can aid in changing people's travel behaviours in Austria. For this study, the focus will be on the province of Styria or originally called Steiermark. This brings us to the research questions being answered in this study: What are the significant socio-demographic and transport infrastructure-related determinants of mode choice within Austria?

1. People from which background are more likely to use cars over public transportation (PT), biking, and walking?
2. How does a shift in travel time and the distance to public transportation influence people's adoption of cars, public transportation, biking, and walking?

2. METHODOLOGY

This study used the nested MNL method to try and build a mode choice model for Austria. Three sample districts were chosen within the Austrian province of Styria- Graz, Graz Surroundings and Deutschlandsberg. Each representing urban, semi-peripheral and rural area respectively (see Fig. 1). The sample size comprised of 12,541 observations from these districts all of which were used in the study.

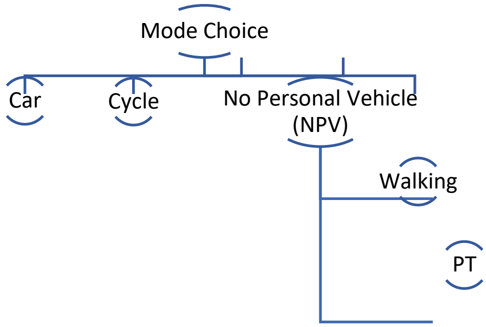

Figure 1: Visualisation of the nested alternatives

A nested model was chosen because the data showed roughly 46% of public transportation users stating 'walking' as an accompaniment. This implies that walking and PT are not mutually exclusive and therefore needed to be nested for this study under 'no personal vehicles' or NPV. The model was run on N-logit. The chart below summarizes the data processing:

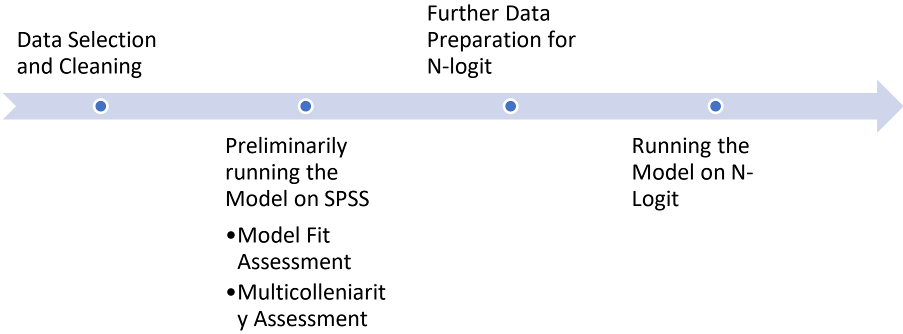

Figure 2: Steps for processing data within this study

2.1 DATA SOURCE

The data was obtained from Austria's Ministry of Climate Action and Energy (BMK) via the nationwide survey *Österreich Unterwegs* (2013–14) (BMIMI, 2014). It includes 96 variables on socio-economic background, travel behavior, and travel environment. For this study, 14 key variables were selected—such as distance, travel time, urbanity, household size, proximity to public transport, income, age, education, travel purpose, occupation, and gender—this was done by scanning the literature for relevant variables (Sadhu, 2023). Some variables were recategorized to improve model predictiveness and minimize the number of dummy variables.

2.2 UTILITY FUNCTION AND MODEL BUILDING

A utility function forms the basis for a logistic regression model (Christensen, 2006). It describes the pleasure or utility derived by an individual from using a given alternative (in this study- a particular mode of transportation) and presents the influence of different factors (explanatory variables) in the utility generation. left.

A general form of a utility function is as follows (Hensher et al., 2005):

$$Uij=Vij+\varepsilon ij \quad (1)$$

Where Vij is the utility derived from alternative j (which is a sum of all the explanatory variables multiplied by their parameter values or Beta) by individual i and εij is the error term associated with the unobserved factors affecting people's choices, such as social norms, personal biases etc. (Hensher et al., 2005).

To run the nested logit model on N-logit, utility functions needed to be built and added to the commands. N-logit then uses these functions and estimates the parameter values. This model considered 'car' as the pivot alternative; therefore, its utility function only has the scalar variable time in it and its alternative specific constant is 0. Car was chosen as the pivot because it is the least sustainable of the four transport options and the mode aim to avoid. By identifying factors that increase the likelihood of choosing walking, cycling, or public transport over cars, policies which promote these greener alternatives can be formulated.

2.3 MODEL FIT

In linear regression, model fit is assessed using R^2 value, which indicates the proportion of variance explained by the independent variables (Helland, 1987). For logit models where the variables are not scalar, model fit is assessed by the McFadden pseudo- R^2 (Hensher et al., 2005). The McFadden pseudo-R^2 value of 0.384 derived in this study roughly equates to an R^2 value between 76-78% which means that within the model, the independent variables can help predict around 76-78% of the dependent variables which is indicative of a good model fit.

2.4 MULTICOLLINEARITY

In order to combat the issue of multicollinearity, this study computed a correlation matrix between all the explanatory variables. Only one pair of variables showed a high correlation of 0.7. This strong correlation was seen between the dummy variables of distance categories to the nearest bus stop 1 and 2. However, for the sake of isolating the impact that different distances to PT have on mode choice and PT adoption, this study retained the variables intact.

3. RESULTS & DISCUSSION

A descriptive modal split of the study area yields 65% car users, 13% pedestrians, 12% PT users and 10% cyclists (see Fig. 3).

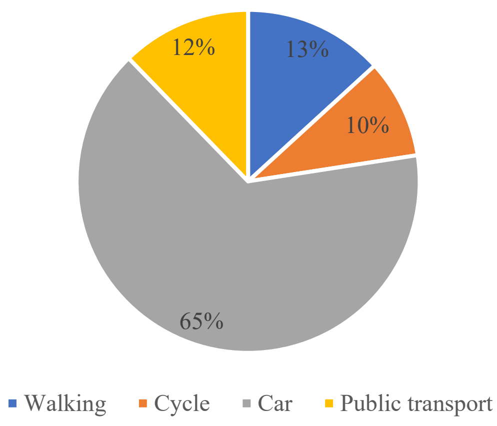

Figure 3: Modal split in Graz, Graz surroundings and Deutschlandsberg

The model ran logistic regression to test relations between 46 sets of explanatory variables and mode choices. Of these, 40 relations were significant at a confidence interval of 95% with a p-value lesser than 0.05. The nested logit model was built keeping the alternative ‘car’ as the pivot and then comparing the likelihood of using the other alternatives against it. The parameter estimates derived are shown in Table 1 below.

Table 1: Nested Logit Model results, showing parameter estimates (β) and p-values for each mode and variable. Most relationships are highly significant; insignificant ones are bolded and italicised.

Nested Logit Model- With 2 levels (Car as the 'pivot')						
	PT		**Cycle**		**Walking**	
Variable (PT)	*(β) Values*	*Inverse Odds Ratio**	*(β) Values*	*Inverse Odds Ratio*	*(β) Values*	*Inverse Odds Ratio*
Alternate Specific Constant	6.84		6.01		8.76	
Urban**						
Semi-periphery	-1.24	3.5	-1.39	4	-0.75	2.1
Rural	-2.35	10.5	-1.62	5.1	-0.41	1.5
Single-person HH**						
HH with 2 people	-0.96	2.6			-0.71	2
HH with more than 3 people	-1.51	4.5			-1.3	3.7
PT Stop within 5 mins on foot**						
PT stop 6-15 minutes on foot	-0.3	1.3	-0.54	1.7	-0.58	1.8
PT stop above 15 minutes on foot	-0.68	2	***-0.12***	***1.1***	-1	2.7
Lower-income HH**						
Middle-income HH	***-2.81***	***16.6***	-5.49	242.3	-6.01	407.5
Upper-income HH	-4.37	79	-6.08	437	-7.34	1540.7
Student**						
Employed	-0.71	2	-0.89	2.4	-0.82	2.3
Pensioners	***-0.28***	***1.3***	-1.03	2.8	-0.48	1.6
Other occupations	-0.61	1.8	-1.14	3.1	***-0.34***	***1.4***

Purpose- working**						
Purpose-education	2.06	0.1	0.69	0.5	1.52	0.2
Purpose-shopping	-1.28	3.6	-0.76	2.1	***-0.06***	***1.1***
Purpose- Others	-0.87	2.4	-0.45s	1.6	0.53	0.6
Gender (Female)**						
Gender (Male)	-0.41	1.5				
Age Group below 19 years**						
Age group 20-54 years	-1.34	3.8				
Age group above 55 years	-1.35	3.9				
Uneducated/Un-trained**						
Education-School/trained			0.77	0.5		
Education- University and above			1.25	0.3		

*An inverse odds ratio is the ratio between the log odds of the reference variable divided by the log odds of the comparison variable

** reference variable

3.1 DETERMINANTS OF MODE CHOICE

The model also showed that the degree of urbanity affects people's mode choices. Urban households were 3.5 times more likely to use PT than semi-peripheral households and 10.5 times more likely than rural households. They were also four times more likely to cycle and five times more likely to walk than rural households. Interestingly, rural residents were more likely to walk than semi-peripheral ones, likely due to shorter local trip distances and fewer traffic-related barriers, echoing infrastructure and comfort-based factors cited in Alfonzo (2005) and Carlson et al. (2018).

Household income emerged as a key determinant in the model. Compared to upper-income households, lower-income households were 79 times more likely to use PT, 437 times more likely to cycle, and 1,541 times more likely to walk than to drive. Similarly, compared to middle-income households, lower-income households were 242 times more likely to cycle and 408 times more likely to walk. These results align with the modal split by income, which shows a greater reliance on non-car modes among lower-income households as shown in Figure 4. This supports Pucher & Buehler (2006) and Plaut (2005), and contradicts earlier claims of rising active mobility among higher-income groups (Dill & Voros, 2007). In Styria's case, lower income households were most likely to rely on public transportation.

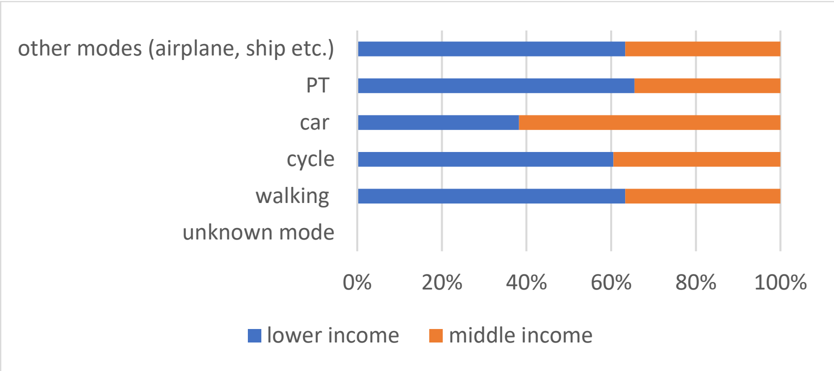

Figure 4: Modal-split based on income-levels

Distance to PT was critical. Having a stop within 5 minutes' walking distance increased the likelihood of choosing PT or walking. For instance, moving a stop from over 15 mins to within 5 minutes doubled the chances of PT use. These results support Buehler (2011), emphasizing infrastructure's role in facilitating sustainable mobility.

Upon examining the effect of occupation on mode choice, it was found that the students were the most likely to use sustainable modes over cars. They were twice as likely to use PT, 2.4 times more likely to cycle, and 2.3 times more likely to walk than employed individuals.

It was also found that larger households demonstrated a higher propensity for car use Single-person households were 2.6–4.5 times more likely to choose public transport (PT) or walking over cars compared to households with 2 or more people. Larger households, especially those with 3+ members, tended to prefer cars, possibly due to the presence of children or coordination needs. This aligns with previous findings linking household size with higher car ownership (Gardenhire & Sermons, 2001; Holtzclaw et al., 2002).

The model also showed that women were 1.5 times more likely to opt for PT over cars compared to men. This aligns with Simma & Axhausen (2003)and

Scheiner & Holz-Rau (2012), who suggest that men's higher access to cars and work responsibilities influences this difference between genders

Another very interesting finding was the impact of education levels on people's propensity to cycle. The study showed that as people got more educated, their likelihood to cycle increased. When compared with uneducated and untrained individuals, those who went to school or university were 2-3.5 times more likely to opt for cycling. This supplements the research by Balsas (2003) who found a higher share of active mobility on campuses. The average education level of cyclists was also found to be higher than that of users of other modes.

3.2 ELASTICITIES OF TRAVEL TIME FOR VARIOUS MODES

To understand how travel time impacts mode choice, this study examines the direct and cross elasticities of travel time and how changes in travel time can lead to changes in people's travel preferences (Louviere et al., 2000). Table 2 presents the direct and cross-elasticity values derived from the model, quantifying the sensitivity of mode choice to a 1% change in travel time. Direct elasticities (marked with an asterisk*) refer to changes in the likelihood of choosing the same mode, while cross-elasticities indicate shifts toward alternative modes. Walking and PT are grouped within the same nest, leading to similar elasticity values. For instance, 1% increase in walking time reduces its walking 0.4% and PT use by 0.4%, while slightly increasing the likelihood of cycling and car use (both by 0.1%). A 1% increase in PT travel time reduces its own use by 0.67%, and also decreases walking by 0.67% due to nesting. The direct elasticity of travel time on car choice was -0.04%, indicating that a 1% increase in car travel time leads to only a 0.04% decrease in the likelihood of choosing a car. This highly inelastic response—the lowest among all modes—reflects a strong behavioural lock-in among car users. Despite the costs and known environmental impacts, many continue to rely on cars due to these 'locked-in' effects (Bamberg et al., 2003). Contrasting to cars were bicycles which showed a significantly elastic response to travel time. Increase in travel time by cycling by 1% led to a decrease in its usage by 1.8%. This result aligns with a previous study by Frank et al. (2008) and is testament to how people are easily dissuaded from using cycles if the infrastructure does not guarantee a timely commute, good cycling infrastructure and safety (Puello et al., 2020).

Table 2: Direct and cross-elasticity values of travel time on mode choice

	Elasticity Value (Nested)- Impacted Choice Probability			
Mode Choice (with travel time as the attribute)	Walking	PT	Cycle	Cars
Walk-ing	*-0.4	-0.4	0.1	0.1
PT	-0.67	*-0.67	0.06	0.06
Cycle	0.6	0.6	*-1.8	0.6
Cars	0.17	0.17	0.17	*-0.04

3.3 POLICY IMPLICATIONS

This study identifies four key barriers to sustainable transport in the study region. First, rural dependence on cars stems from poor last-mile connectivity, with PT stops three times farther than in urban areas. Short-term solutions include introducing e-car or bike-sharing services in rural areas (Shergold et al., 2012), while long-term strategies involve expanding PT infrastructure by increasing PT stops, and optimizing routes in rural areas. Second, high travel time elasticity for biking indicates people are easily deterred from cycling. Addressing safety and perception through increasing the no. of segregated bike lanes, training programs, and better bike parking can improve adoption (Ajzen, 1991; Puello et al., 2020).

Third, higher- and middle-income households prefer private cars, unlike lower-income groups. Income-targeted policies such as taxing additional household vehicles and adjusting fuel taxes with income-based subsidies can help shift these preferences. Fourth, larger households (3+ members) also rely heavily on cars likely due to family responsibilities. Soft measures like personalized travel planning and targeted messaging (e.g., emphasizing climate impacts on children) can nudge these households toward greener modes (Pelletier & Sharp, 2008; Riggs & Kuo, 2015). Finally, since higher education levels correlate with increased bike use, integrating traffic education in elementary schools may further support modal shift.

4. LIMITATIONS AND EXTERNAL VALIDITY

The findings of this study are based on an Austrian national survey which was calibrated with data from Styria. Due to Austria's socio-demographic and infrastructural comparability, the results are regionally valid and broadly indicative of national trends. While the model offers useful insights for other developed EU countries, differences in factors like population density and living standards limit its external validity. However, the model itself includes several significant mode choice determinants and can be adapted for use in other regions with local data. This study has some limitations. First, income data was self-reported, introducing potential bias. Second, like many trip-based transport research, access trips (e.g., walking to PT stops) are included within PT trips, based on walking time—a common approach in the literature (Chen & Li, 2017; Ding & Zhang, 2016). More precise modelling, such as activity-based approaches, was beyond this study's scope. Lastly, key behavioural factors like norms and attitudes, which have proven to be important (Ajzen, 1991; Bamberg & Möser, 2007) were not assessed due to data constraints. Future research should explore these social and behavioural aspects to better understand and influence mode choice.

5. CONCLUSION

This study highlights key socio-demographic and infrastructural determinants of sustainable mobility choices. Higher-income households were significantly more likely to choose cars over other more sustainable modes, confirming a strong negative correlation between income and active or public transport use. Closer proximity to public transport stops—especially within 5 minutes—can double the likelihood of choosing PT over cars. Students, women, and highly educated people less inclined to using cars. Also, the rural-urban discrepancy in the usage of cars was also seen to be quite high. Policy recommendations include expanding PT access in rural and semi-peripheral areas by the way of increasing PT stops, improving last-mile connectivity, increasing, expanding bike lanes, and employing behavioural nudges to reduce car dependence. These findings reinforce the need to shift from auto-centric policies to planning approaches that enable and encourage public and active transport.

ACKNOWLEDGEMENTS

The author expresses deep gratitude to Dr. Georg Jaeger and Dr. Alfred Posch for their supervision as the government of Austria for sharing the data with the institute. The author would also like to note that Grammarly was used for polishing the language.

REFERENCES

Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Alfonzo, M. A. (2005). To Walk or Not to Walk? The Hierarchy of Walking Needs. Environment and Behavior, 37(6), 808–836. https://doi.org/10.1177/0013916504274016

Balsas, C. J. L. (2003). Sustainable transportation planning on college campuses. Transport Policy, 10(1), 35–49. https://doi.org/10.1016/S0967-070X(02)00028-8

Bamberg, S., Ajzen, I., & Schmidt, P. (2003). Choice of Travel Mode in the Theory of Planned Behavior: The Roles of Past Behavior, Habit, and Reasoned Action. Basic and Applied Social Psychology, 25(3), 175–187. https://doi.org/10.1207/S15324834BASP2503_01

Bamberg, S., & Möser, G. (2007). Twenty years after Hines, Hungerford, and Tomera: A new meta-analysis of psycho-social determinants of pro-environmental behaviour. Journal of Environmental Psychology, 27(1), 14–25. https://doi.org/10.1016/j.jenvp.2006.12.002

BMIMI.(2014).Österreich unterwegs 2013/2014. https://www.bmimi.gv.at/themen/verkehrsplanung/statistik/oesterreich_unterwegs.html

BMK. (2021). Austria’s 2030 Mobility Master Plan. Federal Ministry for Climate Action, Environment, Energy, Mobility, Innovation and Technology (BMK). https://www.bmk.gv.at/en/topics/mobility/mobilitymaster-plan2030.html#:~:text=The%202030%20Mobility%20Master%20Plan,of%20transport%2C%20and%20shared%20mobility.

Breffle, W. S., Eiswerth, M. E., Muralidharan, D., & Thornton, J. (2015). Understanding how income influences willingness to pay for joint programs: A more equitable value measure for the less wealthy. Ecological Economics, 109, 17–25. Scopus. https://doi.org/10.1016/j.ecolecon.2014.10.001

Buehler, R. (2011). Determinants of transport mode choice: A comparison of Germany and the USA. Journal of Transport Geography, 19(4), 644–657. https://doi.org/10.1016/j.jtrangeo.2010.07.005

Carlson, S., Whitfield, G., Peterson, E., Ussery, E., Watson, K., Berrigan, D., & Fulton, J. (2018). Geographic and Urban–Rural Differences in Walking for Leisure and Transportation. American Journal of Preventive Medicine, 55. https://doi.org/10.1016/j.amepre.2018.07.008

Chen, J., & Li, S. (2017). Mode Choice Model for Public Transport with Categorized Latent Variables. Mathematical Problems in Engineering, 2017, e7861945. https://doi.org/10.1155/2017/7861945

Christensen, R. (2006). Log-Linear Models and Logistic Regression. Springer Science & Business Media.

Dill, J., & Voros, K. (2007). Factors Affecting Bicycling Demand: Initial Survey Findings from the Portland, Oregon, Region. Transportation Research Record, 2031(1), 9–17. https://doi.org/10.3141/2031-02

Ding, L., & Zhang, N. (2016). A Travel Mode Choice Model Using Individual Grouping Based on Cluster Analysis. Procedia Engineering, 137, 786–795. https://doi.org/10.1016/j.proeng.2016.01.317

Frank, L., Bradley, M., Kavage, S., Chapman, J., & Lawton, T. K. (2008). Urban form, travel time, and cost relationships with tour complexity and mode choice. Transportation, 35(1), 37–54. https://doi.org/10.1007/s11116-007-9136-6

Gardenhire, A., & Sermons, M. (2001). Understanding automobile ownership behavior of low-income households: How behavioral differences may influence transportation policy. Transportation Research Circular, E-C026, 179–195.

Helland, I. S. (1987). On the Interpretation and Use of R2 in Regression Analysis. Biometrics, 43(1), 61–69. https://doi.org/10.2307/2531949

Hensher, D. A., Rose, J. M., & Greene, W. H. (2005). Applied Choice Analysis: A Primer. Cambridge University Press.

Holtzclaw, J., Clear, R., Dittmar, H., Goldstein, D., & Haas, P. (2002). Location Efficiency: Neighborhood and Socio-Economic Characteristics Determine Auto Ownership and Use - Studies in Chicago, Los Angeles and San Francisco. Transportation Planning and Technology, 25(1), 1–27. https://doi.org/10.1080/03081060290032033

IEA. (2022). How much CO2 does Austria emit? https://www.iea.org/countries/austria/emissions

Louviere, J. J., Hensher, D. A., & Swait, J. D. (2000). Stated Choice Methods: Analysis and Applications. Cambridge University Press.

Pelletier, L. G., & Sharp, E. (2008). Persuasive communication and proenvironmental behaviours: How message tailoring and message framing can improve the integration of behaviours through self-determined motivation. Canadian Psychology / Psychologie Canadienne, 49(3), 210–217. https://doi.org/10.1037/a0012755

Plaut, P. O. (2005). Non-motorized commuting in the US. Transportation Research Part D: Transport and Environment, 10(5), 347–356. https://doi.org/10.1016/j.trd.2005.04.002

Pucher, J., & Buehler, R. (2006). Why Canadians cycle more than Americans: A comparative analysis of bicycling trends and policies. Transport Policy, 13(3), 265–279. https://doi.org/10.1016/j.tranpol.2005.11.001

Puello, L., Cherchi, E., & Geurs, K. (2020). Role of perception of bicycle infrastructure on the choice of the bicycle as a train feeder mode. International Journal of Sustainable Transportation, 15, 1–14. https://doi.org/10.1080/15568318.2020.1765223

Riggs, W., & Kuo, J. (2015). The impact of targeted outreach for parking mitigation on the UC Berkeley campus. Case Studies on Transport Policy, 3(2), 151–158. https://doi.org/10.1016/j.cstp.2015.01.004

Ritchie, H., & Roser, M. (2023). Cars, planes, trains: Where do CO2 emissions from transport come from? Our World in Data. https://ourworldindata.org/co2-emissions-from-transport

Sadhu, S. (2023). Discrete Choice Analysis of Travel Behaviour: Case study of Styria, Austria [Graz]. https://resolver.obvsg.at/urn:nbn:at:at-ubg:1-199571

Scheiner, J., & Holz-Rau, C. (2012). Gendered travel mode choice: A focus on car deficient households. Journal of Transport Geography, 24, 250–261. https://doi.org/10.1016/j.jtrangeo.2012.02.011

Shergold, I., Parkhurst, G., & Musselwhite, C. (2012). Rural car dependence: An emerging barrier to community activity for older people. Transportation Planning and Technology, 35(1), 69–85. https://doi.org/10.1080/03081060.2012.635417

Simma, A., & Axhausen, K. W. (2003). Interactions between Travel Behaviour, Accessibility and Personal Characteristics: The Case of Upper Austria. European Journal of Transport and Infrastructure Research, 3(2). https://doi.org/10.18757/ejtir.2003.3.2.3686