E-Bikes in Travel Demand Models

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Abstract

Electric bicycles are rapidly transforming the active mobility landscape. They extend the practical range of cycling, facilitate travel in hilly terrain, open up cycling to new user groups, and reduce physical exertion, which is particularly relevant for trip purposes such as commuting or shopping. However, most travel demand models, both in research and practice, do not distinguish between electric and conventional bicycles. This lack of differentiation may compromise their predictive accuracy and limits their ability to evaluate e-bike-specific policies. This thesis therefore addresses two key research questions: How can the electrification of bicycle traffic be accounted for in travel demand models? And does doing so actually improve model quality and usefulness?

To answer these questions, the thesis is structured around four journal articles. The first paper presents a literature review covering the current state of macroscopic bicycle travel demand modelling and related fields, including factors influencing electric bicycle ownership, mode choice, and route choice, as well as differences between conventional and electric bicycles in these domains. The second paper models conventional and electric bicycle ownership in Germany using large-scale survey data from the "Mobility in Germany" survey. Both nested logit and multivariate probit models are applied. The third paper uses similar data and a nested logit model to examine mode choice behaviour. It explores differences and similarities between the two bicycle types, along with associated elasticities and substitution patterns. The fourth paper introduces the first macroscopic travel demand model that dynamically differentiates between electric and conventional bicycle traffic across ownership, mode, and route choice and that accounts for differences in preferences between the two. This differentiated model's quality is benchmarked against an undifferentiated model that has been calibrated to the same standard and its value is demonstrated through e-bike-specific case studies.

The central findings show that while electric and conventional bicycle ownership and mode choice are influenced by similar factors at the level of individuals, modelling these components separately yields richer insights into behavioural patterns and supports more nuanced scenario analysis in travel demand models. Our results also reveal that e-bikes often replace car trips, particularly in contexts with previously low levels of cycling. For e-bike-specific impedance functions used in mode and route choice, it is important to emphasize that electric bicycles are not simply faster versions of conventional bicycles. To model them accurately, modellers should account for differences in trip distances, user groups, trip purposes, and gradient. Other factors, such as infrastructure, also show potential for differentiation, but current research remains inconclusive. The case study demonstrates that a differentiated modelling approach offers analytical advantages over traditional undifferentiated models. However, our findings also indicate that the overall improvement in model quality resulting from this differentiation is marginal. This is at least partially due to model quality being assessed at

an aggregate level, without distinguishing between model results regarding conventional and electric bicycles in the analysis. Based on these insights, practical recommendations on when and how to incorporate e-bikes in travel demand modelling are provided.

Modelling electric bicycle traffic remains challenging, particularly due to persistent data limitations in travel surveys and count data. Further research is needed to fully understand behavioural differences between electric and conventional cyclists. Nonetheless, even with current data constraints, it is evident that the electrification of bicycle traffic should be accounted for in travel demand models, at the very least as a scenario parameter, to avoid systematically underestimating future levels of cycling.

Kurzfassung

Elektrische Fahrräder (Pedelecs, umgangssprachlich "E-Bikes") treiben derzeit einen tiefgreifenden Wandel in der aktiven Mobilität voran. Sie verringern die körperliche Anstrengung, machen auch längere Strecken im Alltag mit dem Fahrrad bewältigbar, erleichtern das Fahren in hügeligem Gelände und erschließen neue Nutzergruppen und Wegezwecke wie Arbeitswege oder den Weg zum Einkaufen. In der Forschung wie auch in der Praxis unterscheiden die meisten Verkehrsnachfragemodelle jedoch nicht zwischen elektrischem und konventionellem Radverkehr, mit potentiell negativen Folgen für ihre Prognosefähigkeit und die Möglichkeit, pedelecspezifische Fragestellungen zu untersuchen. Diese Arbeit geht daher zwei zentralen Forschungsfragen nach: Wie kann die Elektrifizierung des Radverkehrs in Verkehrsnachfragemodellen abgebildet werden? Und verbessert dies tatsächlich die Modellqualität und ihren praktischen Nutzen?

Die vorliegende Dissertationsschrift ist entlang von vier Fachartikeln strukturiert. Der erste Artikel präsentiert eine Übersichtsarbeit zum aktuellen Stand der makroskopischen Modellierung der Radverkehrsnachfrage und angrenzender Forschungsbereiche, darunter Einflussfaktoren auf den Besitz von Pedelecs, auf die Modus- und Routenwahl sowie Unterschiede zwischen konventionellen und elektrischen Fahrrädern in diesen Bereichen. Der zweite Artikel modelliert den Besitz von konventionellen und elektrischen Fahrrädern in Deutschland auf Basis von Daten der Studie „Mobilität in Deutschland“. Es kommen sowohl Nested-Logit- als auch multivariate Probit-Modelle zum Einsatz. Der dritte Artikel verwendet ähnliche Daten und ein Nested-Logit-Modell zur Analyse der Moduswahl. Dabei werden Unterschiede und Gemeinsamkeiten zwischen den beiden Fahrradtypen sowie Elastizitäten und Substitutionsmuster untersucht. Der vierte Artikel stellt das erste makroskopische Verkehrsmodell vor, das den elektrischen und konventionellen Radverkehr dynamisch über Besitz-, Modus- und Routenwahl hinweg differenziert abbildet und Unterschiede in den Präferenzen verschiedener Personengruppen berücksichtigt. Die Qualität dieses differenzierten Modells wird mit einem undifferenzierten Modell verglichen, das auf denselben Standard kalibriert wurde. Anhand pedelecspezifischer Fallstudien wird ein analytische Mehrwert demonstriert.

Die zentralen Ergebnisse zeigen, dass Besitz und Nutzung von elektrischen und konventionellen Fahrrädern auf Ebene der Individuen zwar durch ähnliche Faktoren beeinflusst werden, eine getrennte Modellierung dieser Entscheidungsstufen jedoch zu differenzierteren Einblicken in Verhaltensmuster führt und eine Szenarioanalyse in Verkehrsmodellen ermöglicht. Unsere Resultate belegen zudem, dass Pedelecs häufig Autofahrten ersetzen, insbesondere in Kontexten mit zuvor geringem Radverkehrsanteil. Für pedelecspezifische Widerstandsfunktionen in der Modus- und Routenwahl ist es wichtig zu beachten, dass elektrische Fahrräder nicht einfach nur schneller als konventionelle Fahrräder sind. Für eine realitätsnahe Modellierung sollten Unterschiede hinsichtlich Weglängen, Nutzergruppen, Wegezwecken und Steigungsaversion berücksichtigt werden. Weitere Einflussfak-

toren wie die Infrastruktur zeigen ebenfalls Potenzial zur Differenzierung, jedoch ist der Forschungsstand hierzu bislang uneindeutig. Die Fallstudien zeigen, dass eine differenzierte Modellierung analytische Vorteile gegenüber traditionellen undifferenzierten Modellen bietet. Allerdings deuten die Ergebnisse auch darauf hin, dass die resultierende Verbesserung der Modellqualität insgesamt sehr gering ausfällt. Dies liegt zumindest teilweise daran, dass die Modellqualität auf aggregierter Ebene verglichen werden muss, ohne pedelecspezifische Modellergebnisse berücksichtigen zu können. Auf Basis dieser Erkenntnisse werden praxisorientierte Empfehlungen gegeben, ob und wie elektrischer Radverkehr in die Verkehrsmodellierung integriert werden sollten.

Die Modellierung des elektrischen Radverkehrs bleibt herausfordernd, insbesondere aufgrund großer Datenlücken in Mobilitätsbefragungen und Verkehrszählungen. Weitere Forschung ist notwendig, um verhaltensbezogene Unterschiede zwischen Nutzenden elektrischer und konventioneller Fahrräder besser zu verstehen. Dennoch lässt sich bereits anhand der heutigen Datenlage zeigen, dass die Elektrifizierung des Radverkehrs in der Verkehrsmodellierung berücksichtigt werden sollte, mindestens als Szenarioparameter, um die zukünftige Bedeutung des Radverkehrs nicht systematisch zu unterschätzen.

Danksagung

Diese Dissertation entstand während meiner Zeit am Lehr- und Forschungsgebiet Radverkehr der Bergischen Universität Wuppertal. In diesen drei Jahren wurde ich von vielen Menschen begleitet und unterstützt – ohne ihren Beitrag wäre dieses Projekt in dieser Form nicht möglich gewesen.

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Declaration

I hereby declare that I have composed the submitted dissertation independently and without unauthorized assistance. I have used only the resources and aids indicated in the dissertation, and all passages that are quoted verbatim or paraphrased from other works are clearly identified as such. I furthermore declare that I have not previously submitted a doctoral dissertation, nor have I made any prior applications for doctoral studies that were unsuccessful, either in Germany or abroad.

Throughout the writing process, I used the language model ChatGPT (by OpenAI) for editorial assistance, namely improving style, grammar, and clarity. The substantive content and final wording of the dissertation are my own, and I take full responsibility for its content.

Cologne, 1 September 2025

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Chapter 1

Introduction

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1.1 Motivation

To the dismay of many, the future is unknown. For transportation planners, policymakers, and researchers responsible for shaping transportation systems, this uncertainty is especially troubling. Faced with decisions like how to plan a city's cycling network, which route variant to choose for a new metro line, or evaluating the societal impacts of congestion pricing, they turn to travel demand models as their testbed. Within these models, free from the temporal and financial constraints of the real world, they can experiment with interventions and evaluate their potential effects before laying a single patch of asphalt.

In more abstract words, travel demand models are tools used for analysing the current state of a transportation system and predicting the impacts of outside trends or planned interventions (Pillat & Manz, 2021). They do so by representing the transport supply (e.g., road infrastructure, bus lines, and tolls) and land use (e.g., residential areas, work places, and schools) in an appropriate software environment. Using behavioural models and parameters, they then recreate all relevant decision making processes of travellers (e.g. location choice, ownership choice, trip generation, destination choice, departure time choice, mode choice, and route choice) to generate demand matrices, traffic volumes on individual network elements, overall indicators (e.g., car mileage, total time spent travelling, or modal splits) and indicator matrices (FGSV, 2022). By changing the model input (e.g., adding a new bicycle path, increasing the population of an area with new residential development, or reducing the emission rates of a vehicle fleet), users are then able to compare model results for two scenarios and quantify likely effects of the trend or intervention examined (Bhat & Koppelman, 2003).

This ability to model and compare different scenarios makes travel demand modelling a vital tool in transportation planning. Its importance becomes even clearer when we consider the nature of transportation systems themselves: they require substantial investment and are designed to last for decades. Yet, the world around them does not stand still. Over the lifespan of any given infrastructure, the conditions under which it operates can shift dramatically from those present during its planning. Many of these local changes and global trends are routinely incorporated into travel demand models. Whether the development of new residential areas or the construction of an additional motorway exit, whether demographic shifts or the rise of electric cars: we can and do represent these evolving circumstances in travel demand models to account for their influence on the future impacts and effectiveness of proposed interventions.

One such trend has emerged visibly in recent years, yet has received surprisingly little attention in transport modelling practice: the rise of electric bicycles (e-bikes). E-bikes have been around for a long time, with the oldest patent originating in the late 19th century (Bolton, 1895). Nowadays, the term e-bike can be used refer to to a wide variety of vehicle types: On one end, bicycle-style e-bikes build closely on the design of a conventional bicycle (c-bike) but incorporate an electric motor that assists the rider by reducing (not replacing) the pedalling effort required. These are particularly popular in Europe and North America (Fishman & Cherry, 2016). In Germany, the term e-bike is used colloquially in place of the term pedelec. These are bicycle-style e-bikes that provide motor assistance up to 25 km/h, with support ceasing at higher speeds. As a result, they are subject to the same relaxed traffic and vehicle registration regulations as c-bikes (Schleinitz, Petzoldt, Franke-Bartholdt, Krems, & Gehlert, 2017). On the other end of the e-bike range, so-called scooter-style e-bikes have no pedals and speed is instead controlled using a throttle, like on a motorbike. This type is commonly used in South and East Asia (Fishman & Cherry, 2016). In this thesis, only bicycle-style e-bikes are investigated, as scooter-style vehicles are more akin to private motorized transport than to bicycles in the context of European traffic regulations.

Despite the idea of equipping a bicycle with an electric motor not being particularly novel, e-bikes globally only started becoming a consumer mass product in the early 2000s (Jamerson & Benjamin, 2012). In Germany, e-bike sales started rising rapidly in the 2010s and have overtaken c-bike sales in 2023 (Zweirad-Industrie-Verband, 2025), as can be seen in Figure 1.1. As a result, in 2023 21 % of households in Germany already had access to an e-bike (Follmer, 2025).

There are several ways in which electrifying bicycle traffic might contribute to an increase in overall cycling:

- E-bikes enable groups that have previously been unable to use a c-bike to take up cycling. For example, the elderly have been the most prominent group of early adopters (Fishman & Cherry, 2016), but other, younger user groups are catching up (de Haas, Kroesen, Chorus, Hoogendoorn-Lanser, & Hoogendoorn, 2022).
- In hilly or mountainous areas, they make cycling feasible where it would otherwise be too strenuous.
- E-bikes act as range extenders, allowing cyclists to cover greater distances than with c-bikes and thereby replace more car trips (Nobis, 2019).

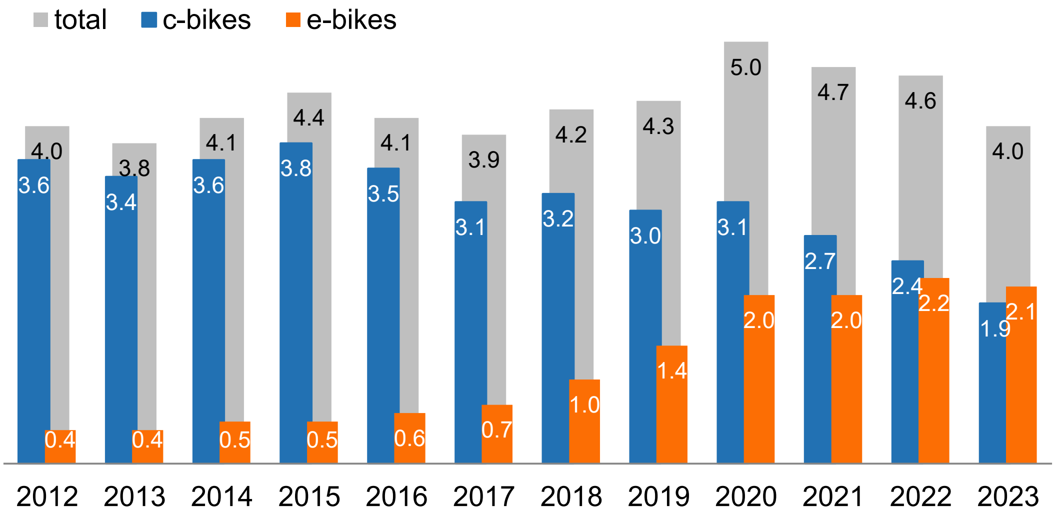

Figure 1.1: Development of yearly bicycle sales [mln.] in Germany based on data from Zweirad-Industrie-Verband (2024), previously published in Arning and Kaths (2025b).

- The reduced physical exertion makes cycling more appealing for trip purposes other than leisure, such as commuting (Nobis, 2019; Smit, Zondag, & Willigers, 2021).
- Finally, electric assistance supports the transport of heavier loads or passengers, such as with cargo bikes or longtails.

The growing market penetration of e-bikes therefore has the potential to address several key challenges in contemporary transport systems. By encouraging more cycling, it may contribute to improved public health. In urban areas, it can promote human-scale mobility, reducing space consumption and enhancing liveability. Furthermore, by replacing more carbon-intensive modes of transport, e-bikes can support efforts to mitigate climate change. However, the shift toward e-bikes is not without potential drawbacks. Some trips previously made by foot or c-bike may now be made by e-bike, potentially diminishing overall physical activity. E-bikes' higher speeds may also influence traffic safety, and while their electricity use is minimal compared to other motorized transport modes, their production and operation are evidently more resource-intensive than those of c-bikes.

While this thesis also contributes to weighing these benefits and drawbacks of increased e-bike use, it primarily addresses a prior analytical step: differentiating between c-bikes and e-bikes within travel demand models. E-bikes are not just faster bicycles; they might present a fundamental change to the paradigm of active mobility, opening up new user groups and use cases to cycling. As will also be discussed in more detail in Chapters 2.1 and 5.1.1, current travel demand models to this day fall short in accounting for the electrification of bicycle traffic. Ignoring the impact of an ageing population would lead to inaccurate model predictions regarding future travel patterns, and ignoring the electrification of cars would render a model unable to predict the impact of electric car subsidies on noise or air pollution. The main motivation behind this thesis is that in a similar fashion, **the neglect of the electrification of bicycle traffic in travel demand models might hamper their predictive accuracy and renders them unable to evaluate e-bike specific policies**.

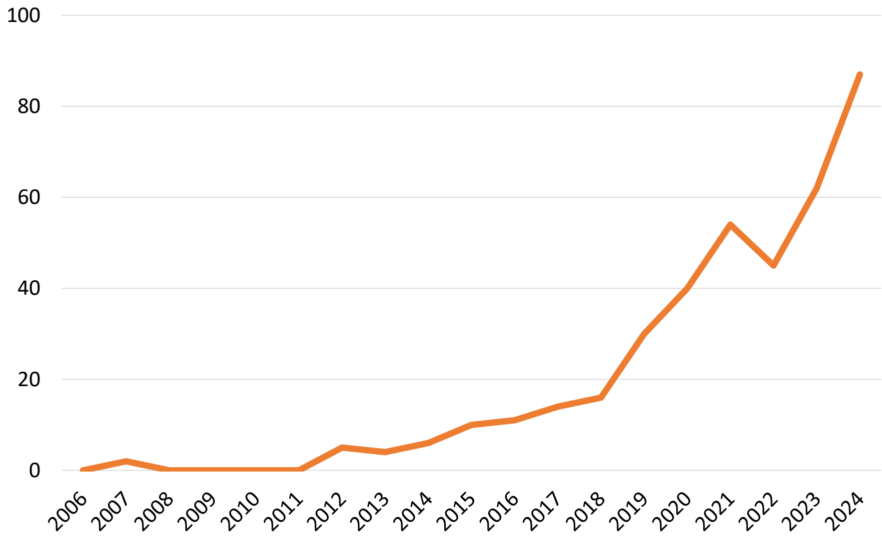

Figure 1.2: Number of yearly publications categorised as "transportation" in the Web of Science Core Collection mentioning the term "e-bike".

More differentiated modelling of electric and conventional bicycle traffic supports more accurate, data-driven analysis and forecasting of shifts in travel patterns. In turn, this serves two key purposes: first, these more differentiated models can be used to more reliably forecast future travel demand and evaluate interventions against the backdrop of different scenarios for e-bike adoption. Second, future research into the health, social, and environmental impacts of e-bike use can build upon more reliable estimates of how higher e-bike market penetration translates into actual changes in travel behaviour.

1.2 Introductory Literature Review

Perhaps due to their novelty, e-bikes have become an attractive topic for transportation researchers in recent years, with research being published at an ever-accelerating rate since the early 2010s (see Figure 1.2). Chapters 2 to 5 of this thesis each provide in-depth reviews of this literature corpus, focusing on: travel demand models used by practitioners and an overview of adjacent fields of research (Chapter 2); research into factors affecting e-bike ownership and the types of discrete choice models used to investigate these relationships (Chapters 3.2.1 and 3.2.2, respectively); and research into e-bike-induced mode shift, along with the discrete choice models used to investigate bicycle mode choice in general and e-bike mode choice in particular (Chapter 4). Lastly, the literature review section in Chapter 5 discusses how e-bikes have been incorporated into academic travel demand models (as opposed to Chapter 2's focus on models used in practice), and systematizes impedance functions used for bicycle mode and route choice. The following introductory literature review highlights overarching research themes most relevant to this thesis, notable contributions, and central research gaps.

1.2.1 Factors Affecting E-bike Ownership, Mode, and Route Choice

Understanding who owns and uses e-bikes, how they use them, and for what reasons, especially in comparison to c-bikes, is crucial for accurately capturing their distinctive usage patterns in travel demand models. Given the considerable overlap between factors motivating e-bike purchase (ownership choice), influencing subsequent use (mode choice), and determining route route choice, this introductory literature review addresses these factors collectively. More detailed analyses for each modelling step are provided in Sections 2.3, 3.2.1, 4.2, and 5.1.2.

E-bikes have proven particularly popular among the elderly, more so than any other socio-demographic group (Fishman & Cherry, 2016; Kroesen, 2017; MacArthur, Harpool, Scheppke, & Cherry, 2018; Nobis, 2019; van Cauwenberg, de Bourdeaudhuij, Clarys, de Geus, & Deforche, 2018). One study however finds e-bike ownership to be more pronounced in younger age groups (Wu, Lee, & Pettit, 2024). In Europe, e-bike use is slightly more common among women than men (de Haas et al., 2022; Haustein & Møller, 2016; Kroesen, 2017; van Cauwenberg et al., 2018), whereas the opposite trend is observed in North America (MacArthur et al., 2018) and Australia (Wu et al., 2024). Given their higher purchase cost compared to c-bikes, one might expect e-bikes to be most popular among high-income households, a pattern supported by several studies (Haustein & Møller, 2016; Jones, Harms, & Heinen, 2016; Kohlrautz & Kuhnimhof, 2024; Kroesen, 2017; Nobis, 2019). Interestingly, Rérat (2021) find that in Switzerland, "e-bike users are slightly overrepresented among those with the lowest income [...] as well as the highest". This pattern is also identified by Wu et al. (2024), however at insignificant levels of certainty. The influence of education level tends to be small or insignificant across studies, especially after controlling for income and age (Kroesen, 2017). In summary, age emerges as the most relevant socio-demographic attribute explaining e-bike ownership and use. Because socio-demographic variables are often interrelated, multivariable analyses are necessary to identify the true determinants of e-bike ownership and use; these are discussed further in Subsection 1.2.2. Beyond these "hard" socio-demographic factors, individual attitudes towards cycling play an important role in determining bicycle use overall (Basaran, Kristoffersen, & Haustein, 2021; O'Reilly, Kollmann, Cohen, & Reichl, 2024; Ramezani, Laatikainen, Hasanzadeh, & Kyttä, 2021), and e-bikes in particular (Haustein & Møller, 2016; P. A. Plazier, Weitkamp, & van den Berg, 2017; Simsekoglu & Klöckner, 2019). However, few studies explicitly examine differences in the importance of attitudes for c-bike versus e-bike use. One exception finds that e-bike riders exhibit higher levels of traffic rule knowledge and greater awareness of cycling risks compared to c-bike riders (Møller, Useche, Siebert, & Janstrup, 2024).

E-bike use varies considerably by trip purpose. Among the dominant group of early adopters (the elderly), e-bikes are most commonly used for leisure trips (de Haas et al., 2022; Haustein & Møller, 2016; Kohlrautz & Kuhnimhof, 2024; MacArthur et al., 2018; Nobis, 2019). However, among working-age individuals, e-bikes are also regularly used for commuting (de Haas et al., 2022; Rérat, 2021). Non-transport cycling trips (e.g., recreational round trips) constitute a considerable share of total bicycle traffic, particularly in cities with low cycling rates. This presents a notable challenge for existing bicycle modelling frameworks(Bostanara, Wu, Roberts, Pettit, & Lee, 2025), especially given the absence of e-bike-specific research on the topic. Similar to c-bikes, e-bike use is more frequent during seasons with mild or warm weather (Kohlrautz & Kuhnimhof, 2024), with this seasonality being particularly pronounced for leisure trips (Nobis, 2019).

While bicycle ownership and mode choice are predominantly influenced by the aforementioned characteristics of the (potential) cyclist and trip attributes, route choice is additionally shaped by route-specific factors. In a comprehensive review of 33 studies utilizing GPS data to investigate bicycle route choice, Łukawska (2024) identifies route length, bicycle infrastructure, slope, traffic lights, turns, land use, road size, traffic volume, pedestrian paths, car speed limit, riding against traffic, and intersections as the most frequently examined factors. Among these, all but land use and pedestrian paths exhibit a clearly positive or negative impact on the probability of route choice. The following three paragraphs highlight differences between c-bikes and e-bikes with respect to route length, bicycle infrastructure, slope, and car speed limit.

E-bike trips are on average considerably longer than c-bike trips (Nobis, 2019). In a naturalistic cycling study, Schleinitz et al. (2017) find that e-bike riders in Germany travel at an average speed of 17.4 km/h, compared to 15.3 km/h on c-bikes. This relative difference of 14% can only partially explain the longer average trip lengths observed for e-bikes. Another potential explanation is that e-bike travel may be less sensitive not only to travel distance but also to travel time, due to the lower physical effort required while riding. Although studies on e-bike route choice preferences could offer more specific insights, most empirical research in this area operates in value-of-distance (VoD) space (Dane, Feng, Luub, & Arentze, 2020; Khavarian, Vosough, & Roncoli, 2024; Meister, Felder, Schmid, & Axhausen, 2023; Prato, Halldórsdóttir, & Nielsen, 2018) rather than value-of-time (VoT) space. Consequently, these studies do not allow us to determine the extent to which the difference in trip length is attributable to higher speed or (additionally) a reduced sensitivity to time spent cycling. Hardinghaus and Weschke (2023) is the only such study operating in VoT space and, surprisingly, finds no significant difference in travel time sensitivity between c-bike and e-bike riders. Overall, it seems plausible that the longer range of e-bike trips results from a combination of factors, including higher speed, differences in trip purpose, and potentially a lower sensitivity to time spent cycling; however, little research explicitly differentiates between these influences.

Cycling infrastructure has long been recognized as an important factor influencing bicycle mode choice (Mueller et al., 2018; Pucher, Dill, & Handy, 2010). In contrast to infrastructure for cars or public transport, the role of bicycle infrastructure is not just about speed and travel time, but more so about the perceived safety of cyclists (Bostanara et al., 2025). Findings regarding differences in infrastructure preferences between c-bikes and e-bikes remain inconclusive: Hardinghaus and Weschke (2023) find that e-bike users are more willing than c-bike users to take detours in order to ride on dedicated bicycle infrastructure. In contrast, Meister et al. (2023) report the opposite. When riding in mixed traffic, cyclists generally prefer roads with motor vehicle speed limits of 30 km/h or lower (Hardinghaus & Weschke, 2022; Huber et al., 2021; Meister et al., 2023; Meister, Liang, Felder, & Axhausen, 2024). An exception is noted by Meister et al. (2023), who find that e-bike users in their study preferred 50 km/h over 30 km/h speed limits. The authors attribute this result to the high prevalence of S-Pedelecs in Switzerland, which are capable of speeds up to 45 km/h, where the study was conducted.

Lastly, e-bikes make cycling uphill significantly easier than c-bikes. As a result, recent studies on e-bike route choice find that e-bike users are less sensitive to steep inclines along their routes than c-bike users (Khavarian et al., 2024; Meister et al., 2023). Based on this, one would expect e-bike ownership and use to be more prevalent in topographically challenging areas than in flatter regions. However, empirical research on this topic remains surprisingly limited, likely because much of the existing literature on e-bikes originates from European countries with high cycling rates but relatively little topographic variation, such as the Netherlands. Notably, no study has been identified that directly examines the relationship between topography and e-bike ownership. For mode choice, only Reck, Martin, and Axhausen (2022) include a measure of elevation gain, finding that it negatively affects the use of shared c-bikes but not shared e-bikes. Three studies from Germany and Switzerland report higher levels of e-bike ownership and use in rural areas (Kohlrautz & Kuhnimhof, 2024; Nobis, 2019; Rérat, 2021). However, it remains unclear to what extent these findings are driven by confounding factors such as older population age, longer average trip distances, or hillier terrain in rural compared to urban areas.

Overall, the factors influencing c-bike use are well-researched, with general consensus established regarding whether each factor has a positive or negative effect on cycling. In contrast, only a fraction of studies focuses specifically on e-bikes, and an even smaller number explicitly compares c-bikes and e-bikes. Such comparative studies are essential to identify which factors must be accounted for in travel demand models to accurately differentiate between the two bicycle types.

1.2.2 Modelling E-bike Ownership, Mode, and Route Choice

This subsection offers a first overview of the model types used to investigate the relationships examined in Section 1.2.1. In addition to enhancing our understanding of choice behaviour and preferences, these models and their insights are also employed in travel demand models to, for example, predict ownership rates, modal splits, or route volumes, which are further explored in Section 1.2.3.

Until the 1980s, travel behaviour was primarily modelled using aggregate approaches, such as modal split models, which operated at a collective level, analysing groups of individuals, spatial zones, or travel relations (Ortúzar & Willumsen, 2011). These models were eventually supplanted by discrete choice models, which offer a more detailed, disaggregate analysis. Typically grounded in random utility theory (Domencich & McFadden, 1975), discrete choice models enable the examination of individual preferences and the prediction of choice probabilities. In this context, ownership, mode, and route decisions are treated as discrete choices, where the dependent variable represents a selection from a finite set of alternatives.

The simplest approach to modelling mobility tool ownership as a discrete choice is through binary models, where the dependent variable indicates whether a person or household owns a specific mobility tool (e.g., a car) or not. In practice, however, individuals and households often make joint decisions regarding a bundle of mobility tools, for instance, whether to own both a car and a bicycle, or just one of the two. Since these mobility tools may serve as partial substitutes to each other, it is essential to model ownership decisions jointly. One common method involves the use of multinomial logit models, in which each alternative represents a distinct combination of mobility tools (e.g., "neither car nor bicycle," "only car," "only bicycle," or "both car and bicycle") (Fatmi, Habib, & Salloum, 2014; Kohlrautz & Kuhnimhof, 2024). However, this approach violates the independence of irrelevant alternatives (IIA) property, as the error terms across alternatives are correlated. To address this limitation, nested logit and cross-nested logit models can be applied (Handy, Xing, & Buehler, 2010; Püschel, Barthelmes, Kagerbauer, & Vortisch, 2023). For ownership decisions (more so than for mode or route choice), probit models are also frequently used. Unlike logit models, probit models assume normally distributed error terms and explicitly allow for correlations across alternatives. This makes them particularly well-suited for capturing joint or interdependent decisions, such as the simultaneous ownership of multiple mobility tools (Becker, Loder, Schmid, & Axhausen, 2017; Yamamoto, 2009). In addition to modelling whether specific mobility tools are available, it is often important, especially at the household level, to account for the number of available tools. In such cases, ordered logit (Maltha, Kroesen, van Wee, & van Daalen, 2017; Pinjari, Eluru, Bhat, Pendyala, & Spissu, 2008) and ordered probit models (Ma, Ye, & Shi, 2018; D. Scott & Axhausen, 2006) are employed. These models estimate not only utility coefficients for each alternative, but also threshold values that indicate, for example, at what level of utility a household transitions from owning one to two cars. To date, only two studies have explicitly modelled e-bike ownership (Gu, Feng, Zhong, Cai, & Li, 2021; Zhang, Li, Yang, Liu, & Li, 2013); however, both focus on scooter-style rather than bicycle-style e-bikes.

Even more so than in the context of ownership, bicycle mode choice modelling frequently employs multinomial logit models (Dahmen, Weikl, & Bogenberger, 2024; Friedrich et al., 2019; Kohlrautz & Kuhnimhof, 2024; Mirzaei, Kheyroddin, & Mignot, 2021; Ortúzar & Willumsen, 2011; Rayaprolu, Llorca, & Moeckel, 2020; Rybarczyk & Wu, 2014) and, to a lesser extent, nested logit models (Ortúzar & Willumsen, 2011; Rayaprolu et al., 2020). The latter are particularly useful for accounting for similarities among alternatives, thereby relaxing the restrictive independence of irrelevant alternatives (IIA) assumption inherent in the multinomial specification (Ortúzar & Willumsen, 2011). In addition to these standard approaches, a range of more advanced modelling techniques has also been applied, including recursive logit models (Meyer de Freitas, Becker, Zimmermann, & Axhausen, 2019), mixed logit models (Reck et al., 2022), and machine learning methods (Dahmen et al., 2024; Tamim Kashifi, Jamal, Samim Kashefi, Almoshaogeh, & Masiur Rahman, 2022). While research specifically focused on e-bike mode choice remains limited, it is more prevalent than research on e-bike ownership. Existing studies that explicitly model e-bike mode choice include Heilig, Mallig, Hilgert, Kagerbauer, and Vortisch (2017), Hallberg, Rasmussen, and Rich (2021), Reck et al. (2022), and Kohlrautz and Kuhnimhof (2024).

Modelling route choice differs from ownership and mode choice in several fundamental ways. First, not just the attributes of alternatives but the choice set itself varies across choice situations, as it depends on the specific origin–destination pair. Second, the number of theoretically possible routes between any given origin-destination pair is practically infinite, requiring researchers to define a manageable subset of likely alternatives in advance. Third, even within this reduced choice set, many alternatives overlap. While some researchers use multinomial logit models (especially in stated preference studies where the composition of alternatives can be controlled (Hardinghaus & Weschke, 2022; Khavarian et al., 2024)), they are less suitable for revealed preference data and real-world network applications due to this overlap. Therefore, path size logit models are commonly employed (Broach, Dill, & Gliebe, 2012; Cho & Shin, 2022; Chung, Yao, Pan, & Ko, 2024; Dane et al., 2020; Łukawska, Paulsen, Rasmussen, Jensen, & Nielsen, 2023; Meister et al., 2023, 2024; Prato et al., 2018; D. M. Scott, Lu, & Brown, 2021; Shah & Cherry, 2021). These models incorporate a path size factor, which quantifies the degree to which each route is distinct from other alternatives in the choice set. This factor is then weighted by a coefficient and included in the utility function, allowing the model to account for shared segments among routes (Ortúzar & Willumsen, 2011). Despite growing interest in bicycle route choice modelling, only few studies to date have specifically examined e-bike route choice as distinct from conventional bicycle use (Dane et al., 2020; Hardinghaus & Weschke, 2023; Khavarian et al., 2024; Meister et al., 2023).

Finally, it is important to note that models frequently integrate multiple choice dimensions within a unified framework to account for their interdependencies. These decisions, such as location, ownership, destination, departure time, mode, and route choice, can be jointly modelled using structures such as nested logit models. In this context, nests do not group similar alternatives, but instead reflect the hierarchical structure of the decision-making process, with each nest corresponding to a subsequent choice stage (Friedrich et al., 2019; Hallberg et al., 2021; Heilig et al., 2017; Liu, Tapani, Kristoffersson, Rydergren, & Jonsson, 2020; Rich & Hansen, 2016). While this is not a strictly simultaneous approach, it permits conditional dependencies between decisions. In contrast, Meyer de Freitas et al. (2019) adopt a recursive logit model, which simultaneously captures iterative decision making between mode and route choice along a network graph. Other fully simultaneous modelling techniques, although not yet widely applied in the context of bicycle research, include cross-nested logit models (Ding, Mishra, Lin, & Xie, 2015; Yang, Zheng, & Zhu, 2013) and mixed logit models (Guo, Feng, & Timmermans, 2020).

1.2.3 E-bikes in Travel Demand Models in Practice and Academia

Travel demand models both in academic research and professional practice combine multiple sub-models into a unified framework that reflects the sequential nature of travel behaviour (FGSV, 2022; Ortúzar & Willumsen, 2011). While the discrete choice models discussed in Section 1.2.2 provide valuable insights for modelling e-bike ownership, mode, and route choice, travel demand models introduce additional layers of complexity that merit separate consideration. Unlike stand-alone discrete choice models, which are often used to analyse behaviour and inform general policy recommendations, travel demand models are typically applied in specific spatial contexts to evaluate the impact of interventions across multiple, interrelated choice dimensions. They also face practical constraints, most pressingly limited data availability for model inputs as well as calibration and validation. Incorporating e-bikes into these models is not simply a matter of distinguishing between conventional and electric bicycles within each sub-model. It also involves assessing whether the added complexity results in meaningfully different outcomes compared to models that do not differentiate between bicycle types. This subsection therefore reviews the extent to which e-bikes have been integrated into travel demand models to date, and assesses the degree to which the value of this integration has been evaluated.

Among travel demand models used in practice, differentiation between c-bikes and e-bikes is very rare. The only model known to the author of this thesis that treats them as distinct choice alternatives is the Dutch National Passenger Transport Model "Growth Model 4" (Smit et al., 2021; Willigers et al., 2021). In this model, age-specific e-bike ownership rates are defined as scenario variables. Separate travel time coefficients for mode and route choice impedance are estimated for c-bikes and e-bikes, however identical indicator matrices are computed for both bicycle types. The Danish "COMPASS" model for the Copenhagen Capital Region does not explicitly differentiate between c-bikes and e-bikes, but it allows for varying scenarios of overall e-bike share. This is achieved by reducing travel time for all bicycle trips as the share of e-bikes increases, based on the assumption that e-bike travel time is 15 % lower than c-bike travel time (Paag, 2022). It is worth noting that even when models do not differentiate between c-bikes and e-bikes but instead have only a combined cycling mode, their parameters are typically based on empirical observations. As a result, the combined cycling mode reflects the average characteristics of c-bike and e-bike traffic, based on the e-bike share present during data collection.

Even though a considerable number of studies developing travel demand models (de Melo & Isler, 2023; Hallberg et al., 2021; Jacyna, Wasiak, Kłodawski, & Gołebiowski, 2017; Liu et al., 2020;

Oskarbski, Birr, & Żarski, 2021; van Dulmen & Fellendorf, 2021) and more specifically agent-based models (Hebenstreit, 2021; Jafari, Both, Singh, Gunn, & Giles-Corti, 2022; Kaziyeva, Loidl, & Wallentin, 2021; Meyer de Freitas, Miotti, & Zani, in press) with a focus on bicycle traffic exist, again only few differentiate between c-bikes and e-bikes. Similar to the COMPASS model, Hallberg et al. (2021) develop a model, also for Copenhagen, where the speed of the combined cycling mode depends on the overall market share of different types of e-bikes. In Hebenstreit (2021)'s agent-based MATSim model of Vienna, the desired speed and aversion to gradient is said to differ between shared c-bikes and shared e-bikes, however the network model does not contain gradient data. In Meyer de Freitas et al. (in press)'s MATSim model, mode choice differentiates between three types of bicycles (conventional, e-bike, and s-pedelec) and takes into account differences in travel time, age, sex, and degree of urbanisation.

As with models used in practice, most models developed for research are employed to evaluate the effects of interventions or trends (Argyros, Jensen, Rich, & Dalyot, 2024; de Melo & Isler, 2023; Hallberg et al., 2021; Hebenstreit, 2021; Liu, Tapani, Kristoffersson, Rydergren, & Jonsson, 2021; Oskarbski et al., 2021; van Dulmen & Fellendorf, 2021). The only study that investigates the influence of e-bike share on the impact of interventions suggests that failing to account for a growing share of e-bikes leads to an underestimation of the benefits of bicycle infrastructure (Hallberg et al., 2021). However, no study examines whether distinguishing between c-bikes and e-bikes improves overall model quality. In both theory and practice, bicycle model development is generally constrained by limited data availability. This is relevant both for model inputs, as noted by Jafari et al. (2022); Kaziyeva et al. (2021), and for calibration and validation, as emphasized by Kaziyeva et al. (2021); Oskarbski et al. (2021); van Dulmen and Fellendorf (2021). Overall, research on whether and how to incorporate e-bikes into travel demand models remains very limited.

1.3 Research Gaps, Contributions, and Structure of this Thesis

Overall, the literature is rich in research on factors influencing bicycle traffic, with most studies focusing on one choice (e.g., ownership, mode, or route choice) at a time. Many studies on mode choice ignore bicycle availability, thereby conflating factors that influence bicycle ownership with those affecting mode choice. However, the influence of these factors is largely similar for both choices. E-bike-specific research, especially studies that allow for explicit comparisons between c-bikes and e-bikes, is much rarer and primarily focused on mode and route choice.

One topic stands out as particularly relevant for differentiating between c-bikes and e-bikes across all choices, yet remains strongly under-researched: topography and gradient. Only a few studies investigate the impact of these factors on e-bike route (Meister et al., 2023) or mode choice (Reck et al., 2022), and none explore their impact on ownership choice. This is likely because most bicycle research is conducted in regions with high cycling prevalence, where topography tends not to be a significant issue.

This thesis therefore aims to incorporate gradient as a factor in differentiating between c-bike and e-bike ownership, mode, and route choice. For ownership (Chapter 3) and mode choice (Chapter 4), dedicated discrete choice models are developed and estimated and inform the respective choice components in a travel demand model (Chapter 5). For route choice, our modelling efforts in Chapter

5 are informed solely by the existing literature.

In a pattern similar to that of research on individual choice steps, there is considerable research and practical experience in modelling bicycle traffic within travel demand models. However, for e-bikes specifically, this is not the case. To date, no travel demand model has been developed that differentiates between c-bikes and e-bikes across all relevant sub-models as dynamic choice alternatives and accounts for differences in preference between the two, rather than treating e-bike market shares purely as a scenario parameter or e-bikes as faster bicycles. Furthermore, evidence on whether differentiating between c-bikes and e-bikes improves model usefulness or quality is rare (Hallberg et al., 2021) and, in the case of model quality, non-existent.

Therefore, this thesis sets out to answer **two main research questions**:

- **How can the electrification of bicycle traffic be accounted for in travel demand models?**
- **Does this improve model quality and usefulness?**

The four publications included in this dissertation, presented as individual chapters, are structured around these two overarching research questions and address more specific sub-questions along the way:

- Chapter 2: What is the current state of practice and literature?
  - How are e-bikes dealt with in current state-of-the-art travel demand models?
  - What methods are used in the literature to investigate e-bike ownership, mode choice, and route choice?
  - What relevant influencing factors are identified for each modeling step?
- Chapter 3: How should e-bike ownership be accounted for in travel demand models?
  - What model types are suitable to model e-bike ownership?
  - What are relevant influencing factors in Germany?
- Chapter 4: How should e-bike mode choice be accounted for in travel demand models?
  - What model types are suitable to model e-bike mode choice?
  - What are relevant influencing factors in Germany?
  - To what degree does e-bike travel currently substitute active mobility, car travel, and public transport, respectively?
- Chapter 5: Does differentiating between c-bikes and e-bikes improve model quality and usefulness?
  - How can existing strategic transport models be enhanced to better reflect differences between c-bikes and e-bikes?
  - Does the available data suffice?
  - Does model quality improve compared to an undifferentiated bicycle mode?
  - Are there e-bike specific effects of interventions aimed to promote cycling?

Finally, Chapter 6 presents a discussion of the key results and fundamental limitations of this work, along with an outlook on future research and a conclusion.

Chapter 2

First Paper: Literature Review

Contents

Disclaimer: This chapter was previously published as: Leonard Arning, Cat Silva, and Heather Kaths (2023). Review of Current Practice and Research on E-Bikes in Transport Models. *Transportation Research Record*, 2677(12). doi: `https://doi.org/10.1177/03611981231168848`. The second author contributed by proof-reading the manuscript and suggesting language revisions. The third author, who is also the supervisor of this thesis, contributed by advising on the study conception and design as well as proof-reading the manuscript and suggesting language revisions.

Abstract

E-bike sales have been growing strongly across the globe in recent years. Despite the differences between e-bikes and conventional bicycles, bicycle traffic is typically considered a uniform mode in macroscopic transport modeling. This is problematic because such models do not allow for dedicated e-bike analysis and could therefore have adverse impacts on accuracy. In this study, we therefore investigated whether and how e-bikes are presently modeled in practice and how e-bikes should be modeled to improve data validity and usefulness. To this end, we conducted a review of 14 exemplary strategic transport models and carried out a structured exploratory literature review of existing empirical research. We queried four fields of research and investigated 29 relevant and unique sources covering influences on e-bike ownership and use as well as the characteristics of e-bike mode and route choice. Based on this work, we identified three key findings: (1) purchase choice and mode choice models must allow for scenario setting; (2) generalized costs should also include factors other than travel time, and the factors' weighting parameters should be estimated separately between conventional bicycles and e-bikes; and (3) it is especially important for e-bike modeling to differentiate between person groups. Future research is needed to investigate route choice parameters for e-bike users, especially concerning the aversion to slopes, and methods to collect e-bike-specific data. Our findings demonstrated that, although modeling e-bikes is worthwhile, appropriate modeling approaches still need to be developed and applied to demonstrate their practicability and usefulness.

2.1 Introduction

Modeling bicycle traffic in transport models is tricky. Even though the subject is still developing with regard to model theory and data availability, initial attempts have been made to create more detailed models that distinguish between conventional bicycles (c-bikes) and electric bicycles (e-bikes). With few exceptions, we were unable to identify existing research dedicated to modeling e-bikes in macroscopic transport models. To fill this gap in the research, we conducted an assessment of current modeling practices and a structured exploratory literature review into relevant adjacent fields of research. We present our key recommendations for future efforts to model e-bikes related to scenario setting, components of generalized costs for mode and route choice, and segmentation by person group.

E-bikes vary with regard to maximum speed, motor power, control mode (throttle control or pedal assist), and more attributes, resulting in a wide range of vehicles from bicycle-style to scooter-style e-bikes (Fishman & Cherry, 2016). In this paper, we focus on electrically power-assisted cycles with no differentiation in the maximum speed, motor power, or local traffic regulations. For example, both pedelecs and speed-pedelecs (i.e., e-bikes with a top speed of 45 km/h) are included in this definition. Scooter-style e-bikes powered by a gas handle are particularly popular in Asia (Lin, Wells, & Sovacool, 2017). However, we excluded scooter-style e-bikes from our research, because in the context of transport modeling these vehicles are more akin to private motorized vehicles than bicycles.

With the rising share of e-bikes in bicycle traffic, most prominently in Europe (Heinrich Böll Stiftung, 2021), the question arises of whether and how e-bikes should be included in macroscopic transport models. Compared with c-bikes, their higher speed and lower physical effort may result in cycling becoming a more attractive mode of transport for different user groups, trip purposes, trip lengths, or in topographically challenging areas. On the other hand, higher costs, a lower level of physical exercise, and the need for secure storage and charging facilities might have adverse impacts on the benefits of e-biking on an individual and societal level (Hallberg et al., 2021).

Strategic transport models are simplified representations of real transport systems and are commonly used for analysis, forecasting, and policy evaluation (Pillat & Manz, 2021). When changes in the transportation system affect the choices its users (can) make, it is necessary to include these new options in the model to ensure that the outcomes continue to be accurate. The rise of e-bikes might also necessitate new analytical approaches and more detailed modeling of e-bikes to evaluate the impact of e-bike subsidies or dedicated bicycle infrastructure, for example.

Aiming to identify whether e-bikes are considered in any major macroscopic transport model, we inspected 14 exemplary European and North American models. We identified models by looking at countries that are particularly strong in bicycle research (e.g., Denmark, the Netherlands, Norway, Sweden) as well as the four most populous countries in Europe and North America (United States, Germany, France, and the UK). Since e-bikes as defined in the previous section are less common outside of these regions, we expected to find dedicated e-bike models here if they existed at all. Where model documentation was not available to the public, we contacted the model creators to provide us with the missing information. All of the models we reviewed adhere to the four-step-modeling framework. The list of all examined models presented in Table 1 does not provide a representative overview of the degree of detail to which cycling is considered in transport models globally, but demarcates the current boundaries of bicycle modeling.

Most European models we investigated include cycling as a combined mode, which is a single cycling mode consisting of both c- and e-bikes, and do so in both mode and route choice. In these cases, e-bikes influence model parameters to the degree that e-bikes are present in the base-year data used for calibration. The COMPASS model currently being developed by MOE for the Greater Copenhagen area will use an approach similar to the work of (Hallberg et al., 2021). This model does not differentiate between separate modes for c- and e-bike, but the cycling travel time is adjusted according to a manually forecasted share of e-bikes. The Dutch national model, GM4 (developed by Significance), stands out as the only model known to us that models e-bikes as a mode and route choice option distinct from c-bikes. We are not aware of any strategic transport model used in practice in which ownership of or access to c- or e-bikes is modeled dynamically as an independent choice (as opposed to the model-user setting static scenarios) that feeds into the later model stages.

By providing an overview of exemplary transport models from Europe and North America, we demonstrated that differences between c- and e-bikes are rarely considered in practice. Nevertheless, modeling practitioners in Denmark and the Netherlands are making the first advancements to differentiate e-bikes in transport models. In the consequent main part of this paper, we present the results of a literature review to inform such efforts to include e-bikes in future transport models.

In the two sections to follow, we describe the methods and results of a structured exploratory literature review that focused on gathering knowledge from four fields of research. In the discussion, we synthesize what our findings revealed about the requirements for the dedicated modeling of e-bikes. We then point out the limitations of this review, possible modeling approaches, and future research needs.

2.2 Structured Exploratory Literature Review

A preliminary literature review yielded very few works dedicated to e-bikes in transport modeling. Hence, we investigated related fields of research focusing on factors affecting e-bike ownership and use, and how e-bikes might differ from c-bikes in mode and route choice. The first two research fields deal with factors that could influence and change the propagation and usage characteristics of e-bikes in the future. Finding a distinct body of research on the influence of price on e-bike acquisition, the impact of price is distinguished as a unique research field and other factors influencing use are

Table 2.1: Exemplary Transport Models and their Considerations in Relation to E-Bikes

Model	**Area**	**Model specification**	**Source**
GM4	Netherlands	Distinct c- and e-bike modes. E-bike levels of service (travel time, distance) same as c-bike, but mode and route choice are adjusted by a separate estimation of the travel time coefficient. Scenario-based e-bike ownership is distinct by age group. Combined cycling mode only for transit access and egress journeys	Smit et al. (2021); Willigers et al. (2021)
COMPASS	Copenhagen	Implicit composite cycling mode. The fraction of cycling trips that use e-bikes (f) and travel time reduction factor for e-bikes (15%) are manual inputs. Travel time of the combined cycling mode is reduced across all cycling trips by multiplying with 1-(f-0.01)*0.15. No differentiation between c- and e-bikes in mode or route choice	Paag (2022)
Verkehrsmodell Berlin 2030	Berlin	Combined cycling mode	L. Richter (2022)
OTM 7	Copenhagen	Combined cycling mode	Tønning and Vuk (2017)
Cynemon	London	Combined cycling mode	Adams (2022)
NTM6/RTM	Norway	Combined cycling mode	Madslien, Steinsland, and Kwan Kwong (2017)
MODUS 3.1	Paris	Combined cycling mode	Tremblin et al. (2021)
LuTRANS	Stockholm County	Combined cycling mode	Strömgren et al. (2020)
Nationales Personen-verkehrsmodell	Switzerland	Combined cycling mode	Justen and Schiller (2020)
Landstrafikmodellen	Denmark	Combined cycling mode, in trip assignment combined with walking	Rich and Hansen (2016)
2016 City of Los Angeles Travel Demand Model	Los Angeles	Combined cycling mode, no trip assignment	Fehr & Peers (2018)
New York Best Practice Model	New York City	Combined cycling mode, no trip assignment	Thisse (2022)
Regional Travel Demand Model	Northeastern Illinois	No cycling mode	Chicago Metropolitan Agency for Planning (2014)
VENOM	Amsterdam Metro area	No cycling mode (new regional models to be devolved from GM4)	Metropoolregio Amsterdam (2017)

grouped together in the first research field. The latter two research fields investigate differences between c- and e-bikes in mode and in route choice. A dedicated search string for each research field was informed by the results from the preliminary literature review. All search strings shared a term restricting results to sources mentioning e-bikes. The remainder of each string further restricted the results to the focus topic of each research field. The research fields were:

- Research Field 1: Impacts of infrastructure, topography, and demographics on e-bike use;
- Research Field 2: Impacts of price on e-bike availability;
- Research Field 3: Impacts of e-bikes on mode choice; and
- Research Field 4: Impacts of e-bikes on route choice.

Using the four search strings, we queried three databases for peer-reviewed publications from January 2015 to June 2022 to focus on recent research, yet also provide sufficient source material. These searches yielded 54 relevant sources. After eliminating duplicates and adding two additional sources from the preliminary literature review, we identified 29 unique relevant sources. Most studies examined the Dutch or Northern European context. The number of sources per publication year was relatively evenly distributed between three (2016, 2018) and five (2017, 2021, 2022), however, no relevant sources were published in 2019.

Table 2.2 summarizes the search strings used for each research field, which databases where queried, and how many sources were identified. Table 2.3 provides an overview over all unique relevant sources identified and to what research field they relate. The results per search string indicate the number of sources that were found to be useful for any part of this review, which were identified using that search string and database. An “F” in the row of a source indicates that a source was found using that search string in at least one of the three queried databases. An “R” indicates for what research field a source was relevant. “F/R” consequentially indicates that a source was both found using a search string and relevant to the respective research field. Two sources from a preliminary literature review that were not identified in the structured exploratory literature review were added manually and are indicated by an “A.”

In our review, we did not explicitly consider trip generation and distribution because the expected impact of e-bikes on these modeling steps was low and analogous to non-mode-specific changes in accessibility and generalized costs. We also did not consider the modeling of onward impacts like changes in health or greenhouse gas or noise emissions, because this fell outside the scope of four-step-models in the narrow sense, despite being a common application of transport modeling software.

Table 2.2: Search setup and results of the structured exploratory literature review

		Research Field			
		1: Infrastructure, topography, demographics	2: Price on availability	3: Mode choice	4: Route choice
Search String		(infrastructure OR locale OR topography OR demograph* OR "user groups") AND (e-bike OR "electric bicycle" OR pedelec) AND (ownership OR purchase OR acquisition)	(subsid* OR campaign OR incentive) AND (e-bike OR "electric bicycle" OR pedelec) AND (ownership OR purchase OR acquisition)	(e-bike OR "electric bicycle" OR pedelec) AND ("mode choice" OR modal)	(e-bike OR "electric bicycle" OR pedelec) AND ("route choice" OR path)
Web of Science	Filter			WOS categories: Transportation OR Transportation Science Technology	
	Results	16	8	35	20
	Useful results	3	3	8	3
TRID	Filter			subject = pedestrians and cyclists	
	Results	15	8	65	18
	Useful results	3 (+1 unavailable)	3	12	3 (+1 not available)
EBSCO	Filter	Peer-reviewed; subject = electric bicycles	Peer-reviewed	Peer-reviewed; subject = electric bicycles	
	Results	20	39	48	41
	Useful results	3	3	7	3

Table 2.3: Coding of included sources by research field

Source	Research Field			
	1: Infrastructure, topography, demographics	2: Price on availability	3: Mode choice	4: Route choice
Fishman and Cherry (2016)	R	F	F	F/R
Astegiano, Tampère, and Beckx (2015)	R	F	R	
Haustein and Møller (2016)	R	F	R	
Jones et al. (2016)	F/R	R		
Hallberg et al. (2021)	R		F/R	F/R
Fyhri and Sundfør (2020)	F		F/R	
MacArthur et al. (2018)	F/R		R	
van Cauwenberg et al. (2018)	F/R		R	
de Haas et al. (2022)	R		F/R	
Kroesen (2017)	R		F/R	
Kazemzadeh and Ronchi (2022)	R		F/R	
Schleinitz et al. (2017)	F			R
de Kruijf, Ettema, Kamphuis, and Dijst (2018)		F/R	F/R	
Anderson and Hong (2022)		A	A	
Bigazzi and Berjisian (2021)		F/R		
Lee, Molin, Maat, and Sierzchula (2015)			F/R	F
Chavis and Martinez (2021)			F/R	F/R

Source (continued)	1: Infrastructure, topography, demographics	2: Price on availability	3: Mode choice	4: Route choice
Fitch, Gao, Noble, and Mac (2022)			R	F
P. A. Plazier et al. (2017)			R	F/R
Andersson, Adell, and Hiselius (2021)			F/R	
Hiselius and Svensson (2017)			F/R	
Reck et al. (2022)			F/R	
Sun, Feng, Kemperman, and Spahn (2020)			F/R	
Ton and Duives (2021)			F/R	
Bigazzi and Wong (2020)			F/R	
Cairns, Behrendt, Raffo, Beaumont, and Kiefer (2017)			F/R	
Fyhri and Fearnley (2015)			F/R	
Bourne et al. (2020)			A	
Langford, Chen, and Cherry (2015)				F/R

F: source was found using the specified search string. R: source is relevant to the specified research field. A: source was added manually.

2.3 Results

2.3.1 Research Field 1: Impacts of Infrastructure, Topography, and Demographics on E-Bike Use

There is widespread agreement in the literature that the key motivations for e-bike ownership are the ability to cover longer distances and overcome hilly terrain while avoiding physical exertion and sweat (Haustein & Møller, 2016; Jones et al., 2016; MacArthur et al., 2018). The ability to continue cycling despite a decline in physical ability is another major motivation (Jones et al., 2016). (Kazemzadeh & Ronchi, 2022) provide a more detailed review of differences between c- and e-bikes focused on comfort, vehicle properties, travel behavior, and mode substitution.

When riding e-bikes compared to c-bikes, people can maintain higher speeds with less effort and perceive a higher subjective safety (Fishman & Cherry, 2016). This perspective is supported by survey studies in Europe and North America, revealing that e-bike riders find it easier to keep up with the speed of motorized traffic (Jones et al., 2016) and that 78.3 % versus 63.7 % of respondents feel safe on e-bikes compared to c-bikes (MacArthur et al., 2018). The latter difference is even larger for seldom or non-cyclists, with only 48.7 % feeling safe riding a c-bike but 75.3 % feeling safe on an e-bike. E-bikes close the gap in subjective safety between cyclists and seldom or non-cyclists (MacArthur et al., 2018).

Regarding demographic attributes, findings from the literature vary. In North America, MacArthur et al. (2018) found that e-bike users are disproportionately white, male, elderly, and educated, with 28.7 % unable to use a c-bike due to physical limitations. A literature review conducted by Fishman and Cherry (2016) supported these findings in both the North American and European contexts. In van Cauwenberg et al. (2018)'s survey of people older than 65 years in Flanders who are physically able to ride both c- and e-bikes, the main factors identified positively influencing e-bike usage were being female, having a high BMI, and a high number of motorized vehicles in the household. In a study on Danish e-bike owners, e-bikes were found to be most common among the elderly, women, and better educated people. Analyzing data from the national Dutch mobility survey, Kroesen (2017) revealed similar results for gender and age. High income was also found to correlate with e-bike ownership. After taking into account the correlation between income and education, higher education was associated with a lower rate of e-bike ownership. In a survey in Ghent, Astegiano et al. (2015) found that e-bikes are used by both genders to a roughly equal degree.

de Haas et al. (2022) and Haustein and Møller (2016) conducted a latent class analysis and cluster analysis, respectively, to segment e-bike users according to their mobility behavior, socio-demographic and attitudinal survey data. They identified five and three user groups, respectively. Both segmentations demonstrate that the proliferation of e-bikes occurs at different speeds and stages in the different user groups. In the context of transport modeling, Hallberg et al. (2021) asserted that differentiating between age groups is recommended because e-bikes provide larger time savings for elderly people and hence different impacts on utility and consumer surplus.

Altogether, e-bikes have the greatest utility for people who cannot or do not want to use a c-bike, like the elderly or commuters avoiding physical exertion. The different motivations for e-bike use among user groups, such as recreation, utilitarian considerations, or the thrill of faster speed, lead to differences in e-bike adoption rates and the types of trips made by e-bike. Research findings on the influence of gender on e-bike adoption are mixed. In North America, where cycling in general is riskier and more male-dominated (Twaddle, Hall, & Bracic, 2010), men also use e-bikes more frequently than women. In the European context, e-bikes appear to have a higher adoption rate among (especially elderly) women (de Haas et al., 2022; Haustein & Møller, 2016; Kroesen, 2017; van Cauwenberg et al., 2018).

Learnings for Modeling: The large variation in e-bike ownership and usage patterns makes it crucial to model e-bikes differentiated by person groups. This is necessary to capture the differences in utility and to afford a reliable estimate of the impact of a rise in e-bike market share. E-bikes lead to higher subjective safety for their users on routes that lack dedicated bicycle infrastructure (Fishman & Cherry, 2016; Jones et al., 2016; MacArthur et al., 2018). This additional utility should be taken into account in transport models, for example by reducing generalized cost penalties on mixed traffic sections for e-bikes. As e-bikes are rarely purchased to replace a private car (Haustein

& Møller, 2016), modeling car and e-bike ownership can be viewed as independent of each other.

We were not able to identify quantitative research exploring the impacts of local topography on e-bike ownership. As necessary data is becoming available in recent years, such as Onderweg in Nederland and the Mobilität in Deutschland surveys, we expect to see future work exploring possible relationships.

2.3.2 Research Field 2: Impacts of price on e-bike availability

As our findings from research field 1 show, high household income correlates universally positively with e-bike ownership. The high price of e-bikes is commonly cited as a barrier to purchasing one (Jones et al., 2016).

Anderson and Hong (2022) combine administrative, insurance, and survey data about e-bike transactions in Sweden before, during, and after a subsidy program. Up to a rebate of around 1,100 USD, 25 % of the purchasing price was subsidized by the government. They showed that retailers passed on the rebate to the consumers almost completely. In their dataset, average monthly e-bike purchases changed from 2,084 before to 3,613 during to 2,135 after the subsidy period. Bigazzi and Berjisian (2021) developed an economic model for e-bike rebates and apply it to Vancouver and Victoria in Canada. Because there are large variations in the price of different types of e-bikes, they differentiated between three different price classes. They assumed price elasticities of -1.0 to -3.0, with a central value of -2.0. This appears adequate when compared to an empirical price elasticity of roughly -3 found by Anderson and Hong (2022).

de Kruijf et al. (2018) reported on an incentive program in the Netherlands aimed at car commuters. Instead of subsidizing the purchase of an e-bike, participants received 8 to 15 Euro-cents per kilometer traveled on their e-bike. This measure was highly effective, as e-bike mode share among commuting trips rose from 0 % to 68 % (de Kruijf et al., 2018). While these results are likely influenced by a self-selection bias of program participants, another possible reason is that being given any incentive at all, even if small, encourages participants to buy and use an e-bike. In other words, such incentives might serve as external initiators for reflecting on and changing one's mobility behavior, even if the monetary benefits are small. Additionally, the way participants' e-bike use was monitored using an app might be argued to constitute gamification, further encouraging participants to ride their e-bikes.

Learnings for Modeling: Concerning transport modeling, these findings reinforce the notion that the price of e-bikes is an important factor in determining personal e-bike availability. However, as we found in research fields 1 and 3, attitudinal factors, which can change over time, also play a large role. This makes it difficult to predict long-term changes in e-bike ownership purely using price elasticities. Accurately forecasting the development of e-bike prices and the economic environment at large poses its own challenges. As we address in the discussion below, our review suggests that modeling e-bike availability will involve at least partial scenario setting.

2.3.3 Research Field 3: Impacts of E-Bikes on Mode Choice

Within the four-step-model framework, mode choice can be assumed to be the most relevant model step for evaluating the transportation impacts of e-bikes. E-bikes must substitute resource-intensive modes instead of only replacing c-bike travel to fulfill their promise of contributing to a more sustainable transport sector. To inform their integration into mode choice models, we aim to gather evidence on e-bike mode shift. We identified 21 studies relevant to this field of research and present the key findings of our review in Table 2.4, below. Most of these studies were conducted in the Netherlands (7), followed by the United States or Canada (3), Sweden (3), Norway, Belgium, Denmark (2 each), the United Kingdom, and Switzerland (1 each).

Table 2.4: Overview of sources about e-bike mode shift

Type of Intervention	**Source**	**Data and locale**	**Mode shift**
Bikesharing	Chavis and Martinez (2021)	GPS data of riders in mixed c- and e-bike sharing system in Richmond, US	Longer average trip distance on e-bikes than on c-bikes (3.9km vs 3.1km)
	Reck et al. (2022)	GPS, booking, survey, context data for e-bike and e-scooter sharing system in Zurich, Switzerland	Personal e-bikes source 48% of their distance traveled from car, 29% from public transport, 14% from c-bike and 9% from walking, compared to 1%, 43%, 29% and 9% for shared e-bikes.
E-bike trial scheme	Andersson et al. (2021)	GPS tracking of car-commuters during e-bike trial scheme in Skövde, Sweden	Mode share of car for commute fell from 74% to 53%, e-bike rose from 0% to 17%
	Cairns et al. (2017)	Survey, tracking, interviews of participants in an e-bike trial scheme in Brighton, UK	Car, walking and bus substituted the most. Car travel from 87km to 69km per week.
	Fitch et al. (2022)	Survey before, during and after e-bike trial scheme in Mountain View, US	Mode share of cycling rises by 35%-points during the trial and stays at 28%-points above the pre-trial value even after the program ends
	Fyhri and Fearnley (2015)	Survey among Norwegian car users during e-bike trial scheme	Cycling from 0.5 to 1.6 trips/day, distance cycled rose from 5.7 to 9.7 km/day, share of cycling of total distance travel from 28% to 48%.
	Ton and Duives (2021)	Survey among Dutch car commuters before, during and after e-bike trial scheme	Mode share of car for commute from 88% to 62%, e-bike from 0% to 18%, c-bike from 5% to 13%
None, data collection and analysis on specific group	Astegiano et al. (2015)	Survey, travel diary, GPS tracking among e-bike users in Ghent, Belgium	E-bike replaces mostly c-bike followed by public transport

Type of Intervention	**Source**	**Data and locale**	**Mode shift**
	Fyhri and Sundfør (2020)	Survey among Norwegian e-bike (almost-) customers	Cycling from 2.1 to 9.2km/day, car from 5.1 to 4.6km/day. Control groups: cycling from 5.1 to 6.0 and 3.0 to 4.0km/day, car from 9.0 to 7.6 and 9.9 to 9.6km/day. Mode share of cycling increased by 32, 2 and 3%-points respectively. Share of cycling of total distance traveled from 17% to 49% for customer group.
	Haustein and Møller (2016)	Survey among Danish e-bike users	E-bikes replace mostly c-bike, followed by car
	Hiselius and Svensson (2017)	Survey among Swedish e-bike users	E-bikes substitute 55.28 person-km/week traveled by car in urban and 61.55 in rural areas. Highest share of substitution for c-bike for leisure trips in urban areas (37%), lowest for work trips in rural areas (11%).
	Lee et al. (2015)	Survey among Dutch e-bike users	E-bike replaces mostly car followed by c-bike. 2.1% induced trips
	MacArthur et al. (2018)	Survey among North American e-bike owners	91.5% ride their e-bike at least once a week, c-bike from 55.4% before to 27.6% after purchase
	P. A. Plazier et al. (2017)	GPS tracking and interview among Dutch e-bikers	Replaces mostly car trips
	van Cauwenberg et al. (2018)	Survey among elderly Belgians	35% more cycling minutes when owning an e-bike
None, analysis of larger data sets	de Haas et al. (2022)	Netherlands Mobility Panel	e-bike only significantly substitutes c-bike
	Kroesen (2017)	National Dutch Mobility Survey	E-bike owners travel 3.0km/day on e-bike and 0.9km/day on c-bike, compared to 2.6km/day on c-bike for non-e-bike-owners. E-bike only very slightly reduces car usage and all other modes, correlates positively with car ownership

Type of Intervention	Source	Data and locale	Mode shift
	Sun et al. (2020)	Netherlands Mobility Panel	1.4 trips and 6.4km/day on new e-bike. Share of distance traveled: c-bike from 20% to 2%, car from 58% to 49%, walking from 9% to 3%, e-bike from 0% to 38%.
Subsidy	Anderson and Hong (2022)	Survey, administrative, insurance data during, before and after e-bike purchase subsidy program in Sweden	E-bike reduces usage in days/week for all modes. Car: 2.57 to 0.88, public transport: 1.10 to 0.29, c-bike: 1.71 to 0.67
	de Kruijf et al. (2018)	GPS tracking of new Dutch e-bike users during monetary per-km incentive program	E-bike substitutes both car (-34%-points of trip mode share) and c-bike (-32%-points)
Other	Hallberg et al. (2021)	Scenarios modeled in a modified transport model of Copenhagen, Denmark	For the base network, a bicycle mix of 95/4.5/0.5% (c-bike/pedelec/speed-pedelec) results in a cycling trip mode share of 22.2%, a mix of 40/50/10% in 24.5%.

In the three North American sources (Chavis & Martinez, 2021; Fitch et al., 2022; MacArthur et al., 2018), e-bikes appear to afford a shifting perspective on cycling away from being a leisure activity toward being a utilitarian mode of transport in the first place. Adopters tend to be former leisure cyclists who then go on to substitute utilitarian car trips with an e-bike (MacArthur et al., 2018). This is different to Fyhri and Sundfør (2020), who found that Dutch e-bike purchasers previously cycled less than the national average. Unlike the European body of research we reviewed, we did not identify any large-scale representative mobility survey including e-bikes in North America, which suggests a limitation of e-bike data available in this geographic region.

One common methodological shortcoming of studies investigating the impact of e-bikes on mode share is a self-selection sample bias, where participants of an e-bike trial or subsidy program may plan to buy an e-bike or change their cycling habits anyway. Kroesen (2017) overcame this limitation by developing a conceptual model to assess the effect of e-bike ownership on travel behavior. They estimated the model on data from the national Dutch mobility survey. However, this cross-sectional data does not allow for the same deductions on the causal relationship between e-bike ownership and travel behavior that longitudinal data would allow. This, as well as the original problem of sample bias, is addressed by Fyhri and Sundfør (2020), who collected before-and-after data of e-bike purchases and also included a control group of subjects who strongly contemplated purchasing e-bikes, but who ultimately did not. By observing e-bike use over a longer time span, they avoided novelty effects among the participants' e-bike use. By using longitudinal panel data, de Haas et al. (2022) and Sun et al. (2020) generate even more naturalistic insights into how mobility behavior changes after e-bikes are introduced to a household. All four of these studies were conducted in the Netherlands, where national survey and panel data includes e-bike ownership and use, and yield perhaps surprising results: e-bike ownership reduces c-bike travel the most, followed by car travel (Kroesen, 2017; Sun et al., 2020). In one case, e-bikes only significantly substitute c-bike travel (de Haas et al., 2022). While one study also found considerable reductions in car travel for new e-bike owners, the effect is similarly strong for the control group of participants that decided not to purchase an e-bike (Fyhri & Sundfør, 2020). Taken together, this is strong evidence that, at least in the Netherlands where cycling is already a well-established mode of transport competitive with the private car, e-bikes mostly replace c-bike travel but may only marginally substitute car travel.

Hallberg et al. (2021) modified and applied a transport model of the Copenhagen Capital Area to investigate the impact of a rising share of e-bikes. They found that for a base network scenario and between two mixes of bicycles consisting of 95 % and 40 % c-bikes each, the total trip mode share of cycling rises from 22.2 % to 24.5 %. Unfortunately, they do not report on mode-specific substitution rates. Working with an agent-based transport model, Reck et al. (2022) investigated the mode choice of users of a mixed e-bike and e-scooter sharing system in Zurich. Their work revealed that the substitution effect of e-bikes depends on whether the person is using a shared or privately owned e-bike.

Many sources investigated the relationship between trip purpose and mode substitution (Astegiano et al., 2015; de Haas et al., 2022; Fyhri & Fearnley, 2015; Hiselius & Svensson, 2017; Lee et al., 2015; P. A. Plazier et al., 2017; Sun et al., 2020). The consensus is that, while e-bikes are used for a variety of trip purposes, mode substitution varies depending on trip purpose. Car substitution is the strongest for commute trips (de Haas et al., 2022; Hiselius & Svensson, 2017; Lee et al., 2015; P. A. Plazier et al., 2017; Sun et al., 2020). Because of the differences in trip purpose and e-bike purchase motivation among different person groups (see research field 1), substitution effects can also be expected to vary by person group. Factors such as age and gender were found to have opposite signs of effect for e-bike ownership and use (Kroesen, 2017). Those who buy e-bikes despite belonging to a user group with otherwise low adoption rates tend to use the e-bike more intensively (Kroesen, 2017). It is unclear whether this observation is restricted to the phase of early adoption.

Concerning mode shift, this review revealed that the impact of e-bikes varies depending on the previous mode share. Usually, the more established of a transport mode the c-bike is the more it is substituted by the e-bike (de Haas et al., 2022; Fyhri & Sundfør, 2020; Kroesen, 2017; Sun et al., 2020). When introduced to very car-centric people groups, e-bikes might increase c-bike use due to complementary effects (Andersson et al., 2021). Congruously, the higher the previous car mode share, the larger the amount of e-bike travel sourced from that mode (Andersson et al., 2021; Cairns et al., 2017; Fitch et al., 2022; Lee et al., 2015; P. A. Plazier et al., 2017). Most e-bike intervention studies reported rather large impacts. It is important to note that low-impact interventions may be under-reported.

Our findings correspond with three other literature reviews we identified. E-bikes considerably substitute all other modes, with the exact amount varying by context (Bigazzi & Wong, 2020). More specifically, Bourne et al. (2020) found that e-bikes source 23 % to 72 % of their trips from c-bikes, 20 % to 86 % from car and 3 % to 45 % from public transport, depending on the region investigated. All three reviews (Bigazzi & Wong, 2020; Bourne et al., 2020; Kazemzadeh & Ronchi, 2022) echo our finding that the prior main mode is substituted the most.

Learnings for Modeling: The learnings from the research field reinforce the notion that it is necessary to model e-bike use differentiated by person group. Different user groups use e-bikes for varying purposes. For example, the elderly use e-bikes as a replacement for c-bikes that they can no longer ride while younger e-bike adopters exhibit a larger substitution of car travel (Haustein & Møller, 2016; van Cauwenberg et al., 2018). Therefore, substitution effects might change as different user groups acquire e-bikes in the future (de Haas et al., 2022). E-bike trips are around 50 % longer than c-bike trips (Cairns et al., 2017) and ownership has a generative effect on the total distance traveled (Kroesen, 2017). Our findings demonstrate that, perhaps unsurprisingly, data intended for e-bike model calibration needs to be differentiated by bicycle type and not only by person group, traditional mode choice, or trip purpose.

Many of the studies above (Anderson & Hong, 2022; Andersson et al., 2021; Astegiano et al., 2015; Cairns et al., 2017; de Kruijf et al., 2018; Fitch et al., 2022; Fyhri & Fearnley, 2015; Fyhri & Sundfør, 2020; MacArthur et al., 2018; Ton & Duives, 2021) actively promoted e-bike purchase or use and reported larger mode shift impacts than may be expected from uninfluenced growth of e-bike ownership, due to a self-selection bias among participants. However, it is important to note that in the context of transport modeling we also do not expect people to acquire e-bikes randomly. Instead, as e-bike availability rises, we expect to see individuals with higher utility of an e-bike to acquire them earlier than those with a lower e-bike utility. We still expect the studies above to overestimate the mode shift impact of e-bike acquisition compared to the impact a transport model would need to replicate. However, the discrepancy between these study designs and reality is smaller than the difference between these study designs and a hypothetical study design where e-bikes are given to a truly random group of people.

Integrating e-bikes into existing mode choice models as an additional choice option is trivial in an abstract sense. Finding parameter values to replicate observed mode choice behavior is more challenging. The decision to use an e-bike or c-bike is not purely rational, as attitudinal factors also play a large role (Ton & Duives, 2021). Modeling these factors and future societal changes is difficult, and we address this issue in the discussion section below. Several sources (de Kruijf et al., 2018; Fitch et al., 2022; P. A. Plazier et al., 2017) additionally point towards the common concept in transport research that fundamental changes in travel behavior, such as choosing an e-bike instead of a c-bike or even instead of non-bicycle modes, are more likely to occur after a considerable external stimulus. This could be a change in home or work location (P. A. Plazier et al., 2017) or the act of participating in a study (de Kruijf et al., 2018; Fitch et al., 2022). Since transport models are frequently used to forecast both short- and long-term changes in travel behavior (Pillat & Manz, 2021), we have to take this time lag in users' reaction to incremental changes in the wider transport system into account. This means that instead of regarding different options' total utility in a choice model, we should consider relative changes in their utility as the true psychological reason for behavior change.

2.3.4 Research Field 4: Impacts of E-Bikes on Route Choice

Speed and hence the resulting travel time is a crucial input for route choice models. In Knoxville, USA, e-bikes were found to travel at an average speed (including acceleration and deceleration, but not stopping time) of 13.3 km/h on mixed-traffic roadways while c-bikes only reach 10.5 km/h (Langford et al., 2015). On dedicated greenways, c-bikes were found to be slightly faster than e-bikes, with 12.6 km/h and 11.0 km/h respectively. The authors attributed this surprising finding to differences in trip purpose (i.e., exercise-focused leisure riders not using e-bikes) and they detected no major differences regarding average wrong-way riding rates or the violation of stop signs or traffic signals.

Schleinitz et al. (2017) conducted a naturalistic driving study in Germany to investigate speed and acceleration of different types of bicycles by age groups, infrastructure and gradient. They found that the average free flow speeds range from 16.1 (c-bike) over 19.0 (pedelec) to 24.9 km/h (speed-pedelec), with higher speeds being associated with younger age groups, dedicated infrastructure, and downhill slopes. Acceleration is much higher for speed-pedelecs, while c-bike and pedelecs have similar values (partially due to e-bike riders being older on average).

Hallberg et al. (2021) provide the only source in our literature corpus that explicitly dealt with bicycle route choice in the context of e-bikes and transport models. They used 27 different speed values (3 bicycle types x 3 cyclists' speed segments x 3 infrastructure types, ranging from 13.6 km/h to 31.5 km/h). At intersections however, only a general delay of 30 s was added for traffic lights and 5 s for roundabouts. Also, travel time was the only variable considered for mode and route choice. The authors set up trip assignment in a way that it differentiated by cyclists' speed segment and bicycle type, assigning trips to the fastest route in an all-or-nothing-approach.

Cyclists feel safer on e-bikes than on c-bikes (Fishman & Cherry, 2016; Jones et al., 2016). This can lead to the assumption that e-bike users exhibit a lower preference for dedicated bicycle infrastructure compared to c-bike users. This is indeed supported by Chavis and Martinez (2021). By analyzing GPS-data from a mixed c- and e-bike-sharing system in Richmond, USA, they found that e-bikes are more likely to travel on major and minor roads, which typically do not have dedicated bicycle infrastructure, and are less likely to travel on cycleways. They excluded round-trips to ensure leisure trips were not included in their analysis. This reduces the risk of distortions due to differences in user demographics or trip purpose between c- and e-bikes. It is important to acknowledge that in some regulatory contexts, certain types of e-bikes (such as speed-pedelecs) are not allowed to use dedicated cycling infrastructure.

In a qualitative study on e-bike commuters' route choice in Groningen in the Netherlands, e-bike commuters cited speed and directness as less important than having beautiful surroundings, nature, or tranquility along their route. In case of bad weather however, cyclists choose routes that are more utilitarian (P. A. Plazier et al., 2017). The authors argue that this supports the idea of a positive utility of travel—i.e. traveling not just serving as a way to get from one place to another, but also offering enjoyment along the ride.

Learnings for Modeling: The results of our review contain several key lessons for modeling e-bike route choice in transport models. Assuming different speeds for bicycle types as well as person groups and infrastructure appears to help capture the heterogeneity of bicycle traffic. While empirical values of link travel speed are widely available, more research is needed to determine what time penalty should be added for different intersection treatments. This should be informed by research into microscopic traffic flow. Factors other than travel time, cost, or physical exertion, such as beauty or tranquillity, should also be included in route choice models for all types of bicycles. In line with findings from research field 1, e-bikes should be modeled with a lower difference in utility between mixed and dedicated infrastructure than c-bikes. Also in line with research field 1, we again were not able to identify research looking into the impact of topography on e-bike route choice.

2.4 Discussion

2.4.1 Learnings about E-Bikes in Transport Models

Through this review of existing research and modeling practices, we synthesized a number of recommendations regarding how to model e-bike ownership, mode choice, and route choice in macroscopic transport models.

Modeling ownership differentiated both spatially and by person group is equally important for both e-bike and car purchase choice models. This is because utility, ownership, and use of e-bikes differ strongly by person group. The price of e-bikes is a main factor in individuals' purchasing choices and affects the total number of e-bikes sold. However, attitudinal and societal factors also play a large role in the decision to purchase an e-bike and it is difficult to predict long-term developments of the price or purchasing power. Learning from the existing research and seeking to fill a gap in current e-bike modeling practices, we propose a hybrid of a scenario-based and a dynamic approach for modeling e-bike ownership. Total e-bike market penetration would be scenario-based and not an emergent model result. At the same time, the distribution of e-bikes among person groups and traffic zones would be dynamic and sensitive to model inputs such as infrastructure and topography. Based on our review, we expect the interdependence between car and e-bike purchase to be negligible.

Components of generalized costs and their weights are crucial to both c- and e-bike mode and route choice. Attributes of choice alternatives and users' personal characteristics that are relevant for route or mode choice of one type of bicycle can be assumed to also be relevant for the other. The difference in preference regarding dedicated infrastructure, slope, or other route attributes between c- and e-bikes demonstrates that model parameters should be estimated separately for c- and e-bikes. Including route attributes other than simply travel time in the computation of generalized costs and differentiating between whether a c- or e-bike is used is also relevant for mode choice, as the generalized costs for an exemplary route is commonly used in mode choice modeling. Our research shows that speed should be differentiated by person group, infrastructure, and bicycle type (Hallberg et al., 2021; Langford et al., 2015; Schleinitz et al., 2017).

Mode choice varies by person group and trip purpose. This is not unique to e-bikes. However, changes in attitudinal and societal factors over time make it difficult to estimate mode choice parameters that stay applicable for long-term forecasts. A fundamental shortcoming of all empirical travel behavior analyses is that they can only observe and describe behavioral changes within the societal context of the past and present. For example, offering a subsidy for an e-bike purchase might objectively increase the utility of that mode, however the subjective utility depends on societal norms and individual attitudes or needs. If societal norms inhibit people to view e-bikes as an appropriate or desirable mobility solution for their individual needs, the subjective utility of the mode would be rather low. Conversely, if norms promote the attractiveness of e-bikes as a natural and ubiquitous way of traveling, the uptake in use and subjective utility of the mode would be higher. Transport models intend to forecast the impacts of measures decades into the future, yet it is challenging to confidently predict the fast-changing societal norms and attitudes towards e-bikes. Similar to purchase choice modeling, we therefore see the need for a certain degree of scenario setting within transport models. Overall e-bike mode share should be defined manually and at the same time, individual mode shares should be computed for every combination of person group, trip purpose, and origin-destination-pair under the constraint of the overall mode share. The impact of different scenarios for future e-bike adaption can then be explored while retaining a degree of sensitivity of mode choice to interzonal characteristics such as climbed elevation.

Most findings regarding route choice relate to the range of different components of generalized costs and their weighting parameters touched on earlier. Besides travel time, other route characteristics, such as physical exertion, nature, and tranquillity, also affect enjoyment and should be included in route choice modeling. We do not identify evidence that e-bikes call for completely new model structures. Instead, since the strength of the influence may vary as shown for example for age or slope, we expect model parameters for route choice also to vary between c- and e-bike models.

2.4.2 Limitations

A number of limitations of this review must be considered. Some sources were relevant to a research field despite not being identified using the search string established for the respective research field. This could indicate that we missed relevant sources from the literature. Excluding non-English language sources constitutes another limitation. It is uncertain to what degree the prominence of Dutch and Northern European source material is explained by the high levels and long traditions of cycling in these countries or by this language restriction. By excluding research on scooter-style e-bikes, no studies included in this review were done in Asia, likely forgoing valuable insights from different contexts. Our research does not address the general challenge of how to model (e-)bike-sharing, because our search strings favor sources investigating personal e-bike purchase. Future research would benefit from exploring what relevance such sharing systems may have for the propagation of new e-bike user groups by overcoming the price-based barriers of entry. Finally, this review focuses on trip-based as opposed to activity-based models or agent-based simulations, which might provide additional directions of research.

2.4.3 Research Outlook

Since the literature agrees that avoiding physical exertion is the main motivation for e-bike purchase, we expect the influence of topography on e-bike ownership, mode choice, and route choice to be strong. Despite a large body of research on how elevation affects mode and route choice of cycling in general, our structured exploratory literature review did not identify empirical evidence on this relationship focusing on e-bikes. We propose carrying out research on mode and route choice parameters differentiated by c- and e-bikes, including route attributes other than travel time such as slope, using existing methodologies of map matching GPS trajectories.

Research on the speed of different types of bicycles is plentiful, but we identified less work on differences in lost time at intersections. Based on the findings related to acceleration, differences in lost time for e-bikes compared to c-bikes should be estimated and, if significantly different, reflected in travel time calculation.

Data availability is a choke point for model calibration and validation, because appropriate data that distinguishes between c- and e-bikes is rare. To most adequately model this growing transport mode, we recommend differentiating between c- and e-bikes when collecting data on, for example, travel distance distributions, vehicle ownership, and traffic counts. We further call for the development of automated counting sensors capable of identifying e-bikes to create new opportunities for large-scale data collection.

Because appropriate data for modeling bicycle traffic is rare, the trade-off between falling specification error and rising data error as a result of increasing model complexity has to be of particular concern. Differentiating between different types of bicycles does not improve model quality unconditionally. Indeed, model quality might suffer from an increase in model complexity if differences in actual bicycle use turn out to be too small, or the increase in data error due to a more disaggregate data collection turns out to be too large.

In our future work, based on the learnings from this review, we will estimate bicycle mode and route choice models that distinguish between c- and e-bikes. We will implements those in selected municipal transport models to explore the capabilities and usefulness of a modeling approach that differentiates between c- and e-bikes.

Chapter 3

Second Paper: Ownership Choice

Contents

Disclaimer: This chapter was previously published as: Leonard Arning and Heather Kaths (2025). Just another bike? Modelling the interdependence of conventional and electric bicycle ownership and the influence of topography using large-scale travel survey data from Germany. *PLoS One*, 20(5). doi: `https://doi.org/10.1371/journal.pone.0322291`. The second author, who is also the supervisor of this thesis, contributed by advising on the study conception and design as well as proof-reading the manuscript and suggesting language revisions.

Abstract

Electrical bicycle ownership rates are growing rapidly. Despite differences to conventional cycling, the two types of bicycles are generally not differentiated in travel demand modelling practice. This article analyses the choices to own electric and conventional bicycles in Germany at the personal level. We use data from the "Mobility in Germany" survey and other sources and estimate both a nested logit model and a multivariate probit model. While the average gradient of terrain near

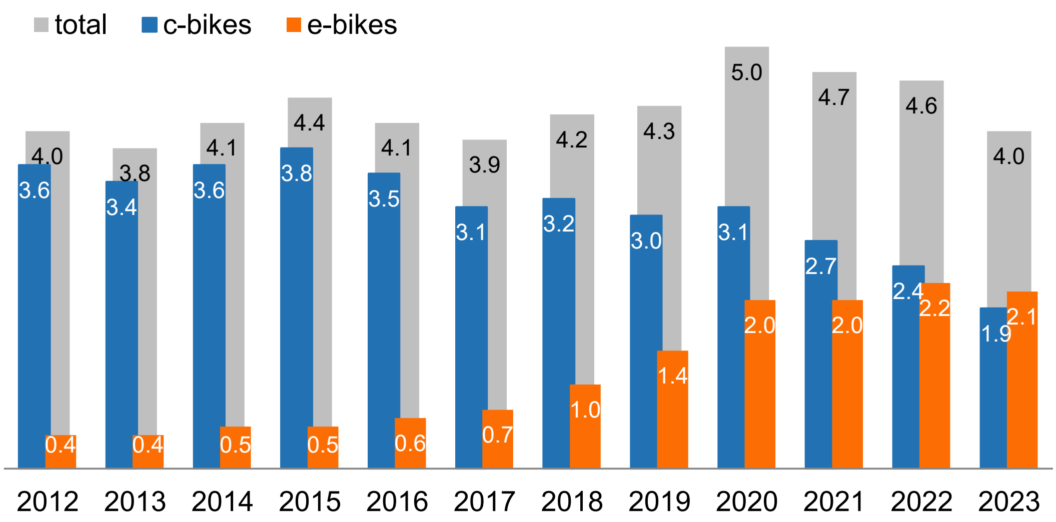

Figure 3.1: Development of yearly bicycle sales [mln.] in Germany based on data from Zweirad-Industrie-Verband (2024)

theresidence has an expected, strong negative influence on the ownership of conventional bicycles, electric bicycle ownership is much less negatively affected. The effect of socio-demographic variables is largely in line with that of the existing literature. A negative correlation of the error terms in the probit model indicates a substitutive relationship between the two ownership decisions. The high nest parameter value in the nested logit model indicates that the decision to own a conventional bicycle is secondary to the decision to own an electric bicycle. The results contribute to a better understanding of the motivations for or against bicycle ownership and create a basis for better consideration of electrical bicycle traffic in transport models.

3.1 Introduction

Between 2012 and 2023, the number of electric bicycles in Germany increased from 1.3 to 9.8 million (Zweirad-Industrie-Verband, 2022). By 2023, they already accounted for more than half of newly sold bicycles in the country (Zweirad-Industrie-Verband, 2024). Despite this dynamic growth (Figure 3.1) and the meaningful differences between electric and conventional cycling, most notably concerning speed, user groups, trip purposes, overcoming hills, and trip lengths, there are still few integrated transport models that take into account the effects of the electrification of cycling and none in which e-bikes are considered as a fully-fledged and independent means of transport across all modelling stages. This neglect of electric bicycles is partly due to a lack of data and understanding about electric bicycle traffic choice behaviour, which might result in uncertainties regarding the accuracy and forecasting ability of existing models (Arning, Silva, & Kaths, 2023).

Differences between conventional and electric bicycles (c-bikes and e-bikes) have been considered in research, particularly with regard to mode and route choice. In reality, however, the choice of whether to travel by c-bike or e-bike is usually preceded by the decision of what type(s) of bicycle to own. C-bike and e-bike ownership should therefore be taken into account when modelling mode choice. This is particularly relevant because the purchase of an e-bike is a more critical decision than the purchase of a c-bike due to the higher investment costs. To be able to analyse and forecast c-bike and e-bike ownership, current bicycle ownership must be examined in detail and modelling approaches must be developed. This study makes such a contribution to representing the diversity of cycling in transport models in a more differentiated way by presenting two models for the combined ownership choice of c-bikes and e-bikes. In particular, we are the first to use discrete choice models to investigate both c-bike and e-bike ownership and to consider average gradient, allowing for insights into how topography affects the two ownership decisions and how they influence each other. Therefore, the following research questions take centre stage:

- Which factors influence the choice to own a c-bike and/or an e-bike?
- What role does topography play in particular?
- How are the two choices interlinked?

The rest of this paper is structured as follows: in section 3.2 we give an overview of factors influencing the ownership of e-bikes as well as types of discrete choice models that are commonly used for modelling the ownership of mobility tools. Section 3.3 describe the data used to estimate the models and the model specifications. In section 3.4, we present and interpret the estimated model parameters and discuss shortcomings, further research needs and implications for modelling practice, before ending with our main conclusions in section 3.5.

3.2 Literature

3.2.1 Influencing Factors on E-bike Ownership and Use

There is comparatively little research investigating influencing factors on e-bike ownership. Socio-demographic factors were most commonly found to have a major influence on whether someone owns an e-bike, with different user groups demonstrating distinct user behaviours. Table 3.1 provides an overview of the findings from researchers in some European and North American countries. South and East Asia, where the term "e-bike" is generally used to refer to motorbike-like vehicles instead of bicycles (Ding, Cao, Dong, Zhang, & Yang, 2019), are not considered here.

The nearly unanimous finding that in particular older people own e-bikes suggests that the main motivation for their purchase is to be able to continue cycling despite advancing age and declining fitness. This is consistent with the results of direct surveys on purchase motivation (Jones et al., 2016). In contexts with low subjective road safety, cyclists also state that they feel like they can compensate for deficiencies in the infrastructure and differences in speed compared to motorised traffic by riding an e-bike instead of a c-bike (Jones et al., 2016; MacArthur et al., 2018). It is well established that personal attitudes such as environmental awareness or enthusiasm for cycling are of high relevance to both ownership and use of e-bikes (Handy et al., 2010; Haustein & Møller, 2016; Pinjari et al., 2008; Ton & Duives, 2021).

Research investigating attitudes towards e-bike use and purchase intentions provides valuable indications of further influencing factors on e-bike ownership. Awareness of e-bikes is a precondition to acquisition. For university employees in California, Handy and Fitch (2020) find that after the introduction of an e-bike sharing system, awareness of e-bikes increases substantially and the

Table 3.1: Literature overview about influencing factors on e-bike ownership

Country, Source	**Personal traits supporting e-bike ownership**	**Associated trip purpose**
Denmark (Haustein & Møller, 2016)	Older age and high income, female, high cycling affinity	Leisure, pick-up and drop-off
Germany (Kohlrautz & Kuhnimhof, 2024; Nobis, 2019)	Older age, middle or high economic status, outside of large cities	Leisure
The Netherlands (Kroesen, 2017)	Older age and high income, female	
The Netherlands (de Haas et al., 2022)	Older age Middle-aged, full-time employed Middle-aged, part-time employed, female	Leisure Commute Leisure, shopping
Switzerland (Rérat, 2021)	Older age, female, suburban and rural, couples with children, very high and very low income	Commute
US and Canada (MacArthur et al., 2018)	White, male, older age, high level of education	Leisure

intention to use an e-bike for commuting increases slightly. In a Norwegian survey, Simsekoglu and Klöckner (2019) find that besides socio-demographic factors such as age, purchase intention is also influenced by respondents' awareness of e-bikes, their perceived benefits, as well as subjective and descriptive norms, i.e. whether they believe that others expect them to own an e-bike and that other people own e-bikes. Kaplan, Wrzesinska, and Prato (2018) report that the intention to use an e-bike in a c-bike and e-bike sharing system is stronger for women and the elderly in Poland. Human needs according to the ERG (existence, relatedness, growth) theory of needs were also found to be important determinants of usage intention, with growth needs relating to a stronger intention to use a c-bike and a weaker intention to use an e-bike. For Polish society overall, Kwiatkowski, Grzelak-Kostulska, and Biegańska (2021) find that public perception of e-bikes is mostly critical; respondents view them as expensive, advantageous only for the elderly, and are largely unaware of other e-bike benefits. P. Plazier, Weitkamp, and van den Berg (2023) investigate current and potential e-bike use in a rural region of the Netherlands. They find e-bikes are "used among a broad population of varied ages and backgrounds and for different purposes" (p. 1449), that e-bikes likely complement car and substitute c-bike ownership, and that personal attitudes towards safety, fun and health benefits of e-bikes are important determinants of e-bike use.

The role of topography with regards to cycling and the potential of e-bikes is frequently discussed, however little research on its influence on c-bike and e-bike ownership exists. An earlier work already demonstrated a negative correlation between varied topography and bicycle ownership and use in Germany (Nobis, 2019). In a North American survey, "Because I live or work in a hilly area" was the most frequently cited reason for purchasing an e-bike (MacArthur et al., 2018). Such findings lead to the hypothesis that e-bikes are particularly attractive in hilly areas where they can mitigate the negative impact of the topography on cycling. On the other hand, there is evidence from other

North American studies that hilliness might have only a small (Tyndall, 2022) or even insignificant (Rybarczyk & Wu, 2014) impact on (mostly conventional) bicycle use, both on the level of metro areas and persons. The influence of topography on e-bike ownership therefore remains unclear. We are unaware of any studies on discrete choice models that take into account the topography near the residential location on e-bike ownership. This may be because countries with a pronounced cycling culture and corresponding data are generally comparatively flat. This study closes this research gap.

3.2.2 Types of Discrete Choice Models for Mobility Tool Ownership

The decisions of individuals or households about whether to own a specific mobility tool is a discrete choice. The utility trade-offs can be described with discrete choice models and the model parameters can be estimated using revealed choice or stated choice data. Past work on mobility tool ownership has focussed primarily on cars and, to a lesser extent, on public transport season tickets (Fatmi et al., 2014). Little attention has been paid so far to modelling bicycle ownership, as the purchase cost of a c-bike is comparatively low and, at least in many European contexts, it can be assumed that every person who is able and willing to ride a c-bike has access to one. The higher purchase cost of an e-bike and the specific motivators for use increase the need for more differentiated modelling of the availability of bicycles.

Logit models are the most common model type for mobility tool ownership. The estimation of separate, binary logit models for each mobility tool would be inaccurate, as the decisions on their ownership are made dependently. Therefore, multinomial logit models are used that formulate choice options that consist of combinations of different mobility tools (bundles). Fatmi et al. (2014) apply such a model to study mobility tool ownership of young adults in Toronto. Kohlrautz and Kuhnimhof (2024) apply a similar approach to data from the German MiD 2017 survey to understand bicycle ownership as well as c-bike and e-bike mode choice, however without differentiating between c-bikes and e-bikes in ownership modelling or taking into account topography.

Multinomial logit models inherently assume the independence from irrelevant alternatives (IIA) property, which may not hold when dealing with bundles of choice options. Nested and cross-nested logit models provide a solution by allowing for correlations among related alternatives. Bundles of mobility tools are placed within nests (cross-nested logit allowing for overlapping nests), with each nesting level representing the decision about one mobility tool. Püschel et al. (2023) use both a nested and cross-nested logit as well as a machine learning model to investigate car, car sharing and public transport season ticket ownership of residents of Hamburg, Germany. Handy et al. (2010) employ a nested logit model to jointly investigate bicycle ownership and consequent use by residents of six small US cities. On the top level a decision between “has no bike” and “has bike(s)” is made, and within the latter, a nested choice between “bikes non-regularly”, “regular transportation-oriented bicyclist”, and “regular non-transportation-oriented bicyclist” is made.

Probit models are widely applied in studies of mobility tool ownership due to their ability to account for interdependencies among choices by modelling correlations between error terms as explicit parameters. For example, individuals holding a public transportation season ticket are likely to have a lower utility for (additional) car ownership, and vice versa. In contrast to the previously mentioned approaches, studies employing multivariate probit models specify utility functions for individual mobility tools rather than a bundled set of tools, enabling more intuitive interpretation of parameters associated with each choice. Becker et al. (2017) use such an approach to model the ownership of cars, public transport season tickets and car-sharing services in Switzerland. D. Scott and Axhausen (2006) introduce the ordered probit model to model the number of public transport season tickets and cars per household in Switzerland. Yamamoto (2009) uses a trivariate binary probit model to compare factors influencing the ownership of bicycles, motorbikes and cars in Osaka and Kuala Lumpur. Ma et al. (2018) apply a multivariate ordered probit model to investigate car, motorcycle, e-bike, and c-bike ownership of households in Hangzhou, China.

At the household level, it is sensible to quantify the number of available mobility tools. This can be achieved with an ordered logit approach. Here, while a single utility function is estimated for each mobility tool, threshold values indicating when a household owns an additional mobility tool (e.g. two cars instead of one) are also estimated. Maltha et al. (2017) use this approach to model car ownership in the Netherlands. Pinjari et al. (2008) combine an ordered logit model for the number of bicycles owned by a household with a binary logit model for the household's choice of residing in a bicycle-friendly neighbourhood in a joint model system. This allows for residential self-selection effects to vary across households. Zhang et al. (2013) use a zero-inflated Poisson model to investigate e-bike ownership in Zhonshan, China. It consists of a binary logit model aimed at predicting whether a household owns an e-bike at all, followed by a Poisson model predicting the number of e-bikes owned by households that own one or more e-bikes. Ding et al. (2019) expand on this work by applying a semi-parametric generalized additive mixed model to the data, which allows for more relaxed assumptions regarding the linearity of the variables.

In contrast to static modelling approaches, dynamic approaches describe the change in ownership over time instead of the momentary stock of mobility tools in a household. For example, Gu et al. (2021) investigate the influence of life course events (moving, birth of a child, etc.) on the change in the ownership of a car using an error component random parameter logit model in which the constants of the utility functions are household-specific and normally distributed. The choice options here consist of combinations of buying or keeping a car as well as the purchase of additional sustainable mobility tools.

3.3 Materials and Methods

3.3.1 Data

This retrospective study is based on household and person-level data from the B3 local dataset package of the "Mobility in Germany 2017" (German: "Mobilität in Deutschland", MiD 2017) survey (Nobis & Kuhnimhof, 2019) and two additional spatial datasets. The data is anonymized, does not contain medical information, and is publicly available from the German Aerospace Center. For this reason, we did not seek approval from an ethics committee. In the MiD, the availability of c-bikes and e-bikes is recorded at the person-level and can assume different values for different people in the same household. For example, survey respondents frequently indicated no e-bike availability for underage household members, even when an e-bike was available to other household members. The socio-demographic variables age, level of education, gender and occupation are also available at the person-level. The variables economic status, household size and grid cell of the place of residence are recorded at the household-level, but are also treated at the person-level in our models for the sake of uniformity. Below, we describe our data processing. The respective source code is available on GitHub: https://github.com/buw-bicycle-traffic/ebike-ownership-model.

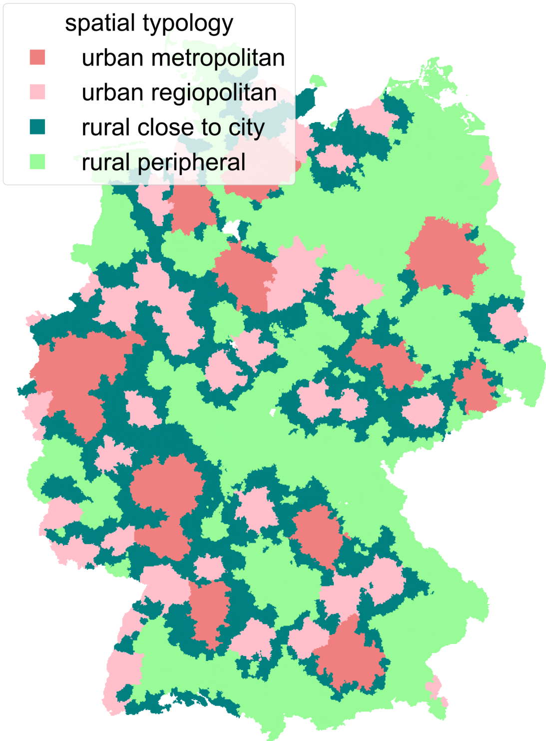

Figure 3.2: Spatial typology of 1km grid cells. Grid cell position from GeoBasis-DE and Bundesamt für Kartographie und Geodäsie (2023) and spatial typology of grid cells based on Bundesministerium für Digitales und Verkehr (2021), both under DL-DE-BY-2.0 license

The spatial variables "spatial typology" (German: "Raumtyp", degree of urbanisation) and "gradient" were linked to the MiD person-level data using the residential location which is coded in the MiD using a standardised grid of 1-by-1-km large cells (GeoBasis-DE & Bundesamt für Kartographie und Geodäsie, 2023). The spatial typology was included as there are clear differences between the use of c-bikes and e-bikes in urban and rural areas in Germany (Nobis, 2019). Spatial typology is defined at the municipality level in the RegioStaR dataset (Bundesministerium für Digitales und Verkehr, 2021), but neither the persons nor the 1km grid cells are assigned to municipalities in the MiD dataset. For the corresponding 250-by-250-m grid cells, however, a bridge between cells and municipalities is available. Therefore, for the sake of simplicity, each 1km grid cell was assigned one 250m grid cell located in its centre (more precisely, southwest of the centre of the 1km grid cell) in order to be able to assign a spatial typology code to each person via the grid cells and the official municipality key. Figure 3.2 shows the spatial typology as assigned to the grid cells. The variable gradient is based on a topographic dataset provided by Burgdorf and Pütz (2019). For every 250-by-250-m large grid cell, it records the average gradient of terrain across that grid cell and its eight surrounding neighbours. We aggregate this further by computing the average gradient of each 1km cell based on its sixteen constituent 250m cells. Even though most bicycle trips can be expected to reach beyond this immediate vicinity around the residential location, testing showed that further increasing the area used for computing individuals' gradient values decreased model fit. The resulting gradient values assigned to the grid cells are shown in Figure 3.3.

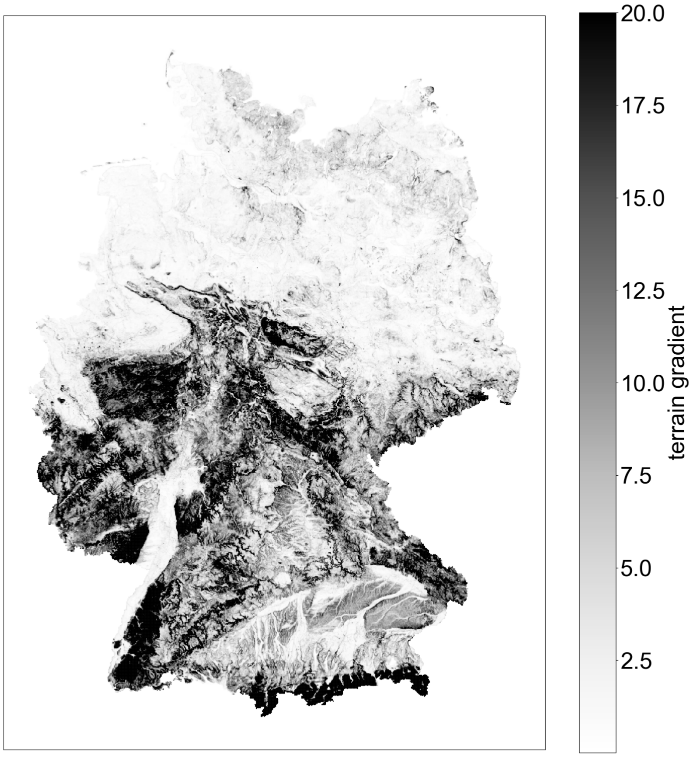

Figure 3.3: Average terrain gradient [%] of 1km grid cells. Grid cell position from GeoBasis-DE and Bundesamt für Kartographie und Geodäsie (2023) under DL-DE-BY-2.0 license, gradient based on data provided by Burgdorf and Pütz (2019).

Table 3.2: Descriptive statistics of variables at person-level

Variable and level	Raw data [%]	Estimation sample [%]	Variable and level	Raw data [%]	Estimation sample [%]
Bicycle ownership			**Household size**		
only c-bike	72.9	73.1	1 person	11.4	16.8
only e-bike	3.0	2.9	2 persons	42.3	48.8
both	5.1	4.7	3 persons	17.7	15.6
neither	18.7	19.3	4 persons or more	28.6	18.9
Age			**Occupation**		
0-17	12.8	2.7	employed	45.8	49.3
18-29	9.4	9.3	education	14.8	7.9
30-39	8.0	9.3	domestic	3.7	3.7
40-49	12.7	13.3	retired	29.3	35.8
50-59	20.0	21.4	other	6.3	3.3
60-69	18.1	20.5	**Economic status**		
70-79	13.9	17.5	very low	3.7	3.5
80 and older	4.8	6.1	low	8.9	8.9
Level of education			middle	39.3	44.0
none (yet)	13.7	2.7	high	38.1	34.1
"Volks-/Hauptschule"	16.8	17.9	very high	10.0	9.5
"Mittlere Reife"	23.9	25.5	**Spatial typology**		
"Abitur"	14.9	16.9	urban metropolitan	N/A	55.7
university degree	28.8	34.4	urban regiopolitan	N/A	20.1
other qualification	1.9	2.2	rural close to city	N/A	12.8
Sex			rural peripheral	N/A	11.3
male	50.3	50.1			
female	49.7	49.9			

All observations for which not all variables were fully recorded were excluded. Most notably, there was no information on bicycle availability for 26 % of all respondents. Due to correlation between the youngest age group and the lowest level of education, we interact age with level of education and omit the lowest level of education from the utility functions in addition to the reference category “Abitur”. A low number of cases of adults with no education therefore also had to be removed. As the variables spatial typology and gradient require spatial localisation, only persons for whom the residential location was recorded at least at the 1km grid cell level were considered. This data processing reduces the available sample size from 316,361 (raw data) to 161,963 persons. Due to high computational demands of a probit model, a random subsample of 30,000 persons was used for model estimation. This sample size ensured a balance between computational efficiency and model reliability. Table 3.2 describes the statistical distribution of the categorical variables in the original raw data and in the sample used for model estimation. Figure 3.4 shows the spread of the continuous variable gradient for the estimation sample as a box plot. Since all previous works identified age as an important influencing factor on e-bike ownership, Figure 3.5 visualises the shares of bicycle ownership across age groups.

Only in one case there is a strong correlation (in its amount larger than 0.60) between independent variables of different groups. This is the case for “age 0-17” x “education ‘no qualification (yet)’”

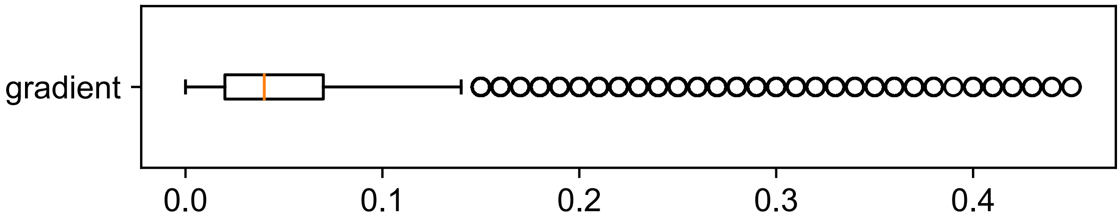

Figure 3.4: Boxplot of average gradient near residential location at person-level

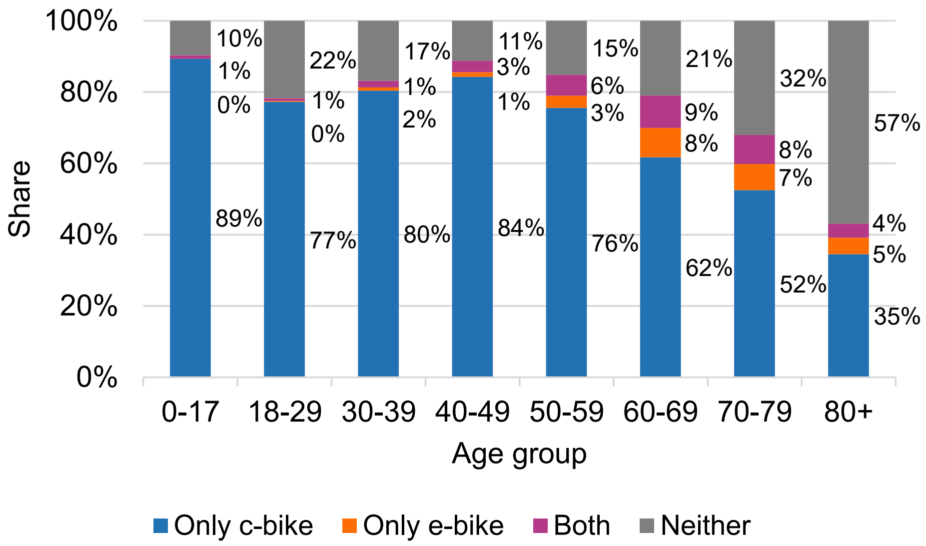

Figure 3.5: Bicycle ownership across age groups

(0.80). To address this, we interact those variables (see section 3.3.2). We do not include other mobility tools as explanatory variables for bicycle ownership because of model hygiene: car ownership and transit cards are influenced by similar socio-economic factors as bicycle ownership, which could introduce endogeneity. Without knowing the sequence of these decisions, including them may obscure the interpretation of bicycle ownership determinants. While a comprehensive model could treat all mobility tools as jointly determined, this would add complexity and reduce clarity. Therefore, we focus solely on bicycle ownership in this model.

3.3.2 Models

Based on findings from the literature, several model variants with analogous utility functions were tested. We report the model specification and results for both a nested logit model and a multivariate probit model. We present two different models because they have distinct advantages: While model parameters of the multivariate probit can be interpreted more intuitively due to its utility functions representing one type of bicycle each instead of bundles, the nested logit allows for the computation of odds ratios and achieves a higher model fit. Furthermore, the nested logit captures the dependency between the two choices by bundling them and accounting for similarities between the bundles using nests, while the multivariate probit does not bundle them but captures the mutual influence as a correlation of the error terms. This allows for different perspectives on the nature of the two choices' relatedness.

The Python package Biogeme 3.2.10 (Bierlaire, 2023) was for the logit model, while the R package mvProbit 0.1-10 (Henningsen, 2015) was used for the probit model. Like for data processing, the source code for model estimation is available on GitHub.

3.3.2.1 Nested Logit

Our nested logit model assumes that each person decides in favour of one of four possible bundles b of bicycle types. These bundles consist of either only a c-bike ($b = 1$), only an e-bike ($b = 2$), both types ($b = 3$), or no bicycle at all ($b = 4$). According to Equation 3.1, each person chooses (dependent variable Y) the option that is associated with the highest utility U.

$$Y = \begin{cases} 1, & \text{if } U_{b=1} = \max(U_b) \\ 2, & \text{if } U_{b=2} = \max(U_b) \\ 3, & \text{if } U_{b=3} = \max(U_b) \\ 4, & \text{if } U_{b=4} = \max(U_b) \end{cases} \tag{3.1}$$

The utility of the reference bundle 4 (owns neither bicycle) is set to 0. For the other three bundles b, the utility U for each person is described by utility functions according to Equation 3.2. They are identical in structure for each of the four bundles and differ only in the parameter values to be estimated. V is the observable part of utility. The alternative specific constant ASC of every bundle is the same across all persons. $\beta_{b,gradient}$ is the bundle-specific parameter for the person-specific variable gradient. Linking gradient with an additional exponential parameter instead of just a linear parameter was tested but rejected due to the negative impact on the model fit. $\hat{\beta}_{b,spatialtyp}$ and $\hat{spatialtyp}$ are vectors of the parameters and values respectively of the three dummy variables for spatial typology. $\hat{\beta}_{b,SD}$ and $\hat{SD}$ represent the same for the socio-demographic dummy variables. The latter is expanded in Equation 3.3. Note the interactions of age with occupation and level of education. This is because the lowest age category correlates with the occupation "in education" and the level of education "none (yet)". With this specification, parameter values for occupation and level of education are estimated only for adults, while the parameter for the youngest age group captures the combined effect of age and age-typical occupation and level of education for that age group. In addition to the reference category, the lowest level of education was also omitted since it only applies to persons in the youngest age category.

$$\begin{aligned} U_b &= V_b + \epsilon_b \\ &= ASC_b + \beta_{b,\text{gradient}} * gradient + \hat{\beta}_{b,\text{spatialtyp}} * spati\hat{a}ltyp + \hat{\beta}_{b,\text{SD}} * \hat{SD} + \epsilon_b \end{aligned} \tag{3.2}$$

$$\begin{aligned} \hat{SD} = (&age_1, age_2, age_3, age_4, age_5, age_6, age_7, age_8, \\ &edu_2 * (1 - age_1), edu_3 * (1 - age_1), edu_5 * (1 - age_1), edu_6 * (1 - age_1), sex_2, \\ &occu_2 * (1 - age_1), occu_3 * (1 - age_1), occu_4 * (1 - age_1), occu_5 * (1 - age_1), \\ &eco_1, eco_2, eco_4, eco_5, hhsize_2, hhsize_3, hhsize_3, hhsize_4) \end{aligned} \tag{3.3}$$

Using the behavioural assumption from Equation 3.1 and the general utility definition from Equation 3.2, the probability of choosing alternative b over the other alternatives b' becomes:

$$P(Y = b) = P(V_b + \epsilon_b > V_{b'} + \epsilon_{b'} \ \forall \ b' \neq b) \tag{3.4}$$

Assuming Gumbel-distributed error terms, one can derive a closed form for the multinomial logit choice probability, as first demonstrated by McFadden (1974):

$$P(Y = b) = \frac{e^{V_b}}{\sum_{b' \in Y_n} e^{V_{b'}}} \tag{3.5}$$

In multinomial logit, the error terms ϵ_b are assumed to be independent and identically distributed (i.i.d.) between individuals and bundles. That assumption would be problematic in this case because the bundles contain overlapping mobility tools. In nested logit, similar alternatives (i.e. options sharing unobserved attributes) are grouped into nests (M). This allows for correlated error terms within each nest but assumes independence between nests. Namely, the error term ϵ_b is decomposed into two parts:

$$\epsilon_b = \xi_n + \eta_b, \tag{3.6}$$

where ξ_n is the component shared by all alternatives in nest n, and eta_b is the i.i.d. component for bundle b. The probability of choosing a specific bundle is the product of the conditional probability of b within its nest n and the probability of selecting that nest:

$$\begin{aligned} P(Y = b) &= P(Y = b | M = n) * P(M = n) \\ &= \frac{e^{V_b / \mu_n}}{\sum_{b' \in Y_n} e^{V_{b'} / \mu_n}} * \frac{e^{\mu_n * \Gamma_n}}{\sum_{n' \in M} e^{\mu_{n'} * \Gamma_{n'}}} \end{aligned} \tag{3.7}$$

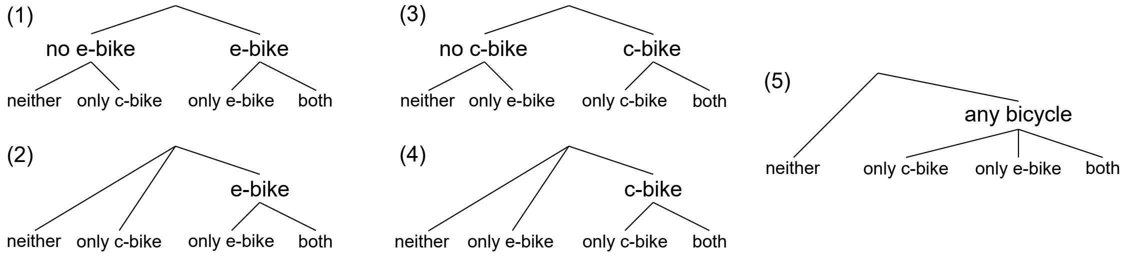

Figure 3.6: Tested nesting structures

where Γ_n, the log-sum term, is given by:

$$\Gamma_n = ln \sum_{b' \in Y_n} e^{V_{b'}/\mu_n}. \tag{3.8}$$

Five nesting structures depicted in Figure 3.6 were tested. Nesting structure 2 was chosen due to highest adjusted ρ^2. In the chosen nesting structure, the single nest parameter μ_{ebike} determines the degree of similarity between options within this nest, namely owning an e-bike but not owning a c-bike, and owning both an e-bike and a c-bike. A value of 1 implies no correlation, reducing the model to multinomial logit, while higher values indicate increasing similarity among bundles within the nest. For further information on nested logit, we refer to Koppelman and Wen (1998).

3.3.2.2 Multivariate Probit

In our probit model, a person does not choose one out of four alternatives, but decides in two binary decisions between two alternatives each. These decisions are whether to own a c-bike and whether to own an e-bike. The two dependent variables Y_t describe whether a person owns a bicycle of type t (conventional and electric) according to Equation 3.9:

$$Y = \begin{cases} 1, & \text{if } U_t > 0 \\ 0, & else \end{cases} \tag{3.9}$$

U_t is the utility of a person to own a specific type of bicycle t. Equation 3.10 describes the structure of these two utility functions, which is identical to the nested logit model in the previous section. However, note the replacement of b by t.

$$\begin{aligned} U_t &= V_t + \epsilon_t \\ &= ASC_t + \beta_{t,\text{gradient}} * gradient + \hat{\beta}_{t,\text{spatialtyp}} * spati\hat{a}ltyp + \hat{\beta}_{t,\text{SD}} * \hat{SD} + \epsilon_t \end{aligned} \tag{3.10}$$

As in the logit model, the error terms ϵ_t represent the unobserved part of the utility. However for probit, they are assumed to be normally distributed between the individuals. In order to take into account the mutual influence of the decisions, they are also assumed be correlated for each person

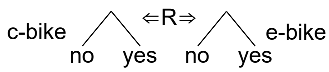

Figure 3.7: Decision structure of the multivariate probit model

between the two decisions. Namely, they follow a bivariate normal distribution:

$$\begin{bmatrix} \epsilon_{cbike} \\ \epsilon_{ebike} \end{bmatrix} \sim N(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & R \\ R & 1 \end{bmatrix}) \tag{3.11}$$

where the global correlation coefficient R is an additional model parameter that is estimated using the data. The joint probability P that $Y_{(t=conv)}$ takes the value $y_{(t=conv)}$ (0 or 1) and $Y_{(t=elec)}$ takes the value $y_{(t=elec)}$ (0 or 1) is given by Equation 3.12:

$$\begin{aligned} &P(Y_{conv} = y_{conv}, Y_{elec} = y_{elec}) = \\ &\Phi_2[(2y_{conv} - 1) * V_{conv}, (2y_{elec} - 1) * V_{elec}, (2y_{conv} - 1) * (2y_{elec} - 1) * R] \end{aligned} \tag{3.12}$$

Here, Φ_2 is the cumulative density function of the bivariate normal distribution. The correlation R captures the mutual influence of the two decisions: If it is positive, unobserved factors increase the likelihood of jointly owning (or not owning) both types of bicycles (i.e. complementary effects), while a negative value of R indicates that unobserved factors reduce the likelihood of jointly owning (or not owning) both types of bicycle (i.e. substitutive effects). The model structure is visualized in Figure 3.7. Note that unlike in the nested logit model, the multivariate probit model considers the decisions about each type of bicycle not hierarchically but separately, being linked by correlated error terms. For further information on multivariate probit, we refer to Greene (1996).

3.4 Results and Discussion

3.4.1 Parameter Values and Model Quality

After presenting the model specifications, we now report the results of model estimation. Tables 3.3 and 3.4 show the estimated model parameters of the nested logit and the multivariate probit model. Reference categories used for model identification are included in cursive. The choice option "no bicycle owned" is the reference choice option for the nested logit model, with its utility set to 0. For each of the two binary decisions in the multivariate probit model, not owning the respective bicycle type is the reference choice option, with ownership being assumed if the utility for owning that type is larger than 0. All parameters are tested against the null-hypothesis of them being 0, with the exception of the nest parameter, where it is tested against the null-hypothesis of being 1. Table 3.5 compares the two models. Note that while for probit, model parameters can be compared across bicycle types, with nested logit every bundle contains the outcome of two decisions regarding c-bike and e-bike ownership and one needs to scale using the nest parameters.

Table 3.3: Parameter values for the nested logit model

Parameter	Only c-bike			C-bike and e-bike			Only e-bike		
	Value	Rob. p-val.	Sig.	Value	Rob. p-val.	Sig.	Value	Rob. p-val.	Sig.
constant	1.99	0.000	***	-1.56	0.000	***	-1.71	0.000	***
gradient	-5.99	0.000	***	-3.48	0.000	***	-3.19	0.000	***
s.t. metrop. urban									
s.t. regiop. urban	-0.089	0.030	*	0.112	0.092	*	0.128	0.058	*
s.t. rural close to city	-0.021	0.668		0.345	0.000	***	0.365	0.000	***
s.t. rural peripheral	0.145	0.007	**	0.407	0.000	***	0.408	0.000	***
age 0-17	0.321	0.392		-1.35	0.219		-7.03	1.000	
age 18-29	-0.628	0.000	***	-1.95	0.000	***	-1.96	0.000	***
age 30-39	-0.310	0.000	***	-0.803	0.000	***	-0.831	0.000	***
age 40-49									
age 50-59	-0.205	0.002	**	0.426	0.000	***	0.447	0.000	***
age 60-69	-0.226	0.006	**	0.755	0.000	***	0.784	0.000	***
age 70-79	-0.584	0.000	***	0.363	0.013	*	0.397	0.007	**
age 80+	-1.67	0.000	***	-0.864	0.000	***	-0.799	0.070	*
edu. none (yet)									
edu. "Volks-/Hauptsch."	-0.212	0.000	***	0.054	0.556		0.096	0.030	*
edu. "Mittlere Reife"	-0.088	0.090	*	0.048	0.580		0.076	0.386	
edu. "Abitur"									
edu. university degree	0.170	0.001	**	0.127	0.136		0.114	0.186	
edu. Other	-0.303	0.004	**	-0.216	0.227		-0.183	0.308	
sex male									
sex female	-0.37	0.000	***	-0.389	0.000	***	-0.368	0.000	***
household size 1									
household size 2	0.533	0.000	***	0.719	0.000	***	0.753	0.000	***
household size 3	0.572	0.000	***	0.565	0.000	***	0.593	0.000	***
household size 4+	0.886	0.000	***	0.906	0.000	***	0.865	0.000	***
occupation employed									
occupation education	0.178	0.085	*	0.304	0.370		0.380	0.269	
occupation domestic	-0.459	0.000	***	-0.053	0.686		-0.042	0.748	
occupation retired	-0.464	0.000	***	-0.018	0.853		-0.015	0.879	
occupation other	-0.526	0.000	***	-0.286	0.076	*	-0.300	0.065	*
eco. status very low	-0.393	0.000	***	-1.06	0.000	***	-1.08	0.000	***
eco. status low	-0.126	0.019	*	-0.508	0.000	***	-0.506	0.000	***
eco. status middle									
eco. status high	0.329	0.000	***	0.515	0.000	***	0.500	0.000	***
eco. status very high	0.420	0.000	***	0.667	0.000	***	0.667	0.000	***

Parameter (cont.)	**Only c-bike**			**C-bike and e-bike**			**Only e-bike**		
	Value	Rob. p-val.	Sig.	Value	Rob. p-val.	Sig.	Value	Rob. p-val.	Sig.
nest e-bike yes	10.0	0.000	***				***/**/* = 0.1/1/10%		

Table 3.4: Parameter values for the multivariate probit model

Parameter	**C-bike**			**E-bike**		
	Value	Rob. p-val.	Sig.	Value	Rob. p-val.	Sig.
constant	1.138	0.000	***	-1.952	0.000	***
gradient	-3.373	0.000	***	0.656	0.004	**
s.t. metrop. urban						
s.t. regiop. urban	-0.087	0.000	***	0.106	0.000	***
s.t. rural close to city	-0.014	0.597		0.203	0.000	***
s.t. rural peripheral	0.074	0.009	**	0.097	0.007	**
age 0-17	0.103	0.542		-0.224	0.347	
age 18-29	-0.237	0.000	***	-0.645	0.000	***
age 30-39	-0.138	0.001	**	-0.244	0.000	***
age 40-49						
age 50-59	-0.078	0.017	*	0.190	0.000	***
age 60-69	-0.202	0.000	***	0.360	0.000	***
age 70-79	-0.389	0.000	***	0.371	0.000	***
age 80+	-0.972	0.000	***	0.101	0.132	
edu. none (yet)						
edu. "Volks-/Hauptsch."	-0.191	0.000	***	0.108	0.005	**
edu. "Mittlere Reife"	-0.116	0.000	***	0.099	0.006	**
edu. “Abitur”						
edu. university degree	0.095	0.000	***	-0.053	0.138	
edu. other	-0.183	0.001	**	0.064	0.418	
sex male						
sex female	-0.186	0.000	***	-0.047	0.043	**
household size 1						
household size 2	0.223	0.000	***	0.261	0.000	***
household size 3	0.272	0.000	***	0.132	0.003	**
household size 4+	0.447	0.000	***	0.114	0.014	*
occupation employed						
occupation education	0.022	0.680		0.044	0.720	
occupation domestic	-0.156	0.001	**	0.175	0.001	***
occupation retired	-0.160	0.000	***	0.148	0.000	***

Parameter (cont.)	C-bike Value	Rob. p-val.	Sig.	E-bike Value	Rob. p-val.	Sig.
occupation other	-0.192	0.000	***	0.029	0.680	
eco. status very low	-0.146	0.001	**	-0.234	0.002	**
eco. status low	-0.114	0.000	***	-0.156	0.000	***
eco. Status middle						
eco. status high	0.173	0.000	***	0.055	0.045	*
eco. status very high	0.192	0.000	***	0.186	0.000	***
R	-0.235	0.000	***	***/**/* = 0.1/1/10%		

ASC: The constants have the expected signs and express the generally higher hurdle (especially price) when buying an e-bike than a c-bike.

Gradient: The average gradient near the residential location has a significant negative influence on the utility of owning a c-bike. In the probit model, an average gradient of 2.8 % is as detrimental to owning a c-bike as the fact that a person is above 80 years old (compared to between 40 and 49). Such a gradient value is common in only very moderately hilly areas. A different picture emerges for e-bikes: The gradient parameter in the probit model is larger than 0, meaning gradient has a positive impact on e-bike ownership. In the nested logit model, the difference between the two types of bicycles appears less extreme at first glance, however the difference in utility between the nested bundles “c-bike and e-bike” and “only e-bike” is scaled by the value of the nest parameter.

Urban vs. rural: The overall picture that emerges from the nested logit model regarding spatial typology is that for rural residential locations, there is a higher utility for an e-bike, but with no clear indications for how it affects c-bike ownership. The probit model allows for a more differentiated picture with regard to e-bikes: Compared to the reference category “metropolitan urban”, utility for owning an e-bike is indeed positive in more peripheral regions. However after also taking into account gradient, there is a clear indication that this added utility peaks in rural areas close to cities and decreases again for very peripheral areas. The impact of spatial typology on c-bike utility appears negligible in magnitude.

Age: As expected, the probit model describes a falling utility for c-bikes from the reference age group of 40-49 years onwards. More surprisingly, there is also a significant disutility for age 18-39 and only an insignificantly positive utility for age group 0-17 – albeit this category also expressing the effects of level of education and occupation for this youngest age group due to the interacting of these variables with age 18+. It therefore stands to reason that the higher rate of c-bike ownership among minors is more adequately explained by other factors, such as household size. For e-bikes, utility peaks around 60-79 years and decreases for both younger and older ages. According to the nested logit model, the utility of owning only a c-bike peaks around 40-49 years and has an additional upward tick for age 0-17, while owning only an e-bike is most attractive for age groups 50-79. We point out that in Germany, while riding so-called S-Pedelecs, which can reach speeds up to 45km/h, is subject to an age restriction of 16 years, the vast majority of e-bikes have no such restriction.

Education: According to the probit model, a higher level of education means a slightly positive utility for a c-bike, while in the case of e-bike ownership, only the slightly positive parameters for “Volks-/Hauptschule” and “Mittlere Reife” are significant. In the nested logit model, even fewer

Table 3.5: Comparison of model properties

Property	**Nested logit**	**Multivariate Probit**
Number of parameters	85	57
Sample size	30,000	30,000
Null-log-likelihood	-41,588.8	-41,588.8
Log-likelihood	-21,694.0	-22,333.4
Adjusted ρ^2 (Bierlaire, 2023)	0.476	0.462

parameters are significant, with the results for bundle "only c-bike" mirroring the findings of the probit model.

Gender: According to the probit model, women show a lower utility for owning a c-bike compared to men, analogous to their slightly lower bicycle use (Nobis, 2019). For e-bikes, the impact of gender is much lower, albeit not zero. The nested logit model confirms this regarding c-bike ownership, however the two bundles containing e-bike are associated with a similar disutility to bundle "only c-bike".

Household size: The utility of any bundle increases with household size in the nested logit model. This was expected, as the probability that there is at least one bicycle in the household that can be shared increases as the number of people in the household rises. While probit mirrors this for c-bike, we find that e-bike utility peaks for two-person households. We hypothesise that this reflects the use of e-bikes primarily for leisure activities by couple households without children.

Occupation: Compared to the reference group of adult working people, housemen/-women, retirees, and other occupations show a significantly reduced utility for owning a c-bike. Owning an e-bike, on the other hand, is very clearly associated with a positive utility for retirees and housemen/-women. The nested logit model is less clear regarding the impact of occupation, other than that domestic and retired occupation goes along with a high disutility of owning only a c-bike.

Economic status: The higher the economic status, the greater the utilities of both a c-bike and an e-bike in the probit model. Likewise, in the nested logit model every combination of bicycle ownership also sees increased utility with higher economic status. This shows that bicycles are not generally used by low-income households as a substitute for a more expensive car, but instead are the result of a lifestyle choice.

R and nest parameters: The probit model's parameter R, i.e. the correlation of the error terms between a person's utility functions for the two different types of bicycle, can capture substitution effects, e.g. giving up a c-bike after purchasing an e-bike, as well as complementary effects. One conceivable complementary effect is that people with cycling-orientated attitudes (which are not explicitly included in our models and are therefore part of the error terms) have an additional positive utility for both a c-bike and an e-bike. R's negative, highly significant value of -0.235 shows that the substitution effects clearly dominate and that the assumption of an independent distribution of the error terms is not tenable. This contrasts with findings by Ma et al. (2018), who (between c-bikes and Chinese-style e-bikes) find a value of only +0.027. The nest parameter of 10.0 indicate very strong correlation between the alternatives in the "e-bike" nest. We note that when testing nesting structure 1 (Figure 3.4), the nest parameter of "no e-bike" came out as 1. This suggests that the decision of whether to own an e-bike is far more critical than the decision to own a c-bike.

3.4.2 Suitability of model types and implications for policy and modelling practice

Both model types have advantages and disadvantages. Nested logit model coefficients can be interpreted as odds ratios and the model presented here achieves a higher model fit than the probit model even after accounting for the higher number of parameters. By modelling bundles, it can better depict their specific benefits for different groups of people, e.g. the phenomenon of e-bike-only owners among older senior citizens, while accounting for correlation between bundles using nest parameters. The probit model, on the other hand, can consider such correlations between the mobility tools of a bundle only with a global parameter R. However, the consideration of bundles represents a disadvantage for questions focussing on a single mobility tool, where the probit model can be interpreted more intuitively. This becomes even more relevant when more than two mobility tools are taken into account, as the number of bundles would grow exponentially. While it is possible to parametrise a nested logit model to allow for additive effects, this would forego the model's ability to capture bundle effects. The two models presented here therefore complement each other in terms of the findings and interpretations they allow.

Our model can be used as a predictive sub-model within a larger integrated transport model. For such use cases, the interpretability of model parameters is less relevant than predictive power. We therefore recommend using the nested logit model, as this variant achieved a higher model fit. We demonstrated that not only socio-demographic characteristics but also the variables of spatial typology and especially gradient significantly influence the utility of c-bike and e-bike ownership. Therefore, these variables should be included, especially when they vary substantially across the model area. Where data on c-bike and especially e-bike ownership is not available in Germany, our model can be used to gauge their magnitude, which is relevant for bicycle retailers and providers of bike sharing systems. For modelling efforts outside of Germany, our work can inform suitable model types and relevant explanatory variables. The model furthermore sheds light on the true causal relationships behind c-bike and e-bike ownership. For example, we were able to demonstrate that higher e-bike ownership rates in very rural areas identified in previous works are not primarily due to the urban structure itself, but rather due to more varied topography and older residents. With e-bikes already being viewed as a valuable mobility solution by the elderly and residents of hilly areas, targeted purchase incentives could further increase their uptake and consequently cycling among other groups.

3.4.3 Limitations and further research needs

While our study has provided valuable insights into what factors influence c-bike and e-bike ownership, several limitations and avenues for future research remain to be explored. Bike-sharing systems were not considered, although they are a low-threshold option for getting to know e-bikes or substituting private e-bike ownership, particularly in urban areas. It was not possible to consider the price of bicycle types, which also would have made it possible to determine willingness to pay for other variables, due to a lack of data and the character of the MiD as a cross-sectional and revealed preferences survey (and thus a lack of variance in the purchase costs). It is conceivable that the variable gradient correlates with other factors such as local infrastructure quality or cycling culture, which were not analysed. Instead of gradient and spatial typology, which capture singular aspects of bicycle accessibility, future research could benefit from using a more holistic accessibility measure for c-bike and e-bike travel as an explanatory variable. As personal attitudes were not recorded in the MiD 2017, these could not be taken into account, although there is broad evidence in the literature for their relevance. The dynamic development of e-bike sales is probably largely due to changing attitudes and they are therefore of particular importance for predictive models. Since e-bike sales have already risen significantly again since 2017 (Zweirad-Industrie-Verband, 2024), the present approach should be repeated in the form of a replication study once newer data becomes available.

3.5 Conclusion

This study contributes to a better understanding of the choice of owning conventional and electric bicycles and suitable model types by estimating a nested logit and a multivariate probit model based on data from the MiD 2017 survey and other sources. While the results of the multivariate probit model were more intuitively interpretable, the nested logit model achieved a higher model fit and could capture some bundle-specific effects. Regarding research question 1 (Which factors influence the choice to own a conventional and/or electric bicycle?) we can generally confirm the relationships known for the socio-demographic factors age, level of education, gender, household size, occupation, and economic status from the literature for the European context. Regarding research question 2 (What role does topography play in particular?) we find that while the utility for c-bike ownership decreases with average gradient around the residential location, this is not the case for electric bicycles. To our knowledge, we are the first to quantify this influence of the gradient of terrain near the residence location on conventional and electric bicycle ownership. Lastly, regarding research question 3 (How are the two choices interlinked?), the negative correlation of the error terms in the probit model suggests that unobserved substitution effects between the two types of bicycles outweigh unobserved complementary effects, providing the first evidence of its kind on this relationship. The adopted nesting structure and resulting nest parameter value of the nested logit model suggest that the choice to own a conventional bicycle is subordinate to the decision to own an electric bicycle.

Future surveys and analyses should take into account not only the influencing factors of gradient, spatial typology and socio-demographic variables but also personal attitudes in order to enable predictive ownership choice models. Building on this work, in subsequent research projects we will look at mode choice behaviour differentiated according to conventional and electric cycling and incorporate bicycle ownership into this.

Chapter 4

Third Paper: Mode Choice

Contents

Disclaimer: This chapter was previously published as: Leonard Arning and Heather Kaths (2025). Further, Steeper, Greener: Implications from an Electric Bicycle Mode Choice Model. *International Journal of Sustainable Transportation*, 1-16. doi: `https://doi.org/10.1080/15568318.2025.2533307`. The second author, who is also the supervisor of this thesis, contributed by advising on the study conception and design as well as proof-reading the manuscript and suggesting language revisions.

Abstract

Electric bicycles are transforming the active mobility landscape, potentially increasing active mode uptake and delivering environmental and health benefits. This study examines electric bicycle mode choice and which modes they replace. It employs a trip-level nested logit mode choice model with six alternatives, including conventional and electric bicycles. The model is estimated using 194,524 trips from the “Mobility in Germany” survey, augmented with data on gradient, spatial typology, public transport departures, and bicycle infrastructure coverage. We validate the model to infer generalizability, derive elasticities, and compute substitution rates. Our results reject nesting electric with conventional bicycles, underscoring their distinct characteristics and minimal shared unobserved attributes. The choice to use an electric bicycle is less affected by the availability of bicycle infrastructure and the length of a trip compared to the decision to use a conventional bicycle. In fact, electric bicycles are closer to cars than to conventional bicycles in terms of distance sensitivity. For both types of bicycle, mode choice is strongly and similarly dependent on gradient, with this effect furthermore depending on age. 43.1 % of electric bicycle trips and 63.2 % of electric bicycle mileage would have been undertaken using a car if no e-bike had been available, highlighting their substantial potential to reduce transport-related CO2 emissions. These findings support the role of e-bikes in advancing sustainable mobility by displacing car trips and broadening access to active transportation.

4.1 Introduction

Electric bicycles are not new — in fact, the first patent for a battery-powered bicycle dates back to the late 19th century (Bolton, 1895). However, it is only in the past two decades that electric bicycles have gained significant popularity in Europe, and their market share is growing at a rapid pace (RAI Vereniging & BOVAG, 2023). This surge in popularity has sparked research interest in understanding the motivations for their use, impact on travel behavior, and potential for mode shift towards more sustainable forms of mobility. It is well established that due to the higher speed and reduced physical exertion required by riders of electric bicycles (e-bikes) compared to conventional bicycles (c-bikes), e-bikes are particularly appealing to different user groups (such as the elderly) and for different types of trips (such as commutes to work, longer distances, or hilly terrain) (Bourne et al., 2020). Consequently, e-bikes could play a key role in promoting active mobility, contributing to public health and reducing greenhouse gas emissions.

State of the art strategic transport models used by policymakers include the bicycle alongside other modal options such as walking, car, or public transport. Despite remarkable differences between c-bikes and e-bikes, usually no distinction is made between them (Arning et al., 2023). This is problematic because ignoring the ongoing electrification of bicycle traffic compromises the predictive accuracy of these models and does not enable the evaluation of e-bike-specific policies such as purchase incentives or dedicated infrastructure. To adequately represent both types of bicycles in strategic transport models, discrete choice models on ownership, mode, and route choice must be developed and estimated. This can inform suitable model specifications and parameter values. Furthermore, such models can be used to investigate which modes e-bike users would have used if no e-bike had been available to them, adding to the literature on e-bike substitution rates. For this study, the following research questions take center stage:

- How do factors influencing mode choice differ between c-bikes and e-bikes?
- To what degree does e-bike travel substitute active mobility, car travel, and public transport, respectively?

We present a trip-level mode choice model that distinguishes between c-bike and e-bike as well as walking, car as passenger, car as driver, and public transport. We begin with a literature review about e-bike mode shift and modelling. The paper continues with our choice of variables, data processing, and descriptive statistics. We then explain the model specification and perform validation to evaluate generalizability. The model results offer insights into the motivations and preferences for using a c-bike or e-bike. Furthermore, we calculate elasticities to derive policy implications for promoting c-bike and e-bike travel and derive substitution rates to examine the potential of e-bikes to facilitate sustainable mode shift. Lastly, we discuss our findings and summarize key learnings.

4.2 Literature

Our literature review is divided into three parts: First, we summarize findings on mode shift as a result of e-bike introduction. This allows us to identify relevant explanatory variables for our model and to compare our substitution rates with existing work. We also give a brief overview of trip-level mode choice models, separated by whether or not they differentiate between c-bikes and e-bikes. This also informs our choice of variables as well as model type. We focus on bicycle-style e-bikes as opposed to scooter-style e-bikes, which are common in South and East Asia, because they fall under separate regulatory frameworks in Europe. Also, in the context of mode choice, the latter are more akin to car transport (Hu, Sobhani, & Ettema, 2021).

4.2.1 E-Bike Mode Shift

The introduction of e-bikes has led to a substitution of c-bikes and other forms of active mobility, displaced car and public transport trips, and generated new trips. Understanding the magnitude of these shifts and their influencing factors is essential not only for accurately modelling e-bike use and its impacts but also for informing sustainable transport policies, addressing public health goals, and advancing equity in mobility access.

The substantial body of literature on the situation in the Netherlands reports contradictory results: de Haas et al. (2022) and Kroesen (2017) both find that e-bikes mainly replace c-bike travel and only slightly reduce car and public transport usage. A more evenly distributed mode shift is found by Sun et al. (2020), who show that a person acquiring an e-bike reduces the c-bike's share in terms of distance travelled from 20 % to 2 % and the car's from 58 % to 50 %. Similarly, Lee et al. (2015) conclude from a survey among e-bike owners that 41 % of e-bike trips replace c-bike trips, 40 % replace car trips, 7 % replace public transport trips, and 2 % are induced. de Kruijf et al. (2018) evaluate a monetary incentive program promoting e-bike use and also find that both the car (62 % to 28 %) and the c-bike (33 % to 1 %) lose similar amounts of mode share. In a survey of car commuters before, during and after an e-bike trial scheme, Ton and Duives (2021) even find an increase in the mode share of c-bike (5 % to 12 %) as well as e-bike (2 % to 18 %) at the cost of the car (88 % to 63 %), hinting towards the role of the e-bike as a door-opener for establishing cycling habits.

In North America, MacArthur et al. (2018) report that e-bike owners stated that they would have used the car if they had not had an e-bike for 46 % of their e-bike trips, 27 % would have been undertaken by active transport or transit, and 25 % are induced. Similarly to Ton and Duives (2021), Andersson et al. (2021) found that after an e-bike trial in Sweden, the mode share of both c-bike (4 % to 12 %) and e-bike (0 % to 17 %) increased at the cost of the car (74 % to 53 %). Fyhri and Sundfør (2020) find that Norwegian e-bike customers increase their average kilometers travelled daily by bicycle (c-bike and e-bike) from 2.1 km to 9.2 km. Most of this is due to an increase in total distance travelled (10.8 km to 16.6 km), with only 7 % coming from a reduction in car travel (5.1 km to 4.6 km). In a meta-review across 24 studies on (bicycle-style and scooter-style) e-bike mode shift, Bigazzi and Wong (2020) found median values of 33 % of e-bike trips shifting from public transport, 27 % from c-bike, 24 % from car, 10 % from walking, and 1 % being induced. They observed that the substitution of public transport is particularly strong in China, while car substitution is higher elsewhere, in part reflecting the fundamental difference in vehicle technology and usage characteristics between scooter-style e-bikes in East Asia versus bicycle-style e-bikes in Europe and North America. In another meta-review, Bourne et al. (2020) analyzed 42 studies on the impact of (solely bicycle-style) e-bikes on travel behavior. They report that between 23 % and 72 % of trips were previously conducted by c-bike, between 20 % and 86 % by car, and between 3 % and 45 % by public transport.

In conclusion, e-bike mode shift strongly depends on the local context. If the mode share of cycling is already high (such as in the Netherlands), e-bikes are unlikely to further increase the mode share of cycling and are more likely to substitute existing c-bike trips. In regions, person groups or for trip purposes where cycling is a less common mode of transport, e-bikes have the potential to increase levels of cycling at the cost of car and public transport use.

4.2.2 Discrete Mode Choice Models without E-Bikes

At the trip-level, mode choice is a discrete choice made by a person between all means of transport theoretically available to them for that trip. The decision is made depending on attributes of the different choice options (e.g. travel time and costs for each mode), the trip itself (e.g. trip purpose, time of day), available mobility tools (e.g. car ownership, public transport season ticket), the environment (e.g. quality of cycling infrastructure, gradient), and the traveler themselves (e.g. age, preferences).

Multinomial logit (MNL) and nested logit (NL) are the most commonly used model types for trip-level mode choice. Rayaprolu et al. (2020) tested one MNL and two NL models on national household travel survey data from Germany from the year 2008. They found that a NL model with car and public transit nested as "motorized" has a superior R2 value, however, the MNL model predicts mode shares the most accurately. Liu et al. (2020) estimated an NL model with four levels for trip generation, main mode choice, access/egress mode choice, and destination choice. At the level of the choice of main mode, the options are not nested. Similarly, in the estimation of a destination and mode choice model for the Danish National Passenger Model, Rich and Hansen (2016) employed a NL model for mode and destination choice with different nesting structures for each trip purpose. For the use in integrated transport models, Friedrich et al. (2019) provide an advisory overview of suitable model types for all stages of the four-step model. For a standalone mode choice model, they recommend MNL, however, when coupled with destination choice, they suggest NL.

Model types other than MNL and NL are also used. Rybarczyk and Wu (2014) used a binomial logit model, differentiating only between whether a trip was undertaken by bicycle or not, to investigate the impact of urban morphology on bicycle use. Such an approach is suitable when one is interested in assessing specific factors' influence on bicycle use, but less so for application in integrated, multimodal transport models. Meyer de Freitas et al. (2019) estimated a recursive logit model for intermodal mode and route choice in Switzerland. In this approach, travelers do not choose one mode and route out of many, but instead select one link within a multimodal network graph after the other, getting iteratively closer to their destination and allowing for a change of mode during route construction. The main drawbacks of this approach are data requirements (network graph and link-fine route choice observations) and the computationally expensive model estimation. Dahmen et al. (2024) compared a MNL with machine learning models (XGBoost and Random Forest). They found that the XGBoost model has the highest predictive accuracy and that using shapely additive explanation values helps overcome previous limitations of machine learning models regarding interpretability.

4.2.3 Discrete Mode Choice Models with E-Bikes

Lastly, we look at existing research on discrete mode choice models that differentiate between c-bike and e-bike, either as distinct modal options or as model input. In a study on the same trunk dataset this study uses, Kohlrautz and Kuhnimhof (2024) investigated e-bike ownership and its impact on bicycle mode choice in Germany using a MNL model. They show that owning an e-bike significantly increases cycling mode share at the cost of car and public transport. We expand on their work by adding four spatial datasets, differentiating between c-bike and e-bike as two distinct options for mode choice, validating our model, and performing additional analyses. Heilig et al. (2017) estimated a combined destination and mode choice NL model for each trip purpose on mixed stated and revealed preference data. They differentiated between c-bike, e-bike, and bike-sharing systems as well as six other modes. By applying the model to an agent-based travel demand simulation, they demonstrated the suitability of their approach for modelling emerging modes. Hallberg et al. (2021) estimated a combined destination and mode choice NL model for the Copenhagen region. The model application combines different a priori scenarios for future cycle superhighway expansions and e-bike shares in bicycle traffic. The authors then investigated the scenarios' impact on overall cycling mode share and consumer surplus, finding that e-bikes raise consumer surplus for both existing and new users. Reck et al. (2022) estimated a mode choice model using survey, booking and GPS data from Zurich, with a focus on shared and personal micromobility. They used a mixed logit approach to account for the panel structure of their data. By taking the subset of trips undertaken by e-bike, setting e-bike availability to zero and then applying their model to those adjusted trips, they were able to derive (instead of measure) substitution rates on trip-level and km-level. They report that for personal e-bike trips, 48 % of travel distance would have been instead undertaken by car, 29 % by public transport, 14 % by c-bike and 9 % by walking. In contrast, shared e-bikes substitute mostly public transport followed by c-bike, resulting in an increase in CO_2 emission rates. This approach does not account for induced trips.

The Dutch Growth Model 4.0 (Smit et al., 2021) is the only large-scale strategic transport model known to the authors of this paper that differentiates between c-bikes and e-bikes, in addition to six other modes, as distinct modal options throughout all modeling stages. It employs a NL structure with six levels for mode, type of public transport mode, destination, time of day, train access/egress mode, and train station choice. While the decision between different public transport modes takes place within a nest, c-bike and e-bike are not nested.

4.3 Data

We use trip, person, and household-level data from the "Mobilität in Deutschland 2017" ("Mobility in German 2017", MiD) survey (Nobis, Kuhnimhof, Follmer, & Bäumer, 2019) as our trunk dataset. The survey results are available at different levels of spatial aggregation. We use the B3 local dataset package, which reports locations of origins, destinations and places of residence at the cost of more aggregated socio-demographic and economic variables, allowing for the inclusion of additional spatial variables. In this section, we outline our choice of variables, data processing, and report descriptive statistics. Our source code is available on GitHub (https://github.com/buw-bicycle-traffic/ebike-modechoice-model/tree/main).

4.3.1 Choice of Variables and Data Preparation

The dependent variable "choice" represents the chosen mode of transport of each trip, which can take the value walking, c-bike, e-bike, car as the driver (car-d), car as a passenger (car-p), or public transport. In cases where more than one mode was used during a trip, the MiD gives precedence to a main mode (e.g. public transport over car-d, since the car is more likely a feeder mode to public transport than the other way around). Car-d and car-p also include car-sharing. The MiD does not differentiate between private or shared bicycle use and the availability of a bicycle on the survey day includes both. We use adjusted $\bar{\rho}^2$ to compare different specifications during model development.

The socio-demographic variables age, economic status, level of education, occupation, and sex have been shown by various studies in the literature section to be of high relevance to mode choice behavior and are readily available in the MiD dataset. Occupation was omitted because it is highly correlated with other variables and its removal improved adjusted $\bar{\rho}^2$. The availability of mobility tools, namely c-bike, e-bike, car, and public transport season ticket (ticket), is relevant for mode choice behavior and is available in the MiD dataset at the person-level. It is hence included in the model. The MiD records car ownership at the household-level as well as car availability (as driver or passenger) at the person-level, with the latter differentiating between "all day", "part of the day", and "no". It proved favorable to use person-level car availability instead of household-level car ownership and to combine "all day" and "part of the day" into "yes", for both car-d and car-p.

At the trip-level, trip purpose and, regarding cycling, season were included. We included season instead of weather because this variable is more relevant for implementation in strategic transport models. Trips that return home are assigned the trip purpose of the previous destination. A binary variable nighttime was tested for c-bike and e-bike but not implemented due to its negative impact on adjusted $\bar{\rho}^2$.

In previous works, various mode-specific trip-level variables such as travel distance, travel time or monetary costs are used. The value of these variables differs by mode (e.g., travel time by car might be lower for a given trip than travel time by c-bike), but the coefficient is assumed identical across modes (reflecting a similar value of time, regardless of the mode chosen). The MiD provides both travel time and travel distance for each trip, however only for the chosen mode. To retroactively compute mode-specific travel distances or travel times for the non-chosen modes would necessitate a Germany-wide, routable and multimodal network graph as well as more precise locations of trips' origin and destination. Instead, we used the reported trip distance as a mode-neutral trip attribute. This assumes that trip distances for the non-chosen modes are similar to the distance reported for the chosen mode, with differences in average detour factors between modes being captured with different distance coefficients. We believe that this simplification is acceptable for a mode choice model focused on bicycle traffic. Trips over 100 km were removed to avoid interfering with dedicated long-distance modes such as airplane and high-speed rail. To account for the non-linearity in distance decay, distance was logarithmized using base e.

In addition to the MiD data, we integrated four spatial variables based on external sources. The MiD records the locations of trip origin and destination using a standardized grid of 1-by-1-km large cells (GeoBasis-DE & Bundesamt für Kartographie und Geodäsie, 2023), allowing us to match the spatial data to individual trips. We remove trips from the dataset that do not report origin and destination location at 1-by-1-km accuracy. Local gradient, bicycle infrastructure, public transport departures, and spatial typology are interrelated, as larger cities are typically situated in flatter areas and tend to offer better cycling infrastructure and more frequent public transport services. By including all four variables in our analysis, we can better isolate and examine their individual effects on c-bike and e-bike utility. This comprehensive approach allows us to uncover more accurate causal relationships, in contrast to studies that consider only a subset of these factors and risk conflating their effects.

4.3.1.1 Gradient

It is well known that their ability to overcome challenging terrain is an important motivation for buying and using an e-bike (Arning & Kaths, 2025b; Bourne et al., 2020; MacArthur et al., 2018). This sets them apart from c-bikes in mode and route choice (Fishman & Cherry, 2016; Meister et al., 2023), but few previous studies investigating e-bike mode choice include a measure for hilliness, Reck et al. (2022) being a notable exception. In our data, we have no information about the chosen route. Especially in very hilly areas, cyclists are unlikely to follow a straight line between origin and destination, prohibiting measuring gradient along such a virtual route. We therefore compute the average gradient of the terrain surrounding the origin and destination of each trip. By "gradient of terrain," we refer to the average rate of elevation change over horizontal distance, expressed as a percentage. This serves as a non-linear proxy for the hilliness a traveler would encounter when moving between two points in that area. The gradient data are derived from the topographic dataset by Burgdorf and Pütz (2019), which provides the average gradient for each 250-by-250-meter grid cell in Germany, calculated using the elevation differences between a given cell and its eight surrounding neighbors. To construct our variable, we aggregate these data to a 1-kilometer-resolution by averaging the gradients of the sixteen 250-meter cells within each 1-km cell. Figure 4.1 (left) depicts the resulting gradient values for all 1 km grid cells in Germany. For every trip, the variable gradient is assigned the larger gradient value of the origin and the destination cell. This is because initial testing showed this method increased adjusted $\bar{\rho}^2$ compared to choosing the average or minimum of the two values.

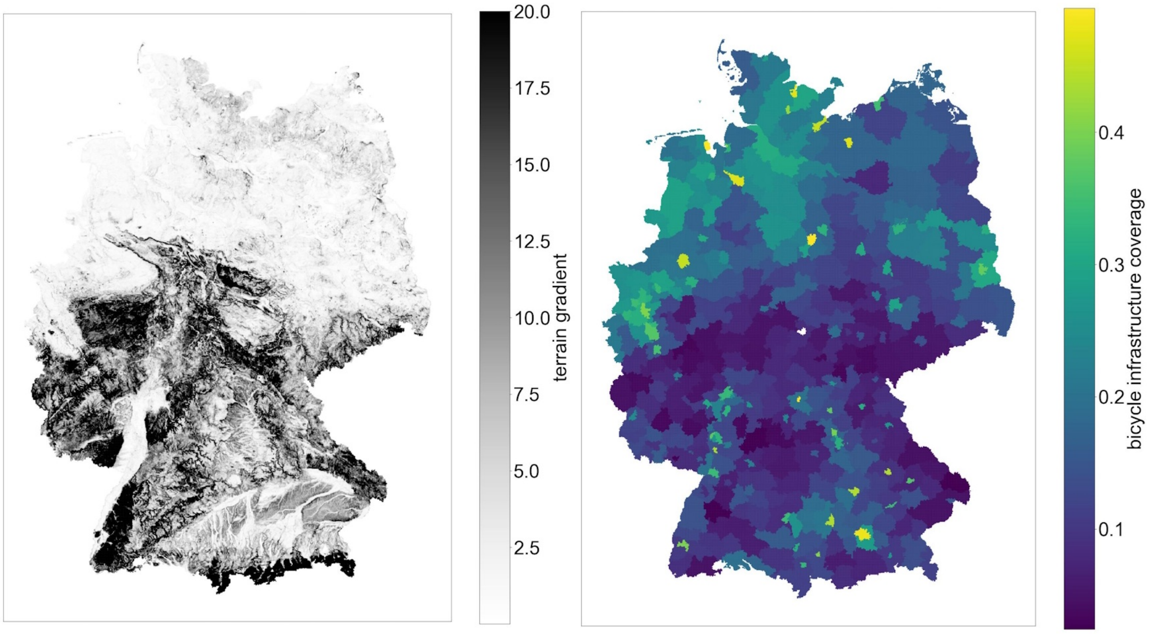

Figure 4.1: Average gradient [%] of terrain for 1km grid cells (left) and ratio of bicycle infrastructure length against total road network length of NUTS3 regions (right)

4.3.1.2 Bicycle Infrastructure

The provision of bicycle infrastructure influences the decision to cycle. Some studies suggest a difference between users of c-bikes and e-bikes regarding their preference for bicycle infrastructure in route choice (Allemann & Raubal, 2015; Hardinghaus & Weschke, 2023; Khavarian, Vosough, & Roncoli, 2023; Meister et al., 2023). To investigate whether this difference exists for mode choice, we compute a pragmatic and scalable measure for spatial bicycle infrastructure coverage. It is calculated for each of the 400 NUTS3 regions in Germany using OpenStreetMap data. Namely, we measured the total length of the road network (only roads typically permitting bicycle access) and the total length of dedicated bicycle infrastructure for each region using the overpass turbo API. For the typically bicycle-accessible roads, we queried ways tagged as highway=primary, secondary, tertiary, residential, living_street, or unclassified. For bicycle infrastructure, we queried bicycle=designated, bicycle_road=yes, bicycle:lanes=yes, cyclestreet=yes, highway=cycleway, cycleway=cyclestreet, lane, track, or opposite_track, and cycleway:left or cycleway:right=lane or track. For the complete code we refer to the GitHub repository. For every region, the length of the dedicated bicycle network was divided by the length of the bicycle-accessible road network. The resulting variable is shown in Figure 4.1 (right). Every trip was assigned the bicycle infrastructure value of the NUTS 3 region where its origin and destination grid cells are located. For inter-regional trips, the average was calculated. We acknowledge that this variable can only be considered a rough proxy for the amount and quality of bicycle infrastructure likely encountered during a trip, but it appropriately captures the regional differences in levels of bicycle infrastructure provision in Germany.

Table 4.1: Mode-level reweighting factors

Mode	walking	c-bike	e-bike	car-p	car-d	public trans.
Reweight factor	10.014	12.295	10.487	1.102	0.629	0.592

4.3.1.3 Public Transport Departures

As evident from the literature, e-bike travel is a relevant substitute for public transport. To reflect the varying levels of public transport's competitiveness with cycling, we include a variable describing the number of daily public transport departures around the origin and destination of each trip. DELFI e.V. (2023)'s ZHV dataset provides a comprehensive list of public transport stops in Germany, including location and timetable data. We summed up the number of public transport departures of all stops within 2 km around the center of each 1 km grid cell. This value was logarithmized using base e to account for decreasing marginal utility of additional departures. Negative values after logarithmization (i.e. 0 departures) are adjusted to 0. A map of the resulting values for all 1 km grid cells in Germany is depicted in Figure 4.2 (left). For each trip, a variable departures is calculated as the mean of the logarithmized departures value of the cells of trip origin and destination.

4.3.1.4 Spatial Typology

The degree of urbanization of a place has been shown to affect travel behavior, in particular c-bike and e-bike mode choice (Kohlrautz & Kuhnimhof, 2024). We used the RegioStaR 4 dataset (Bundesministerium für Digitales und Verkehr, 2021), which assigns every municipality in Germany one of four spatial typologies, namely "urban metropolitan", "urban regiopolitan", "rural close to city", and "rural peripheral". Figure 4.2 (right) depicts this categorization for Germany. The respective spatial typology code was mapped to each individual trip, again using the 1 km grid cell location of origin and destination. The more peripheral code takes precedence in cases of different spatial typology at origin and destination.

4.3.2 Descriptive Statistics

The original MiD B3 dataset contains 960,619 trips, undertaken by 259,509 persons in 136,357 households. After data processing described in the previous section, 194,524 trips by 78,843 persons in 61,748 households remain. While the MiD aims to gather representative data, differences in individuals' selection probability necessitate the use of weights, which the MiD reports at the trip-level, if one wants to investigate market shares of the underlying population. Removing trips with missing variables disproportionally affected trips undertaken by foot, c-bike, and e-bike. To counteract this, we apply a mode-level reweighting factor to the original trip-level weights so that the weighted modal split of the final sample is the same as the weighted modal split of the original dataset. We report those reweighting factors in Table 4.1. In Table 4.2, we report descriptive statistics of the final sample for categorical variables both completely unweighted, i.e. by the sheer number of recorded trips in the final sample, and weighted with trip-level weights that were furthermore adjusted with the mode-level reweighting factors.

Table 4.3 reports mean values of the continuous variables. Figure 4.3 depicts the respective box plots with median values, first and third quartile, and farthest data points within 1.5 times the

Table 4.2: Descriptive statistics of categorical variables at trip-level

Variable	Unweighted share [%]	Weighted share [%]	Variable	Unweighted share [%]	Weighted share [%]
choice			**education**		
walking	2.1	21.9	none (yet)	1.7	2.7
c-bike	0.9	10.6	"Volks-/Hauptsch."	14.1	23.6
e-bike	0.1	0.6	“Mittlere Reife”	25.9	27.6
car-p	13.0	13.9	"(Fach-)hochschulr."	20.0	18.7
car-d	70.1	43.1	university degree	38.2	27.4
public trans.	13.8	9.8	**sex**		
mobility tools			female	50.2	52.8
c-bike	80.4	78.4	male	49.8	47.2
e-bike	7.3	5.9	**trip purpose**		
car	93.6	84.9	work commute	18.1	16.6
ticket	19.3	22.4	commercial	4.0	3.6
age			education	1.8	2.2
0-17	1.4	2.0	shopping	22.8	23.9
18-29	8.7	14.4	other errands	18.8	18.1
30-39	10.1	15.4	leisure	25.9	28.3
40-49	16.0	16.6	escort	8.6	7.4
50-59	23.7	18.5	**season**		
60-69	20.9	15.6	winter	20.8	21.7
70-79	15.3	13.4	spring	32.4	27.3
80+	3.9	4.2	summer	30.8	30.1
eco. status			autumn	15.9	20.8
very low	2.4	6.3	**spatial typology**		
low	7.5	13.1	urban metrop.	53.9	52.2
middle	41.3	45.3	urban regiop.	19.9	19.6
high	38.0	29.2	rural close to city	14.3	16.3
very high	10.7	6.1	rural peripheral	11.8	11.9

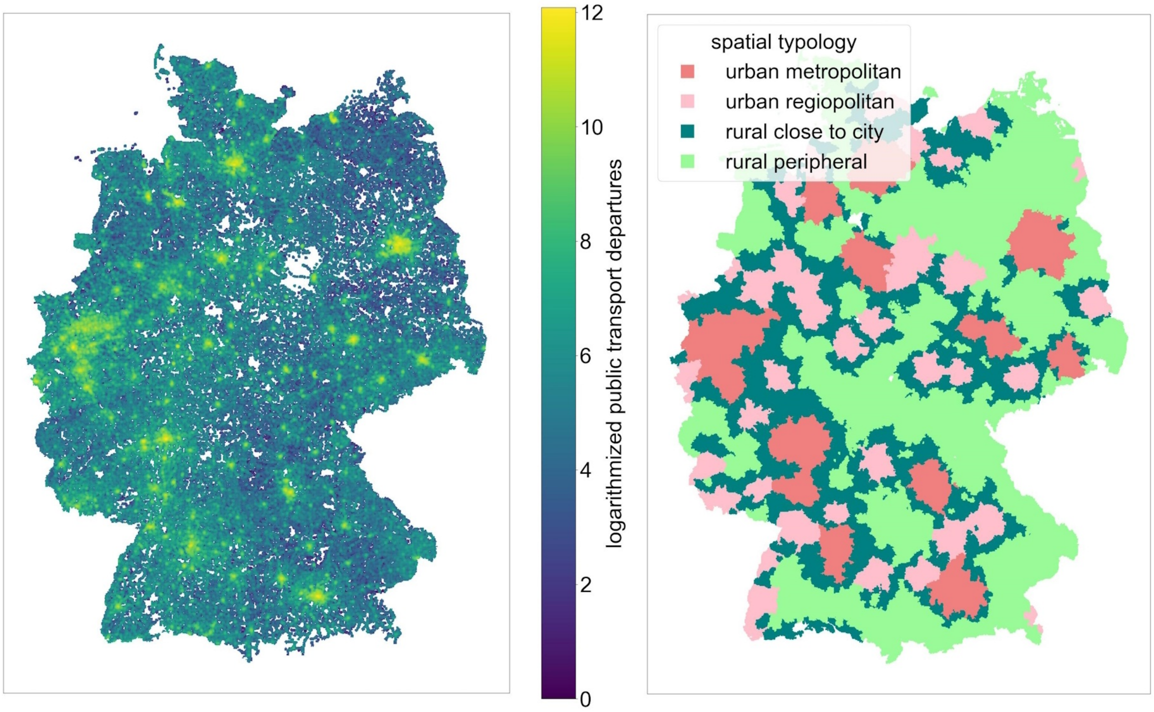

Figure 4.2: Logarithmized public transport departures within 2 km of the center of each 1 km grid cell (left) and spatial typology (right)

Table 4.3: Descriptive statistics of continuous variables at trip-level

Variable	**Unweighted mean**	**Weighted mean**
distance [km]	10.0	7.6
gradient [%]	6.6	6.2
bic. infrastructure [%]	22.5	21.9
departures []	21,747	22,191

interquartile range from the box. Values for distance and departures are reported before logarithmization.

4.4 Model

Based on the review of model types, we construct an NL model. During model development, we tested four nesting structures, namely nesting (i) car-d and car-p, (ii) c-bike and e-bike, (iii) walking, c-bike, and e-bike, and (iv) c-bike and e-bike as well as car-d and car-p. In all cases, the nest parameters for the active mobility nests were very close to and not significantly different from 1. This was the case both with and without using weights. Only the car nest exhibited significant nest parameters, which is why we adopt nesting structure (i). Comparing this NL variant to an MNL model with otherwise identical model specifications, nesting improves log-likelihood from -116,210.6 to -116,167.5. This gives a likelihood ratio test statistic of $\chi^2 = 2 * (-116,167.5 - (-116,210.6)) = 43.1$, which is much larger than 3.8, the critical value of the χ^2-distribution with one degree of

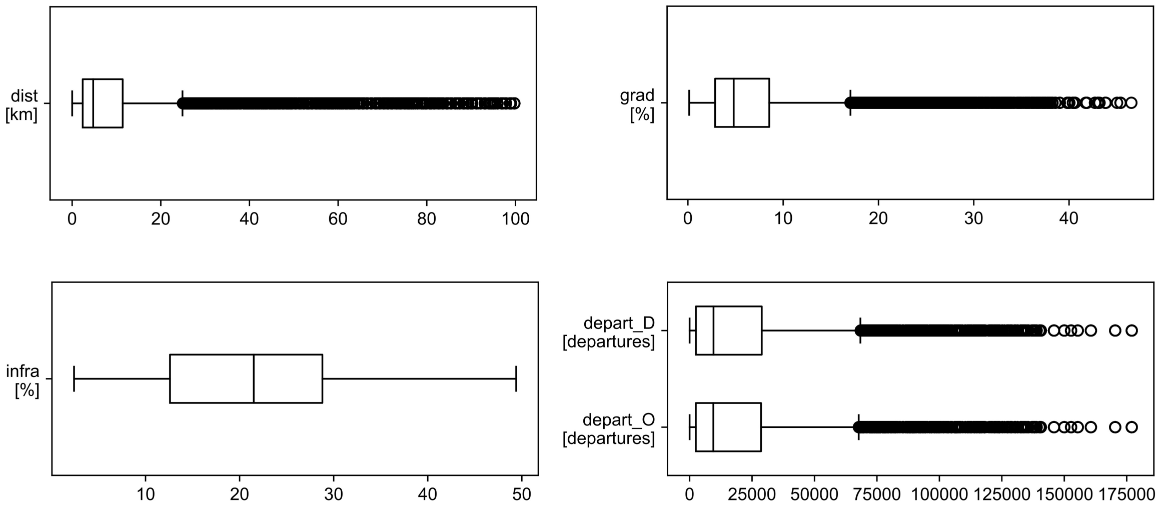

Figure 4.3: Box plots for continuous variables at trip-level (unweighted)

freedom and a significance level of 5 %. We can therefore reject MNL in favour of NL.

Because of the cross-sectional nature of the data and the resulting low number of trips recorded per person, we treat characteristics of persons and households as attributes at the trip-level and do not consider a mixed logit approach. Mobility tool availability is a necessary condition for choosing c-bike, e-bike, car-p and car-d. In other words, for every trip where no e-bike is available to the decision maker, the probability of choosing e-bike is assumed to be zero and the trip does not contribute to estimating the coefficients of the e-bike utility function. In contrast, the availability of a public transport season ticket was included as a binary variable in the public transport utility function instead of being considered a necessary condition, because other ticket options are available.

In Equations 4.1 to 4.6, we explain the utility functions of the six modes in order of ascending complexity. The model was identified by setting the utility of walking to 0. All other utility functions contain an ASC (alternative specific constant). For legibility reasons, we bundle dummy variables with values 0 or 1 for all expressions of the categorical variables age, economic status, level of education, trip purpose, spatial typology, and sex, excluding one reference category each, in a vector $\hat{categ}$. In Equation 4.2 (car as passenger) and Equation 4.3 (car as driver), $\hat{\beta}_{carp,categ}$ and $\hat{\beta}_{card,categ}$ contain the coefficients for the categorical variables in vector form. After applying the natural logarithm to $dist$, the variable is multiplied with coefficient $\beta_{carp,dist}$ or $\beta_{card,dist}$. Besides these observable parts, utility U also consists of a random error term ϵ, which is assumed to be independent and identically Gumbel distributed. For legibility, an index indicating trip-level is omitted.

$$U_{walking} = 0 + \epsilon \tag{4.1}$$

$$U_{carp} = ASC_{carp} + \hat{\beta}_{carp,categ} * \hat{categ} + \beta_{carp,dist} * ln(distance) + \epsilon \tag{4.2}$$

$$U_{card} = ASC_{card} + \hat{\beta}_{card,categ} * \hat{categ} + \beta_{card,dist} * ln(distance) + \epsilon \tag{4.3}$$

Equation 4.4 gives the utility function for public transport. In addition to the components of the previous utility functions, the binary variable ticket and the continuous, logarithmized variable departures are multiplied with coefficients β_{ticket} and $\beta_{departures}$.

$$U_{pt} = ASC_{pt} + \hat{\beta}_{pt,categ} * \hat{categ} + \beta_{pt,dist} * ln(distance) + \beta_{ticket} * ticket + \beta_{departures} * ln(departures) + \epsilon \tag{4.4}$$

Besides the indices *cbike* and *ebike*, the utility functions for c-bike and e-bike in Equations 4.5 and 4.6 are identical to each other. We hence only explain the c-bike variant. For *season*, three dummy variables with respective coefficients are included. The continuous variable for bicycle infrastructure coverage *bicinfra* is multiplied with the coefficient $\beta_{cbike,bicinfra}$. We interact *gradient* with *age*. Namely, the three coefficients $\beta_{cbike,grad,age123}$, $\beta_{cbike,grad,age45}$, and $\beta_{cbike,grad,age678}$ are estimated only on trips undertaken by persons in age classes 1, 2, and 3 (age 0-39), 4 and 5 (age 40-59), or 6, 7, and 8 (age 60+) respectively. Summing mutually exclusive dummies for the categorical expressions of age serves as a logical "or" operation, multiplication of the resulting value 0 or 1 with the following term as a logical "if" operation. We also note that the gradient-related coefficients enter the utility function in exponential rather than linear form, and that their contributions are specified as negative. This specification reflects the outcome of testing multiple model formulations, with this version yielding the highest adjusted $\bar{\rho}^2$, indicating the best model fit.

$$\begin{aligned}
&U_{cbike} = ASC_{cbike} + \hat{\beta}_{cbike,categ} * \hat{categ} + \beta_{cbike,dist} * ln(distance) + \\
&\beta_{cbike,bicinfra} * bicinfra + \hat{\beta}_{cbike,season} * \hat{season} - \\
&(age_1 + age_2 + age_3) * gradient^{\beta_{cbike,grad,age123}} - (age_4 + age_5) * gradient^{\beta_{cbike,grad,age45}} - \\
&(age_6 + age_7 + age_8) * gradient^{\beta_{cbike,grad,age678}} + \epsilon
\end{aligned} \tag{4.5}$$

$$\begin{aligned}
&U_{ebike} = ASC_{ebike} + \hat{\beta}_{ebike,categ} * \hat{categ} + \beta_{ebike,dist} * ln(distance) + \\
&\beta_{ebike,bicinfra} * bicinfra + \hat{\beta}_{ebike,season} * \hat{season} - \\
&(age_1 + age_2 + age_3) * gradient^{\beta_{ebike,grad,age123}} - (age_4 + age_5) * gradient^{\beta_{ebike,grad,age45}} - \\
&(age_6 + age_7 + age_8) * gradient^{\beta_{ebike,grad,age678}} + \epsilon
\end{aligned} \tag{4.6}$$

In addition to the interaction of gradient with age, several other interactions for c-bike and e-bike were tested but not included in the model. We briefly report on those to inform future research and for transparency regarding the ratio of the number of true relationships to the number of no relationships among those tested (Ioannidis, 2005). For distance, interactions with age, economic status, purpose, season, and sex were tested but dismissed, either due to a decrease in adjusted $\bar{\rho}^2$ or, in the cases of interacting distance with whether the trip is a leisure trip or not, no statistically significant difference between the distance sensitivities for leisure trips versus utilitarian trips. For gradient, interactions with distance (Reck et al., 2022) and sex were also tested but dismissed in favor of interaction with age due to a larger increase in adjusted $\bar{\rho}^2$. Effect coding instead of dummy coding was tested for economic status and level of education but dismissed due to lower adjusted $\bar{\rho}^2$. In model estimation, the adjusted weights were multiplied with each trip's contribution to the log-likelihood. Estimation and simulation were implemented using Python Biogeme 3.2.14 (Bierlaire, 2023).

Table 4.4: Observed and simulated mode shares (5-fold cross-validation)

	walking	c-bike	e-bike	car-p	car-d	public trans.
Obs.	21.183 %	11.298 %	0.922 %	14.349 %	44.093 %	8.155 %
Sim.	21.181 %	11.289 %	0.932 %	14.352 %	44.091 %	8.154 %

4.5 Results

In this section, we report on validation, the estimation results, highlight interesting coefficient values, and compute and interpret elasticities and substitution rates.

4.5.1 Validation

Our validation framework is based on Parady, Ory, and Walker (2021). To investigate reproducibility, we conduct internal validation through k-fold cross-validation, namely mode share predictions by distance class, trip purpose, and age group. We also superficially investigate spatial transferability by predicting mode shares for two German cities with pronounced cycling affinity and averseness.

4.5.1.1 K-fold cross-validation

We split the sample into five parts of almost equal size, estimate the model on four of the five parts, and simulate choice probabilities for the trips in the fifth part. This is repeated five times, so that choice probabilities are simulated for every trip based on a model that did not use that trip in model estimation. To calculate simulated mode share, one can either count the number of trips where a mode has the highest choice probability of all six modes and divide it by the total number of trips or sum the choice probabilities of each mode across all trips. The latter is more appropriate because the former systematically disadvantages less frequently chosen modes. This is because the logit model by design returns choice probabilities, not individual predictions: we do not aim to predict a single individual's choice but to predict market shares for subsets of trips. For the same reason, validation measures such as fitting factor or confusion matrix are also not appropriate.

Table 4.4 reports the observed mode shares among the sample and compares them to simulated mode shares. Identical reweighting factors from Table 4.1 are applied to both rows to have model results resemble real-world mode shares. This reweighting does not sugarcoat validation; in fact, it slightly increases root-mean-square errors (RMSE). Table 4.4 shows that simulated mode shares are almost identical to the observed mode shares. The RMSE is 0.00006, indicating that the model very accurately predicts mode shares at the national level.

In Table 4.5, we report observed and simulated mode shares for different distance classes, trip purposes, and age groups to investigate whether the reproducibility of the model is restricted to the national scale or can also be assumed when applied to unrepresentative subsets of trips.

The RMSE across distance classes, trip purposes, and age groups are 0.00733, 0.00115, and 0.00002, respectively. These values reflect a high reproducibility regarding mode share predictions. Even in the worst case analyzed (distance), mode share predictions for individual modes are typically only 0.6 percentage points off the true value.

Table 4.5: Observed and simulated unweighted mode shares by trip distance, trip purposes, and age class (5-fold cross-validation)

		walking	c-bike	e-bike	car-p	car-d	public trans.
dist <5 km	Obs.	31.94%	14.72%	0.97%	11.06%	36.03%	5.27%
	Sim.	32.28%	14.54%	0.96%	10.92%	35.97%	5.34%
5 <= dist <10	Obs.	4.07%	8.13%	0.95%	18.57%	53.82%	14.47%
	Sim.	3.25%	8.19%	0.99%	19.15%	54.53%	13.89%
10 <= dist <50	Obs.	1.14%	3.24%	0.78%	20.75%	61.72%	12.36%
	Sim.	0.54%	3.78%	0.86%	21.00%	61.35%	12.47%
50 <= dist	Obs.	0.00%	1.69%	0.29%	26.90%	60.53%	10.60%
	Sim.	0.02%	1.10%	0.44%	24.69%	61.02%	12.73%
work commute	Obs.	13.79%	10.56%	0.54%	4.69%	55.04%	15.39%
	Sim.	13.81%	10.55%	0.54%	4.69%	55.03%	15.39%
commercial	Obs.	12.81%	16.41%	1.17%	7.15%	54.72%	7.74%
	Sim.	12.84%	16.41%	1.15%	7.17%	54.69%	7.73%
education	Obs.	21.19%	12.82%	0.00%	10.18%	18.61%	37.19%
	Sim.	21.22%	12.79%	0.01%	10.76%	18.18%	37.05%
shopping	Obs.	23.67%	11.43%	0.83%	14.76%	45.08%	4.22%
	Sim.	23.66%	11.42%	0.85%	14.78%	45.07%	4.22%
other errands	Obs.	20.73%	10.67%	1.32%	15.72%	44.74%	6.81%
	Sim.	20.72%	10.67%	1.33%	15.72%	44.75%	6.81%
leisure	Obs.	26.26%	12.65%	1.11%	20.25%	31.56%	8.17%
	Sim.	26.26%	12.65%	1.13%	20.21%	31.59%	8.17%
escort	Obs.	12.21%	5.03%	0.24%	9.43%	70.66%	2.43%
	Sim.	12.20%	5.01%	0.24%	9.43%	70.69%	2.44%
0-29	Obs.	23.81%	12.47%	0.00%	18.69%	26.85%	18.18%
	Sim.	23.83%	12.48%	0.00%	18.65%	26.87%	18.18%
30-49	Obs.	19.02%	11.13%	0.26%	11.80%	48.90%	8.89%
	Sim.	19.02%	11.13%	0.28%	11.77%	48.91%	8.89%
50-69	Obs.	19.53%	11.73%	1.08%	13.85%	47.67%	6.14%
	Sim.	19.52%	11.71%	1.09%	13.87%	47.67%	6.14%
70+	Obs.	25.88%	9.97%	1.84%	16.17%	39.78%	6.36%
	Sim.	25.87%	9.96%	1.85%	16.21%	39.75%	6.35%

Table 4.6: Observed and simulated unweighted mode shares (city cross-validation)

		walking	c-bike	e-bike	car-p	car-d	public trans.
Münster	Obs.	27.57%	13.54%	0.00%	13.65%	37.41%	7.82%
	Sim.	15.30%	17.90%	1.05%	16.23%	42.22%	7.28%
Wuppertal	Obs.	21.54%	1.10%	0.00%	19.65%	45.66%	12.04%
	Sim.	22.14%	2.12%	0.20%	16.71%	45.20%	13.64%

4.5.1.2 City cross-validation

We investigate spatial transferability within Germany by looking at two extreme cases in terms of cycling, namely the cities of Münster and Wuppertal. While Münster is known as a bicycle-friendly city with a strong cycling culture and high mode share of cycling, Wuppertal features challenging terrain and low levels of cycling. Both cities are roughly equal in size (320,000 and 350,000 inhabitants), located in North-Rhine Westphalia, and have universities. For each city, we split the complete sample into a city sample (trips undertaken by residents of that city) and an out-of-city sample (all other trips). We estimate the model on the out-of-city sample and use it to simulate choice probabilities for the city sample. In Table 4.6 we compare the resulting simulated mode shares for trips by residents of each city with the observed mode share of those trips, validation against external mode share data was not possible because of differences in survey methodology.

We expect larger differences between observed and simulated shares compared to the national mode share predictions because of the lower sample size and consequent random effects. Specifically, the above mode shares are based on only 323 trips for Münster and 1261 trips for Wuppertal, with no e-bike trips being recorded in either city. For the same reason, we expect a higher RMSE. They are 0.05785 and 0.01463, respectively. In conclusion, we judge our model to achieve a reasonable degree of generalizability within Germany. We note that in practical application within a strategic transport model of a specific city or region, it would still undergo calibration to adjust it to specific local mode share data, further enhancing its predictive accuracy.

4.5.2 Coefficient Values

Estimation results based on the complete sample are reported in Table 4.7. Biogeme reports coefficient values with three significant digits. We further rounded to a maximum of three decimal places. Coefficient values significantly different from 0 with 95 % confidence are bolded. First, we point out some noteworthy results for the non-cycling modes. No significant coefficients have implausible signs. Coefficient values for spatial typology decreased in magnitude after including more specific spatial variables, but remained relevant. Regarding the magnitude of the linear coefficient for departures, one has to consider that it is usually multiplied with values larger than 1.

In the following paragraphs, we describe our findings for c-bike and e-bike in more detail. We point out that for the c-bike, e-bike, car-d, and car-p, mobility tool availability is a "hard" prerequisite for choosing the respective mode instead of "soft" components of the utility functions. In other words, the model coefficients represent the impact of the respective variable on mode choice only, not on mobility tool ownership. When interpreting coefficients of these modes, one needs to picture a person who has access to the respective mobility tool. Furthermore, because we identified the model by setting walking as the reference alternative, one needs to compare coefficient values both within each mode across categories, but also across modes within each category. For example, the effect of older age categories on the utility of choosing to use the c-bike is insignificant, because it is relative to walking. This does not indicate that increasing age does not reduce the likelihood of choosing the c-bike; instead, this is captured by an increase in utility of car-p and public transport compared to walking and c-bike.

The linear coefficients for the logarithmized variable **trip distance** demonstrate that people are less sensitive to longer distances on e-bike than on c-bike, reflected in more added utility per distance compared to walking. In fact, e-bike distance sensitivity is closer to both car-d and car-p than to c-bike.

For c-bike, compared to the reference **age** category of 40-49 years old and relative to the baseline of walking, there is a dip in utility for the age group 18-39. This might be due to raising small children. For e-bike, we observe counterintuitive findings at first glance, since earlier works depict e-bike ownership and use in Germany as a phenomenon of the elderly (Arning & Kaths, 2025b; Kohlrautz & Kuhnimhof, 2024). Our findings demonstrate that this observation can partially be attributed to differences in e-bike ownership, and that among the persons who have access to an e-bike, age plays a smaller role in determining actual mode choice. The significant and opposite impacts of age groups 18-29 and 30-39 might be due to adult children living at home whose parents own e-bikes versus young parents acquiring e-cargo-bikes to transport their small children, respectively.

The impact of **economic status** on bicycle mode choice is mostly negligible after accounting for bicycle ownership. The strong positive effect of very low economic status on the propensity to choose e-bike is likely because households with limited financial resources who decide to acquire an e-bike have a strong use case for it. For c-bike mode choice, there are few meaningful differences to walking, car-d or public transport across different **levels of education**. A comparative advantage of c-bike among university graduates is likely due to personal attitudes towards cycling, which are not explicitly captured in our model, correlating with education. The implications of the highly significant, negative impact of both the highest and lowest level of education on the utility of choosing e-bike is less clear. For "none (yet)", it might be due to correlation with the youngest age group. Regarding sex, we find that using an e-bike might have a slightly smaller disutility for women compared to c-bikes, however the difference between the coefficients is insignificant.

The **trip purpose** "education" interestingly does not significantly contribute to the utility of choosing c-bike, even more so when compared to its positive contribution to choosing public transport. This indicates that the high usage of c-bikes for ways to school is most adequately explained by other factors such as c-bike availability, young age or short trip distance. The surprisingly positive influence of "commercial" is abated by similarly strong coefficients for car-p and car-d, which are more common modes for such trips. Comparing e-bike to c-bike, the larger coefficient values for "commercial", "other errands", and to a lesser degree "shopping" indicate a better suitability for transporting goods.

While almost all **spatial typology** coefficients are significantly positive, with the contribution being stronger for more peripheral regions, there are no large differences across modes. In other words, these results simply reflect a particular utility for walking in urban areas. After including the more specific spatial variables departures, gradient and bicycle infrastructure, the influence of spatial typology on the utility of c-bike and e-bike compared to motorized modes is negligible. For both types of bicycle, season is the most impactful categorical variable. Compared to the reference category

Table 4.7: Estimation result

Variable		c-bike value	p-value	e-bike value	p-value	car-p value	p-value	car-d value	p-value	public trans. value	p-value
ASC		**0.415**	0.015	-0.476	0.504	-0.067	0.843	**1.48**	0.000	**-10.1**	0.000
ln(dist)		**1.23**	0.000	**1.88**	0.000	**2.30**	0.000	**2.23**	0.000	**2.47**	0.000
age	0-17	0.409	0.191	-0.887	0.319	-0.174	0.503	**-1.67**	0.000	0.253	0.248
	18-29	**-0.386**	0.013	**-2.51**	0.000	-0.079	0.381	**-0.339**	0.000	**-0.335**	0.000
	30-39	-0.295	0.052	**1.70**	0.037	-0.046	0.546	-0.136	0.064	-0.068	0.399
	40-49										
	50-59	0.025	0.800	0.477	0.277	-0.015	0.812	-0.021	0.730	0.060	0.378
	60-69	0.179	0.147	0.650	0.249	0.004	0.955	-0.111	0.074	**0.243**	0.001
	70-79	0.039	0.764	0.849	0.146	-0.048	0.508	**-0.195**	0.003	**0.373**	0.000
	80+	0.042	0.842	**1.41**	0.027	**0.386**	0.000	0.167	0.099	**0.885**	0.000
eco.	very low	0.263	0.142	**1.30**	0.006	0.208	0.065	0.219	0.051	**0.327**	0.006
	low	0.086	0.443	0.030	0.934	-0.085	0.204	-0.022	0.741	0.073	0.309
	middle										
	high	**0.178**	0.011	0.040	0.849	**0.152**	0.000	**0.179**	0.000	**0.112**	0.017
	very high	0.004	0.973	0.307	0.286	**0.193**	0.003	**0.222**	0.001	-0.001	0.989
edu.	none (yet)	-0.111	0.706	**-2.51**	0.000	0.092	0.645	-0.031	0.876	0.311	0.134
	Volks-/Hauptsch.	-0.174	0.120	-0.201	0.462	0.094	0.162	-0.024	0.711	0.041	0.569
	Mittlere Reife	-0.085	0.360	-0.221	0.387	**0.125**	0.025	0.094	0.089	0.050	0.417
	(Fach-)hochschulr.										
	university degree	-0.025	0.759	**-0.707**	0.006	**-0.206**	0.000	**-0.196**	0.000	-0.081	0.144
sex	*male*										
	female	**-0.171**	0.004	-0.111	0.518	**0.433**	0.000	-0.038	0.328	**0.187**	0.000
purp.	*work commute*										
	commercial	**0.628**	0.000	**1.27**	0.007	**0.745**	0.000	**0.504**	0.000	-0.108	0.415
	education	-0.211	0.405	**-3.55**	0.000	-0.206	0.248	**-0.474**	0.004	**0.498**	0.003
	shopping	0.126	0.234	0.568	0.117	**1.35**	0.000	**0.860**	0.000	**-0.387**	0.000
	other errands	0.064	0.571	**0.769**	0.032	**1.04**	0.000	**0.541**	0.000	-0.118	0.119
	leisure	-0.179	0.075	0.232	0.505	**0.412**	0.005	**-0.272**	0.000	**-0.624**	0.000
	escort	-0.173	0.340	0.139	0.835	**1.76**	0.000	**1.60**	0.000	**-0.491**	0.000
sp. typ.	*urban metrop.*										
	urban regiop.	**0.229**	0.003	0.304	0.186	**0.274**	0.000	**0.267**	0.000	0.093	0.070
	rural close to city	**0.547**	0.000	**0.770**	0.001	**0.561**	0.000	**0.582**	0.000	**0.597**	0.000
	rural peripheral	**0.431**	0.000	**0.625**	0.030	**0.567**	0.000	**0.570**	0.000	**0.575**	0.000
ticket										**2.46**	0.000
ln(departures)										**0.859**	0.000
gradient	grad. x age 0-39	**0.391**	0.000	**0.622**	0.000						
	grad. x age 40-59	**0.367**	0.000	**0.275**	0.009						
	grad. x age 60+	**0.422**	0.000	**0.383**	0.000						
bic. infra.		**1.15**	0.000	-0.947	0.315						
season	winter	**-0.765**	0.000	**-2.04**	0.000						
	spring	**-0.386**	0.000	**-0.491**	0.005						
	summer										
	autumn	**-0.340**	0.000	**-0.834**	0.003						
N_{car}								**2.90**	0.000		

Coefficients: 152. Sample size: 194,524. Null log-likelihood: -300,359.2. Final log-likelihood: -116,167.5. Adjusted $\bar{\rho}^2$: 0.613. Reference categories in *cursive*. Coefficient values with $p \leq 0.05$ **bolded**.

Table 4.8: Point-elasticities for c-bike and e-bike mode share

	ln(distance)	gradient	bic. infrastructure
c-bike	-0.369	-0.510	0.237
e-bike	-0.182	-0.387	-0.164

summer and the reference alternative walking, all other seasons have highly significant negative impacts on the utility of choosing a c-bike or e-bike, with the effect of winter being particularly strong. Interestingly, the seasonality effects are much stronger for e-bike compared to c-bike, perhaps due to interactions between season and leisure trips or e-bike use confounding with physical fragility.

Due to the formulation of the utility functions, larger **gradient** coefficient values indicate a stronger negative impact of gradient on utility. The exponential specification of the gradient term—selected based on superior model fit—implies that even modest increases in gradient result in a sharp decrease in c-bike utility compared to completely flat areas. However, as gradient increases further, the additional negative impact on utility diminishes. This pattern may reflect the fact that the average slope of road infrastructure is not linearly related to terrain gradient, as routes often avoid the steepest segments of the landscape. In terms of magnitude, gradient is a highly relevant variable for c-bike mode choice. For illustrative purposes, compare the c-bike utility of two trips that take the lower and upper quartile value of gradient respectively but are otherwise identical (40-49 years old, grad of 2.86 % vs 8.54 %). The difference in utility of 0.727 due to different gradient values is about the same as the difference between summer and winter (0.765). Comparing gradient coefficients across age groups and bicycle types, e-bikes generally appear less sensitive (with the exception of the youngest age group, which is only based on five observations), and sensitivity increases for the elderly. Not all differences between the six gradient coefficients are significant at 95 % certainty, however. Significant differences in gradient sensitivity can only be attested for three cases: 0-39 versus 40-59 (e-bike), 40-59 versus 60+ (c-bike), and 0-39 versus 60+ (e-bike). While gradient averseness regarding mode choice might actually not be that different between c-bike and e-bike, our inability to attest significant difference is at least in part also due to the high standard errors in e-bike coefficients, which reflect the low sample sizes, particularly for e-bike trips in the young and middle age groups.

A larger share of dedicated **bicycle infrastructure** in the road network positively and highly significantly influences the propensity to choose c-bike. For e-bike, the coefficient is negative and not significantly different from 0. This indicates that the provision of bicycle infrastructure is much less relevant for e-bike mode choice.

4.5.3 Elasticities

Elasticities describe the relative change of a dependent variable, in this case mode share, as a reaction to a relative change of an explanatory variable, and are of particular policy relevance. We calculate aggregate c-bike and e-bike point-elasticities for continuous variables using Biogeme's Derive functionality and report them in Table 4.8.

An increase in logarithmized trip distance of 1 % would lead to a reduction in c-bike mode share by 0.367 % (not percentage points). In other words, for a hypothetical city with a c-bike mode share of 15 %, an increase of logarithmized trip distance by 10 % for each trip (for a 5 km trip, this would mean a new trip distance of 5.87 km) would lead to a new c-bike mode share of 15 % * (1 - 10 * 0.00369) = 14.4 %. Applying the same scenario to e-bikes, e-bike mode share would only decrease to 15 % * (1 - 10 * 0.00182) = 14.7 %. This difference illustrates that while e-bike in competition with car and public transport still loses market shares as distance increases, it does so less rapidly than c-bike.

The average gradient of terrain cannot be meaningfully altered by policy measures, but the elasticities allow for a more intuitive interpretation than the exponential model coefficients. For c-bike in particular, if one were to halve the average gradient of terrain, it would increase c-bike mode share by around a quarter.

Infrastructure is the most policy-relevant model variable. The elasticity of e-bike mode share is based on an insignificant model coefficient and should hence be interpreted with caution. For c-bike, the value of 0.237 indicates that doubling bicycle infrastructure would increase c-bike mode share by almost a quarter (ignoring decreasing marginal utility with network expansion for illustrative purposes). It is important to highlight that the model is based on the assumption of a one-way causal relationship between the explanatory and dependent variables. In reality, decision-makers in regions with inherently more bicycle traffic might also have a higher motivation to expand bicycle infrastructure to please their electorate. We cannot say to what degree the coefficient and elasticity values might be overestimated due to the bidirectional nature of this relationship.

4.5.4 Substitution Rates

As shown in the literature section, reported e-bike substitution rates vary. To contribute to this discussion, we take all trips undertaken on e-bike, change e-bike availability to 0, and simulate new choice probabilities, thereby investigating what modes the trips would have been undertaken with if an e-bike had not been available (following the methodology of Reck et al. (2022)). We sum the new choice probabilities across all weighted trips. The resulting modal substitution rates have to be corrected using the reweighting factors from Table 4.1. By additionally weighting each trip by its length, we compute substitution rates for mileage as well as the number of trips. We report these results for trip and mileage substitution rates in Table 4.9 (Method 1). Note that unlike in the previous section, we have to use the original trip weights and readjust the resulting substitution rates with the reweighting factors instead of using adjusted trip weights, which would have consisted of both the original weights and the reweighting factors. This is because we are only looking at trips observed to be undertaken by e-bike, meaning all adjusted trip weights would be adjusted using the same reweighting factors. We cannot categorically rule out that the removal of entries with missing variables during data processing somehow systematically eliminated disproportionally many trips with a high bicycle potential from the sample. Comparing unweighted average e-bike trip length, a good indicator for cycling potential, does not support this concern, however, since it drops from 6.7 km to 6.2 km during data processing instead of increasing.

We find surprisingly high substitution rates for car-p (18.7 % of e-bike mileage) and car-d (49.3 % of e-bike mileage). In this light, it appears prudent to investigate possible reasons for an overestimation of car substitution rates. Firstly, our model does not consider the option of not undertaking a trip if the e-bike had not been available, in other words it ignores induced demand. Considering induced demand is likely lower than 12 % (1.5 x interquartile range of studies reviewed by Bigazzi and Wong (2020)), this would still leave a considerable car trips and mileage substitution

Table 4.9: E-bike substitution rates

		walking	c-bike	car-p	car-d	public trans.
Method 1	**Trip-based**	32.9%	13.1%	13.2%	35.1%	5.8%
	Km-based	11.5%	11.6%	18.7%	49.3%	8.9%
Method 2	**Trip-based**	27.9%	24.0%	11.8%	31.3%	5.0%
	Km-based	10.2%	18.4%	17.4%	45.8%	8.1%

rate. Secondly, Method 1 assumes that ownership of other mobility tools (c-bike, car, and ticket) would be identical if the person had not had access to an e-bike, when it seems likely that many people undertaking e-bike trips gave up a c-bike in exchange for an e-bike in the past. Specifically, c-bikes were unavailable for 38 % of all e-bike trips. For those cases, Method 1 assumes a c-bike choice probability of 0. To counteract this, we report a second set of substitution rates in Table 4.9 (Method 2), with the only difference to Method 1 being that as we change e-bike availability to 0, we also change that of c-bike to 1. Even when assuming every person who undertook an e-bike trip would have had access to a c-bike instead of an e-bike, substitution rates remain low for c-bike and high for car-p and car-d. In summary, even using the more conservative Method 2, we find that 43.1 % of e-bike trips and 63.2 % of e-bike mileage would have taken place using car-d or car-p if no e-bike had been available.

4.6 Discussion

In this section, we discuss our results related to c-bike and e-bike mode choice by comparing them to other findings from the literature and highlighting policy relevance. We also address limitations and further research needs.

4.6.1 Contextualization and Policy Relevance

Our work is one of the first to investigate the impact of gradient on c-bike and e-bike mode choice using discrete choice modelling. Although c-bike and e-bike ownership are themselves closely associated with the average gradient surrounding an individual's place of residence (Arning & Kaths, 2025b), the influence of terrain extends beyond ownership patterns. Specifically, the gradient at the origin and destination of a trip continues to play a significant role in shaping mode choice. Steeper terrain is found to reduce the attractiveness of cycling overall, diminishing the utility of both conventional and electric bikes. While the model suggests that e-bikes are somewhat less sensitive to gradient than c-bikes, the difference in coefficient estimates is not statistically significant. Besides actual indifference, this might also be due to the low sample size of e-bike trips, in particular for the young age groups. This indicates that, although e-bikes may offer a modest advantage in hillier terrain, their relative resilience compared to c-bikes with regard to mode choice—after having accounted for the impact of gradient on c-bike and e-bike ownership—should be interpreted with caution. We therefore suggest that a measure for gradient should be included in bicycle mode choice modeling whenever possible, but we cannot attest based on our data whether a differentiation between c-bike and e-bike is always needed. In deductive modelling specifically, not including gradient could lead to misattributing its impact to correlated spatial variables, for example spatial typology or population density. For both types of bicycle, there are significant differences in gradient sensitivity between age groups, with the elderly being more gradient averse. To increase bicycle mode share in hilly areas, providing low gradient bicycle infrastructure such as cycling superhighways remains a relevant policy measure, even against the backdrop of the electrification of bicycle traffic.

Previous studies on e-bike route choice report mixed results on differences between c-bike and e-bike infrastructure preferences, with most indicating a lower sensitivity of e-bike to the provision of dedicated bicycle infrastructure (Allemann & Raubal, 2015; Khavarian et al., 2023; Meister et al., 2023) and some reporting the opposite (Hardinghaus & Weschke, 2023). Our findings regarding mode choice align with the former, despite the vast majority of e-bikes in Germany being allowed to use bicycle infrastructure, as opposed to S-Pedelecs, which are not allowed to use bicycle infrastructure and have higher market shares in some of the above studies. It seems unlikely that increasing bicycle infrastructure coverage truly reduces overall e-bike mode share (as pointed out earlier, the respective elasticity is based on an insignificant coefficient value), but small-scale substitution effects between c-bike and e-bike, where cyclists mitigate a lack of safe infrastructure by using e-bikes, seem plausible. While infrastructure design aimed at accommodating different needs of c-bike and e-bike should be informed by more in-depth and infrastructure-type-specific research, our findings suggest that differences in infrastructure preference between c-bike and e-bike should be considered in strategic transport models to accurately depict mode and route choice behavior.

After taking account for c-bike and e-bike ownership and interacting age with gradient, differences between c-bike and e-bike regarding age diminish. With this finding we contribute to the existing literature, which identifies age as an important determinant of e-bike use across countries (de Haas et al. (2022); Kohlrautz and Kuhnimhof (2024); MacArthur et al. (2018), to name a few), by clarifying that age first and foremost motivates the acquisition of an e-bike over a c-bike. Actual mode choice given the availability of either bicycles, especially in less hilly areas, is influenced by age to a still significant but smaller degree. Our finding regarding the negligible impact of spatial typology on the relative utility of c-bike and e-bike compared to motorized modes departs from Kohlrautz and Kuhnimhof (2024). This is likely due to the inclusion of more specific spatial variables, such as bicycle infrastructure and gradient, which both correlate with spatial typology.

It is already well-established that e-bikes extend the range of cycling by being faster and less physically exhausting (Bourne et al., 2020; Fishman & Cherry, 2016). We find that the e-bike is closer to car-p and car-d than to c-bike in terms of distance sensitivity. Considering our findings on the differences between c-bike and e-bike, as well as the rejection of nesting the two types of bicycles, it seems problematic to treat them as a single mode in strategic transport models. Only adjusting average mode attributes like speed to reflect the electrification of bicycle traffic might not be appropriate. Instead, c-bike and e-bike should be treated as distinct modes.

Lastly, our findings regarding substitution rates paint a very optimistic picture of e-bike mode shift from an environmental perspective. The more e-bike trips replace trips otherwise undertaken by car instead of cannibalizing c-bike, walking, public transport, or inducing new trips, the higher e-bikes' potential for promoting active mobility and reducing greenhouse gas emissions. Our e-bike-car substitution rates of 43.1 % (trips) and 63.2 % (mileage) are plausible when compared to meta-studies by Bigazzi and Wong (2020) and Bourne et al. (2020), yet represent a notable increase over previously reported values. Even after accounting for methodological constraints, we believe this to be evidence of the fact that the e-bike makes cycling more attractive for trip purposes, places, and user groups which previously would not have used a bicycle under those circumstances. This is especially true for the German context of this study, where overall c-bike mode share is lower than in many countries previously examined regarding e-bike mode shift. As future e-bike use spreads outside the group of early adopters and into groups with a smaller difference in utility between c-bike and e-bike (e.g. younger age groups), we expect e-bike substitution rates for c-bike trips to rise.

4.6.2 Limitations and Further Research

This study is limited primarily by data availability. We enriched the MiD dataset with additional spatial variables using the reported grid cell locations, but it was not possible to consider attitudinal data, which would have been particularly relevant for bicycle use (Bai, Sze, Liu, & Guo Haggart, 2020; Bourne et al., 2020). Monetary trip-level variables, such as ticket prices, fuel costs, or tolls, and travel time for non-chosen modes also cannot easily be computed retrospectively. We were therefore unable to compute willingness-to-pay or the value of time, which would have allowed for additional analyses and a better comparison with other studies. Future works could address this by recording attributes of non-chosen alternatives, or by using a stated preference instead of revealed preference approach. The latter should also include an option "no trip undertaken under these circumstances", which would allow for better investigation of questions about induced demand. Furthermore, while differences regarding gradient sensitivity between age groups and type of bicycle appeared meaningful, larger sample sizes of e-bike trips, particularly in younger age groups, are needed to attest statistical significance.

We computed the variables bicycle infrastructure coverage and gradient for uniform areas around origin and destination of each trip, instead of along a route between the two. This is because the chosen routes are unknown. Computing even just likely routes would have required more precise locations of origin and destination and an accurate, Germany-wide, routable network graph, which was outside the scope of this work. Revealed preference datasets suitable for bicycle mode choice modeling with route-level attributes are generally scarce. Route choice modeling typically relies on GPS tracks, which are often sourced from bike-sharing systems or local data collection initiatives. However, these datasets are usually not integrated into comprehensive travel behavior surveys. As a result, the sampled population tends to be unrepresentative, and only bicycle trips are captured—making it impossible to estimate a mode choice model, which, by definition, requires data across multiple transport modes. Since many attributes relevant for bicycle mode choice are found at the route level, future work should employ combined mode and route choice models for electric bicycle traffic and bridge this data gap. In this vein, built environment variables—identified as relevant factors by Rybarczyk and Wu (2014)—should also be investigated.

We provide evidence that including c-bike and e-bike ownership as necessary conditions for bicycle use in mode choice models, akin to car ownership, enhances model clarity. For practical application in strategic transport models, however, person-group and traffic-zone specific data on c-bike and e-bike ownership are not always available. We suggest further research to compare a mode choice model that does not explicitly regard bicycle ownership to the model presented here to see how much the model's predictive power decreases and whether the ownership decision can be indirectly captured within a mode choice model to a satisfying degree.

Lastly, in 2017, e-bikes were still a fringe phenomenon in Germany, with their overall mode share well below 1 %. Most users during that time can be considered early adopters, and we assume they had particularly large motivation for e-bike use, for example due to low physical fitness, a particularly challenging environment, or high levels of technological affinity. Since 2017, e-bike ownership rates and mode shares have grown rapidly, and we expect model coefficients, substitution rates, and perhaps the appropriateness of nesting c-bike and e-bike to evolve. Consequently, a replication of the present study using newer data, once available, would offer significant value—not only by capturing a larger and more representative sample of e-bike trips, but also by enabling a more nuanced investigation into how travel behavior evolves as e-bikes become increasingly adopted across broader and more mainstream segments of the population.

4.7 Conclusion

We presented a trip-level nested logit mode choice model differentiating between six modes, including conventional and electric bicycle, estimated on revealed preference data from the "Mobility in Germany 2017" survey and additional spatial data. Model validation indicates sufficient generalizability for the German context. Our study is the first to consider gradient and bicycle infrastructure in such an e-bike mode choice model. Our source code is available on GitHub (https://github.com/buw-bicycle-traffic/ebike-modechoice-model/tree/main).

Differences between c-bike and e-bike gradient averseness are not statistically significant for individual age groups, in part likely due to the low sample size of e-bike trips. However, there are significant differences between age groups for each type of bicycle, with older age groups being more averse to gradient. We also find that, akin to some prior works on route choice, e-bike appears to be less sensitive to the provision of bicycle infrastructure than c-bike. We report smaller substitution rates of e-bike mileage stemming from walking and c-bike (10.2 % and 18.4 %) and higher stemming from car (63.2 %) than previous studies. Therefore, e-bikes appear to afford a substantial mode shift away from the car towards active mobility and thus health and ecological benefits, at least concerning the phase of early adoption during which the data was recorded. This suggests that promoting e-bikes, e.g. through e-bike subsidies or dedicated infrastructure, is an effective strategy to increase active mobility, thereby inducing health benefits and reducing transport-related greenhouse gas emissions.

Nesting c-bike and e-bike or walking, c-bike, and e-bike during model testing resulted in nest coefficients not significantly different from 1, indicating little correlation in unobserved factors between these alternatives. This finding, together with the significant differences in model coefficients between e-bikes and conventional bicycles, indicates that e-bikes exhibit unique behavioral patterns and user preferences that are not captured by simply treating them as faster bicycles in transport models. These distinctions instead highlight the need to conceptualize e-bikes as a separate mode of transport within both policy frameworks and transport modelling practices. For policymakers, this means developing targeted infrastructure, incentive programs, and regulations that reflect the specific characteristics and needs of e-bike users. For transport modelling professionals, it underscores the importance of disaggregating e-bikes from c-bikes to more accurately capture travel behavior, mode choice dynamics, and the full potential of e-bikes in contributing to sustainable mobility transitions.

The rapid growth of e-bike market shares, their pronounced differences to c-bikes, and their potential to promote active, environmentally friendly mobility, call for policymakers to pay more attention to the electrification of bicycle traffic.

Chapter 5

Fourth Paper: Application

Contents

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Abstract

Increasing cycling is crucial for building sustainable cities. Electric bicycles reduce the physical effort required for cycling, particularly in hilly areas and for individuals with limited strength, contributing to lower car use and promoting social equity. However, current transport models often overlook the growing impact of electric bicycles on urban mobility. We present a macroscopic transport model for Wuppertal, Germany, the first to dynamically differentiate between conventional and electric bicycles across ownership, mode, and route choice. Our model incorporates bicycle infrastructure, gradient, motor vehicle speed, and turns in value of distance space. In ownership and mode choice, differences in preference between person groups and trip purposes are considered.

While the differentiated modeling approach did not improve the quality of the model compared to a model not differentiating between conventional and electric bicycle traffic, it provides valuable analytical insights. We evaluated three scenarios related to building more bicycle infrastructure and increasing e-bike ownership. Our results confirm that adding infrastructure increases cycling, although to a small degree. Infrastructure expansion primarily increases conventional bicycle use, whereas promoting electric bicycle ownership leads to a strong increase in electric bicycle trips, mostly replacing car trips. Synergies between electric bicycle adoption and infrastructure expansion are minimal but may vary depending on the characteristics of the latter. Furthermore, infrastructure expansion provides substantial benefits for existing cyclists beyond mere travel time savings. Our findings highlight the importance of integrating e-bikes into transportation models to accurately assess their impact on urban mobility and guide effective policy development.

5.1 Introduction

Increasing cycling is an effective strategy to make cities more sustainable and socially resilient. In recent years, electric bicycles (e-bikes) have gained popularity alongside conventional bicycles (c-bikes), especially in Europe and North America. Due to the electric assistance provided by e-bikes, cycling requires less physical exertion, which is particularly relevant in hilly cities, for longer trips, and for individuals with lower physical strength, such as older adults. E-bikes thus not only substitute for c-bike travel but also contribute to an overall increase in cycling, often displacing other modes of transportation. Therefore, e-bikes fundamentally change the role of cycling as a utilitarian mode of transport by reducing transport-related greenhouse gas emissions, contributing to more livable cities, and supporting social equity.

To analyze, forecast, and optimize transportation infrastructure, policies, and operations, cities use transport models. A transport model is a computational representation of a transportation system that simulates travel demand and the flow of traffic through a network. It consists of several sub-models, most commonly traffic generation, destination choice, mode choice, and route choice. Transport models used in practice largely neglect the electrification of bicycle traffic (Arning et al., 2023). This gives rise to several issues: models might be less accurate overall, they might underestimate future rates of cycling and the impact of measures such as new cycling infrastructure, and they cannot be used to analyze e-bike-specific policies. This study addresses the following research questions: How can existing strategic transport models be enhanced to better reflect differences between c-bikes and e-bikes? Does model quality improve compared to an undifferentiated bicycle mode? And are there e-bike specific effects of interventions aimed to promote cycling? To answer these questions, we develop a transport model for a hilly city that fully differentiates between c-bikes and e-bikes, identify practical problems in implementing such a modeling approach, assess the impact on model quality, and investigate the effects of e-bike availability and cycling infrastructure as well as interaction effects.

5.1.1 Literature on Transport Model Application

In this section, we provide an overview of academic publications on transport models with a focus on cycling. For a review of non-academic modeling practice, we refer to Arning et al. (2023). There, only two models were identified that consider the electrification of bicycle traffic, both falling short of modeling c-bikes and e-bikes as two distinct modes of transport throughout all sub-models.

We identified 15 relevant works on the development of transport models with a focus on cycling. We restrict our review to publications since 2017 because before that, bicycle-style e-bikes were still in the phase of early-adoption. They are summarized in Table 5.1. For comparison, we also include a brief description of the work we present in this paper at the bottom of the table. In three cases, multiple publications use the same model. Three out of twelve models are agent-based. The others use flow-based approaches, most commonly using the software PTV Visum. Only three model areas are outside of Europe. We note that in South and East Asia, the term e-bike is often used to refer to electric motorbikes, which are not considered here.

Bicycle **ownership** is considered in only one publication (Hebenstreit, 2021), where it is an attribute assigned to agents with fixed probabilities based on survey data. For **mode choice**, several approaches can be identified. In five models, no dynamic mode choice takes place. Instead, bicycle trip matrices are generated from observed data (de Melo & Isler, 2023; Jacyna et al., 2017; Kaziyeva et al., 2021), obtained from a separate model (Argyros et al., 2024), or mode shares are exogenous scenario variables (Fan & Harper, 2022). In the other seven models, some kind of impedance for bicycle traffic for origin-destination (OD) pairs is defined, which is then used to dynamically model mode shares. Three models use Nested Logit, with mode choice taking place at the nesting level before (Liu et al., 2020) or after (Hallberg et al., 2021; Paulsen & Rich, 2023) destination choice. Two models (Oskarbski et al., 2021; van Dulmen & Fellendorf, 2021) use Multinomial Logit (MNL), neither differentiating by person groups nor trip purposes. In the two MATSim models (Hebenstreit, 2021; Jafari et al., 2022), MATSim's standard scoring and routing parameters (Ziemke, Metzler, & Nagel, 2019) are used.

With two exceptions (Argyros et al., 2024; Fan & Harper, 2022), all models implement some kind of **route choice**. In seven cases, the demand for each origin-destination pair is assigned to the route with the lowest impedance (de Melo & Isler, 2023; Hallberg et al., 2021; Jacyna et al., 2017; Jafari et al., 2022; Kaziyeva et al., 2021; Liu et al., 2020; Paulsen & Rich, 2023). In the other cases, a stochastic assignment or agent routing distributes demand across several suitable routes (Hebenstreit, 2021; Oskarbski et al., 2021; van Dulmen & Fellendorf, 2021).

Table 5.1: Literature on the application of bicycle transport models

Source	**Model type, software**	**Area**	**Differentiation c-bike/e-bike**	**Bicycle ownership**	**Bicycle mode choice**	**Bicycle route choice**	**Intervention**
Jacyna et al. (2017)	Macroscopic, Visum	Warsaw	None	None	None, fixed generation rates from survey data.	Shortest distance via bicycle permissible links.	none
Liu et al. (2020, 2021)	Macroscopic, TransCAD	Stockholm	None	None	NL across trip generation, mode, and destination choice. Same impedance as route choice.	Three impedance formulations tested: travel distance, infrastructure, and travel time (observered and modeled speed). Fastest route.	Infrastructure expansion
Oskarbski et al. (2021)	Macroscopic, Visum	Gdynia	None	None	MNL. Same impedance as route choice.	Travel time calculated using empirical link speed function, based on infrastructure, gradient and surface. Stochastic assignment.	Infrastructure expansion
Hallberg et al. (2021), Rich, Jensen, Pilegaard, and Hallberg (2021)	Macroscopic, Traffic Analyst for ArcGIS	Copenhagen	E-bike share among cycling is scenario input, affecting average speed of cycling.	None	NL across destination and mode choice. Same impedance as route choice with added dummies.	Travel time calculated from empirical link speeds differentiated by bicycle type, infrastructure, three preference groups, and intersection delay. Fastest route.	Infrastructure expansion
Paulsen and Rich (2023, 2024)	Macroscopic, Traffic Analyst for ArcGIS	Copenhagen	None	Simplified version of Hallberg et al. (2021)'s model.			Infrastructure expansion
Argyros et al. (2024)	Macroscopic, Traffic Analyst for ArcGIS	Copenhagen	None	Bicycle traffic demand not modeled in this work, static link flow is based on COMPASS model.			Improve surface quality
Fan and Harper (2022)	Macroscopic, Visum	Seattle	None	None	Cycling penetration is manual scenario variable.	None	Exogenous modal shift

Table 5.1: Literature on the application of bicycle transport models (continued)

Source	**Model type, software**	**Area**	**Differentiation c-bike/e-bike**	**Bicycle ownership**	**Bicycle mode choice**	**Bicycle route choice**	**Intervention**
de Melo and Isler (2023)	Macroscopic, Visum	Sao Paulo	None	None	None, bicycle trip matrix modeled based on traffic counts.	Three impedance formulations tested: travel distance, travel time (including infrastructure and gradient), or suitability (like travel time, plus subjective impacts of gradient, infrastructure, stop signs, and turns), respectively. Fastest/shortest route.	Infrastructure expansion
van Dulmen and Fellendorf (2021)	Macroscopic, Visum	Graz	None	None	MNL. Impedance includes distance and elevation.	Two impedance formulations tested: distance, gradient, infrastructure, and car traffic volume (original), and distance only (simplified). Stochastic assignment.	Infrastructure expansion, exogenous modal shift
Kaziyeva et al. (2021)	Agent-based, GAMA RC1.8 platform	Salzburg	None	None	None, static mode shares.	Two impedance formulations tested: distance and safety. Safety index (infrastructure, car traffic volume, surface) based on Loidl and Zagel (2014), unclear whether VoD or VoT. Fastest/safest route.	None
Hebenstreit (2021) (Case study in Chapter 7 only)	Agent-based, MATSim	Vienna	Desired speed and impact of gradient differs by bicycle type. For shared e-bikes, battery status is modelled.	C-bike/e-bike ownership assigned to agents based on survey data	Impedance includes gradient, safety, comfort, capacity, and speed (not link-specific but derived from link type). Scoring and routing parameters based on Ziemke et al. (2019).		Infrastructure expansion, bike-sharing system, exogenous modal shift
Jafari et al. (2022)	Agent-based, MATSim	Melbourne	None	Unclear	Impedance unclear. Scoring parameters based on Ziemke et al. (2019). Routing via shortest path.		none
This work	Macroscopic, Visum	Wuppertal	Full separation between c-bikes and e-bikes throughout ownership, mode, and route choice.	C-bike/e-bike ownership from discrete choice model.	MNL. Same impedance as route choice with added dummies for person group and trip purpose.	Impedance accounting for distance, infrastructure, gradient, car speed, and turns. Stochastic assignment.	Infrastructure expansion, exogenous increase in e-bike ownership.

All but three publications (Jacyna et al., 2017; Jafari et al., 2022; Kaziyeva et al., 2021) **evaluate an intervention**. In some cases, models are used to evaluate the impact of an exogenous mode shift (Fan & Harper, 2022; Hebenstreit, 2021; van Dulmen & Fellendorf, 2021), improving surface quality (Argyros et al., 2024), or expanding a c-bike and e-bike sharing system (Hebenstreit, 2021). Most often, an expansion of bicycle infrastructure is evaluated (de Melo & Isler, 2023; Hebenstreit, 2021; Liu et al., 2021; Oskarbski et al., 2021; Paulsen & Rich, 2023, 2024; Rich et al., 2021; van Dulmen & Fellendorf, 2021). For Copenhagen, two works evaluate ambitious expansions of an existing cycling superhighway network (Paulsen & Rich, 2024; Rich et al., 2021). They do not report modal shifts, but substantial health benefits due to an increase in distance cycled, leading to benefit-cost ratios of up to 21.37 (Paulsen & Rich, 2024) and a rate of return on investment of up to 0.23 (Rich et al., 2021). Three other sources report more detailed data on mode shift, indicating more modest results: In Vienna, the modal split for cycling increases by only 0.1%p due to three new fast cycle routes (Hebenstreit, 2021). In Gdynia, six infrastructure measures ranging from a seaside bicycle path in a suburb to a new bicycle bridge across the harbor result in increases in the number of bicycle trips (not modal split) of 0.24% and 1.24%, respectively (Oskarbski et al., 2021). Lastly, model results show that several infrastructure investments in central Stockholm mainly attract bicycle trips from other routes, with the increase in bicycle trips due to mode shift in each location being only between 0.8% and 5.5% (Liu et al., 2021).

5.1.2 Literature on Bicycle Impedance

Impedance represents the resistance of distance, time, comfort, and other influencing factors across a route or OD pair to traveler's decisions. It is the core and sometimes sole component of utility formulations for destination, mode and route choice. This subsection reviews the typical factors included.

In the transport models discussed in the previous section, impedance includes either distance or time, corresponding to value-of-distance (VoD) or value-of-time (VoT) space, respectively. When VoD incorporates factors beyond distance, link attributes, such as infrastructure, can alter the perceived length of a link (Liu et al., 2020; van Dulmen & Fellendorf, 2021). Clearly, a link's objective length is not altered due to the type of facility(e.g., bicycle path or in mixed traffic), but the willingness of cyclists to make detours for more preferable infrastructure can be expressed by parameters in VoD space. When including additional factors in VoT, no publication did so to account for subjective differences only. Instead, three studies refine impedance functions to more accurately model objective speed and travel time, for example, by including gradient in speed functions (de Melo & Isler, 2023; Hallberg et al., 2021; Liu et al., 2020; Oskarbski et al., 2021; Paulsen & Rich, 2023), and three other studies present at least one impedance function that combines subjective and objective influences in VoT (de Melo & Isler, 2023; Hebenstreit, 2021; Liu et al., 2020). Factors included in impedance beyond distance and time are bicycle infrastructure (de Melo & Isler, 2023; Hallberg et al., 2021; Hebenstreit, 2021; Kaziyeva et al., 2021; Liu et al., 2020; Oskarbski et al., 2021; Paulsen & Rich, 2023; van Dulmen & Fellendorf, 2021), gradient (de Melo & Isler, 2023; Hebenstreit, 2021; Oskarbski et al., 2021; van Dulmen & Fellendorf, 2021), road surface (Argyros et al., 2024; Kaziyeva et al., 2021; Oskarbski et al., 2021), intersections (de Melo & Isler, 2023; Hallberg et al., 2021; Paulsen & Rich, 2023), and car traffic volume (Kaziyeva et al., 2021; van Dulmen & Fellendorf, 2021). Three studies differentiate impedance based on personal characteristics (Hallberg et al., 2021; Hebenstreit, 2021; Paulsen & Rich, 2023).

In most cases, mode choice impedance mirrors route choice impedance. There are three exceptions where bicycle mode choice includes additional parameters that are not part of route choice impedance (Hallberg et al., 2021; Hebenstreit, 2021; van Dulmen & Fellendorf, 2021). In another exception, one tested route choice impedance includes more factors than mode choice (van Dulmen & Fellendorf, 2021). Generally, it is advisable to include all factors from route choice impedance in mode choice, as indicator matrices (including mode choice impedance) for are calculated based on optimal routes between origins and destinations. For instance, if route choice impedance would account for infrastructure but mode choice would not, new infrastructure may attract trips from parallel routes, increasing trip length and consequentially reducing mode share on that route.

Lastly, we summarize additional academic literature that investigates bicycle route choice using stated or reveled preference data in Table 5.2. For a recent and thorough review, we refer to (Łukawska, 2024). For additional factors relevant to mode choice, namely person groups and trip purposes, we refer to Section 5.3.4.

MNL and Path Size Logit (PSL) are the most commonly used, with the latter addressing the former's independence from irrelevant alternatives problem by taking into account similarity between routes (overlaps). Almost all sources take into account bicycle infrastructure and distance, with the exception of Dane et al. (2020) and Hardinghaus and Weschke (2022, 2023), respectively. Eleven sources consider aversion to turns, intersections, or specific types of these elements (Broach et al., 2012; Cho & Shin, 2022; Khavarian et al., 2024; Koch & Dugundji, 2021; Łukawska et al., 2023; Meister et al., 2023, 2024; Prato et al., 2018; Rupi, Freo, Poliziani, Postorino, & Schweizer, 2023; D. M. Scott et al., 2021; Shah & Cherry, 2021). Aspects of topography are considered in nine works (Broach et al., 2012; Cho & Shin, 2022; de Jong, Böcker, & Weber, 2023; Huber et al., 2021; Khavarian et al., 2024; Łukawska et al., 2023; Meister et al., 2023, 2024; D. M. Scott et al., 2021). Motor vehicle speed limits are included in eight models (Broach et al., 2012; de Jong et al., 2023; Hardinghaus & Weschke, 2022, 2023; Huber et al., 2021; Meister et al., 2023, 2024; Shah & Cherry, 2021) and pavement surface in six models (Hardinghaus & Weschke, 2022, 2023; Huber et al., 2021; Łukawska et al., 2023; Prato et al., 2018; Reckermann, Gutjar, & Kowald, 2024). Other factors are considered in five publications or fewer each. It is notable that while modeling travel time takes center stage in many predictive models from Subsection 5.1.1, it is of little concern for inductive models in this subsection. We believe this is primarily because observed data are more readily available and easier to handle in VoD space, since speed differs between cyclists and even high-quality GPS tracks do not always allow for precise travel time calculations for individual links.

5.1.3 Contributions

Summarizing the current state of research, there is clearly sustained interest in evaluating the benefits of bicycle infrastructure expansion, with transport models and in particular the software PTV Visum being established research tools. From inductive modeling, there is a solid knowledge base on factors that should be included in route choice impedance and their VoD.

However, several research gaps among transport model application studies are evident: Hebenstreit (2021) is the only one to account for bicycle availability, albeit with static ownership rates based on survey data and no dynamic choice model. Furthermore, differences in preference regarding bicycle mode choice between person groups are not considered, and only two transport models consider differences between person groups at all, namely through different speeds (Hallberg et al., 2021; Hebenstreit, 2021). Inductive models reveal great differences between c-bikes and e-bike impedance, but most predictive transport models neglect these distinctions within cycling (Dane et al., 2020; Hardinghaus & Weschke, 2023; Khavarian et al., 2024; Meister et al., 2023). While two publications consider variations in speed between bicycle types, neither treats c-bikes and e-bikes as distinct alternatives in mode choice (Hallberg et al., 2021; Hebenstreit, 2021). As e-bike adoption rises, this omission compromises model accuracy and limits the ability to assess e-bike-specific policies. No transport model described in the literature differentiates between c-bikes and e-bikes throughout all relevant sub-models and accounts for differences between person groups. Lastly, no study known to us compares model quality before and after differentiating between c-bikes and e-bikes.

In presenting, validating, and applying such a novel model, we contribute to the literature in several ways:

- We present the first macroscopic travel demand model that dynamically differentiates between electric and conventional bicycle traffic across all sub-models and accounts for differences in preferences between the two, thereby establishing a groundwork for future researchers and

Table 5.2: Literature on inductive bicycle route choice modeling

Source	**E-bikes**	**Model type**	**Significant variables**
Broach et al. (2012)	no	PSL	Distance, infrastructure, turns, traffic signals, commute, car volume, speed limit
Prato et al. (2018)	no	Mixed PSL	Distance, infrastructure, against one-way, turns, elevation gain, surface, vehicle lanes, land use
Dane et al. (2020)	yes	Mixed PSL	Distance, age, weekday, peak hour, daylight, endpoint at work
Huber et al. (2021)	no	MNL	Distance, infrastructure, gradient, surface, speed limit
Koch and Dugundji (2021)	no	MNL, recursive Logit	Distance, traffic signals, noise exposure, land use, water, trees, tramline, infrastructure
D. M. Scott et al. (2021)	no	PSL	Distance, directness, turns, distance between intersections, length longest leg, gradient, infrastructure
Shah and Cherry (2021)	no	PSL	Distance, infrastructure, turns, speed limit, against one-way, car volume, traffic signals, crashes, peak hour, weekend, registered user
Cho and Shin (2022)	no	PSL	Distance, intersections, traffic signals, infrastructure, gradient
de Jong et al. (2023)	no	Linear model	Distance, land use, speed limit, infrastructure, gradient
Hardinghaus and Weschke (2022)	no	MNL	Travel time, infrastructure, speed limit, surface, parking, trees
Hardinghaus and Weschke (2023)	yes	MNL	Like Hardinghaus and Weschke (2022)
Łukawska et al. (2023)	no	PSL	Distance, gradient, infrastructure, intersections, land use, against one-way, surface
Meister et al. (2023)	yes	PSL and mixed PSL	Distance, infrastructure, speed limit, traffic signals, gradient
Rupi et al. (2023)	no	Oaxaca-Blinder decomposition	Distance, gender, city center, infrastructure, directness, intersections, intersection complexity, turns
Chung et al. (2024)	no	PSL	Distance, infrastructure, land use, peak hour, crosswalks, vehicle lanes, floating population, amenities, public transport stations
Khavarian et al. (2024)	yes	MNL	Distance, street type, infrastructure, car volume, traffic signals, hills, gender
Meister et al. (2024)	no	PSL, recursive Logit	Distance, infrastructure, speed limit, traffic signals, gradient, u-turn
Reckermann et al. (2024)	no	Mixed Logit	Travel time, distance, gender, urbanity, access/egress time, cost, age, income, mandatory trip, street type, infrastructure, age, surface

practitioners and highlighting data needs and challenges in model formulation (Sections 5.2 and 5.3).

- We are the first to systematically evaluate the impact of differentiating c-bike and e-bike modeling on overall model quality by comparing several quality measures between our differentiated model and a simplified version (Section 5.4.1).
- We reveal the impact of policies aiming to promote cycling by evaluating three scenarios related to infrastructure expansion and e-bike ownership, thereby also demonstrating the usefulness of a differentiated modeling approach (Section 5.4.2).

We close with discussions on the policies' impacts (Section 5.5.1), learnings for modeling bicycle traffic (Section 5.5.2), limitations (Section 5.5.3), and a conclusion (Section 5.5.4).

5.2 Background and Data

Wuppertal, Germany, presents a challenging environment for cycling due to its steep topography and limited infrastructure. The city developed along the narrow valley of the Wupper River, with many key destinations on surrounding slopes. For example, reaching the main university campus from the city center requires covering a distance of only 2km but gaining 100m in elevation. Cycling infrastructure is sparse, except for the Nordbahntrasse, an east-to-west rail-to-trail corridor through the northern parts of the city. Wuppertal thus presents an ideal case study for e-bike modeling; if ineffective here, it is likely even less relevant in flatter cities, where e-bikes offer less advantage over c-bikes.

For route choice calibration and validation, we used bicycle traffic volume count data provided by the City of Wuppertal (13 locations) and from earlier teaching exercises (four locations). From all counting locations potentially available to us, we only excluded two due to counting taking place on a holiday or Sunday. The count data includes intersection and cross-section sites. Directional counts are aggregated. The counting periods range from short manual counts spanning only a few hours to automated counts spanning several months. To standardize the data, we convert all counts to uniform average weekday traffic (AWT) values in a multi-step process. First, short-term counts are extrapolated to a full week using the average weekly bicycle traffic flow curve at 15-minute intervals, derived from counting location 13's 2023 and 2024 records (see Figure 5.1). For example, if a manual count covered only only 1 PM–1:15 PM on a Wednesday, its count value is divided by 0.002267 to estimate the full week's traffic. Since all counts cover longer time spans, the corresponding interval shares are summed, and the total count is divided by this value. This approach assumes that the weekly flow curve remains consistent throughout the year. To extrapolate from weekly to yearly values (i.e. account for seasonality), data from counting location 13 cannot be used, as it does not cover all months. Instead, we rely on monthly aggregate data from 2022 to 2024 from 14 permanent counting locations in the neighboring city of Düsseldorf Landeshauptstadt Düsseldorf (2025), which has a comparable climate. This flow curve is also shown in Figure 5.1. Finally, to convert yearly traffic to AWT, we apply a factor of 0.00314906. This factor is derived from data collected at 30 counting locations in Berlin Senatsverwaltung für Mobilität, Verkehr, Klimaschutz und Umwelt (2024), because unlike the other two datasets, this one provides both full-year coverage and daily resolution. Figure 5.2 shows the counting locations. Their original count time and the extrapolated AWT values can be found in Table 5.3.

For calibrating ownership and mode choice, we use data from a mobility survey conducted in September 2020 Stadt Wuppertal (2021), the raw data of which are provided to us by the City of Wuppertal. Most likely due to the Covid-19 pandemic, the total cycling mode share in that survey is higher (8%) than suggested both by the previous 2011 mobility survey and by the more recent counting data (approximately 2% in each case, see Section 5.3.5). Therefore, after a preliminary mode and route choice calibration, we reduce target mode shares across trip purposes and person groups by a factor in such a way that the total modeled and observed bicycle traffic counts match.

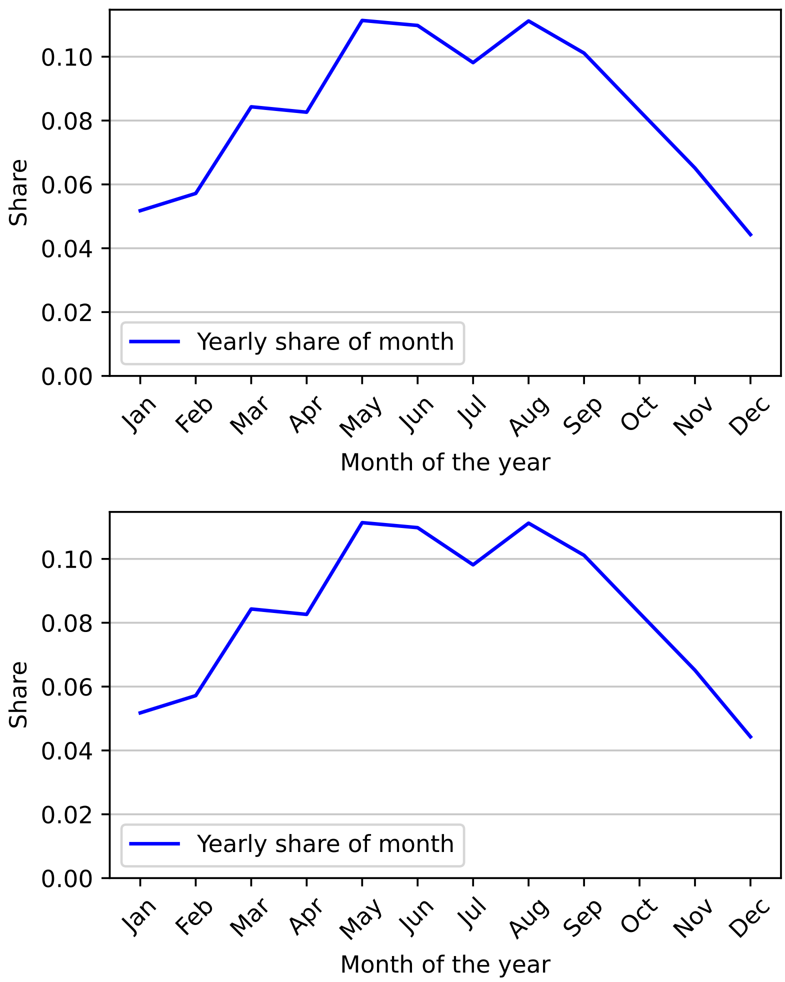

Figure 5.1: Weekly flow curve in 15-minute intervals from counting location 13 (top) and yearly flow curve in monthly intervals from counting locations in Düsseldorf Landeshauptstadt Düsseldorf (2025) (bottom) used for expansion of short-term counts to AWT

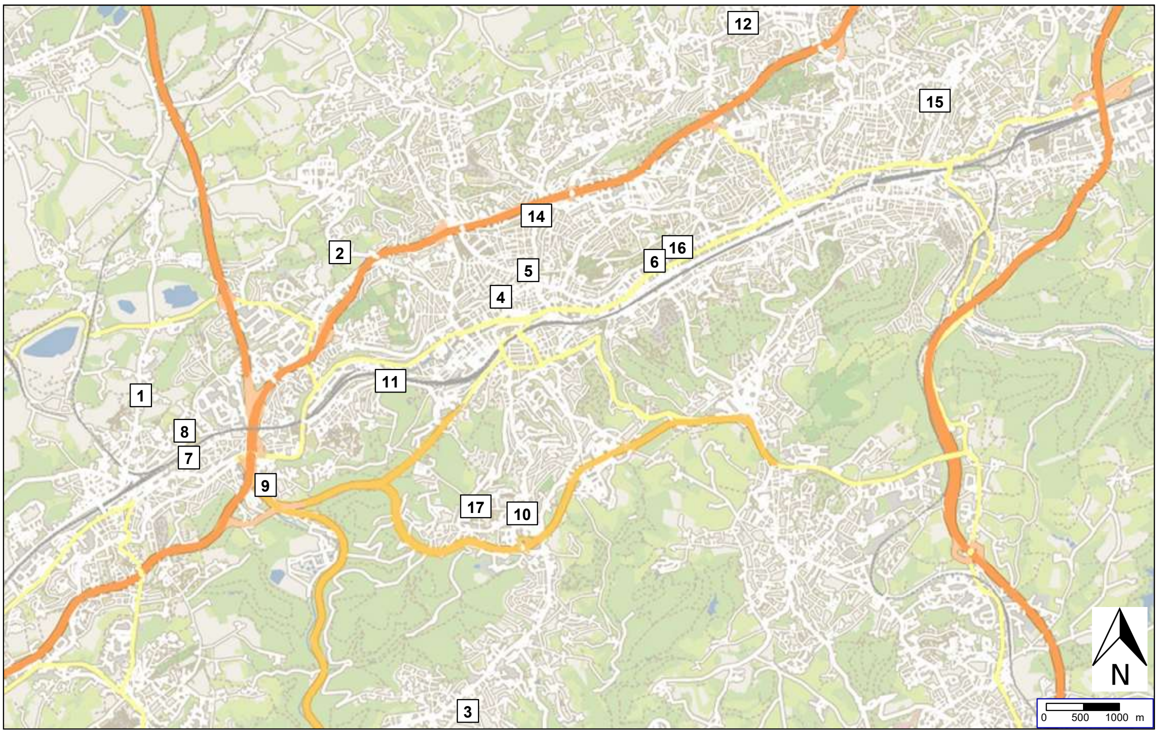

Figure 5.2: Counting locations in Wuppertal. Backgroundmap © OpenStreetMap contributors, CC-BY-SA.

Table 5.3: Counting locations and extrapolated average weekday traffic (AWT) values

Nr.	Location	Source	Original counting period	AWT
1	Bahnstr.	City	Tue, May 23, 2023, 8:30–9:30&15:30–16:30	236
2	In der Beek	City	Thu, Aug 29, 2024, 7:00–9:00&15:00–17:00	439
3	Sambatrasse	City	Tue, Mar 15, 2022, 7:15–8:45&15:00–17:00	238
4	Luisenstr.	City	Tue, Sep 3, 2024, 7:00–8:45&15:15–17:00	882
5	Karlstr./Friedrichstr.	Own	Wed, May 17, 2023, 7:00-18:00	974
6	Völklinger Str./Hünefeldstr.	Own	Tue, May 23, 2023, 7:00-18:00	509
7	Herderstr.	City	Wed, Mar 22, 2023, 7:00–9:00&15:00–17:00	868
8	Homanndamm	City	Thu, Aug 24, 2023, 7:00–8:30&15:00–17:30	1439
9	Rutenbeck	City	Wed, Mar 3, 2021, 6:45–8:15&14:30–16:30	234
10	Jung-Stilling-Weg/East	City	Wed, Aug 28, 2024, 7:30–10:30&15:00–17:00	295
11	Schwarzer Weg	City	Thu, Sep 23, 2021, 7:00–9:00&15:30–17:30	106
12	Hatzfelder Str.	City	Thu, May 25, 2023, 8:00–10:00&14:00–16:00	159
13	NBT/Wüstenhofer	Own	June-August 2023, February-June 2024	2150
14	NBT/Uellendahler	Own	Tue, May 14, 2024, 7:00-13:00	3191
15	Luhnstr.	City	Thu, Nov 3, 2022, 8:30–9:00&16:00–16:30	1187
16	Hünefeldstr.	City	Wed, Sep 29, 2021, 7:00–9:00&15:00–17:00	385
17	Jung-Stilling-Weg/West	City	Wed, Aug 28, 2024, 7:30–10:30&12:30–14:30	722

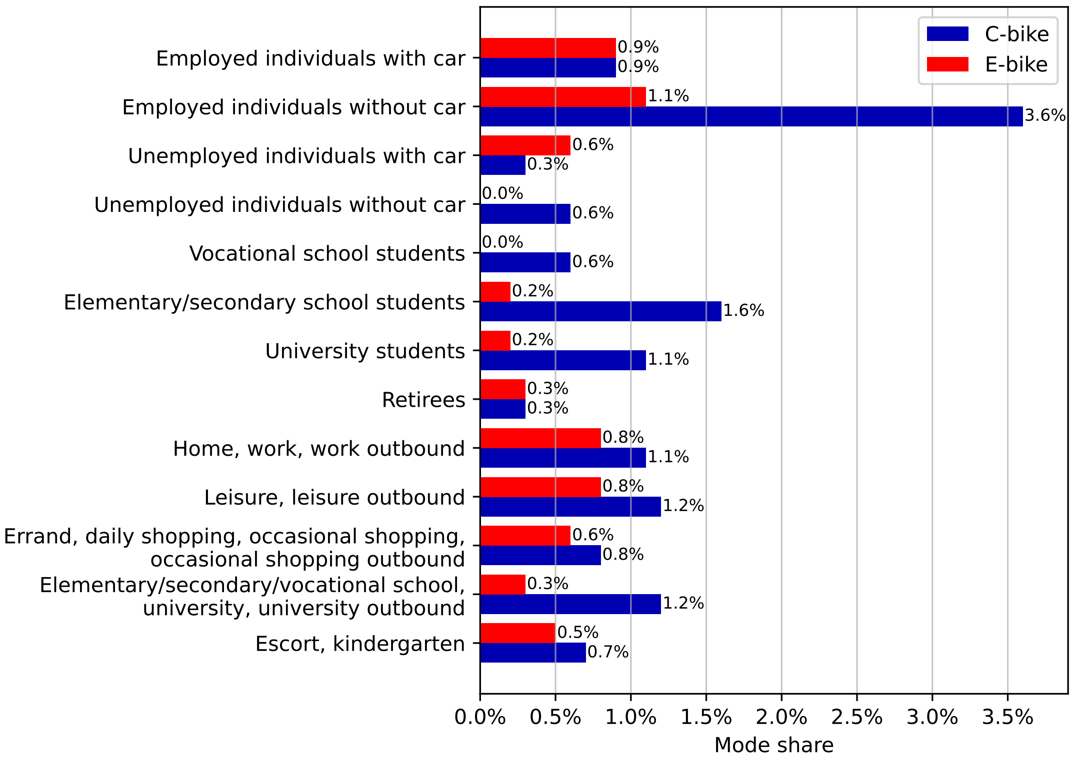

Figure 5.3: Target c-bike and e-bike mode shares by person groups and trip purposes

Figures 5.3 and 5.4 depict these target cycling mode shares and the cycling distance distributions for Wuppertal-internal travel. For inbound travelers and children under the age of 6, no data is available.

5.3 Model and Scenarios

We build on an existing, calibrated PTV Visum model provided by the City of Wuppertal (Verkehrsmodell der Stadt Wuppertal, *base model*) which differentiates between car as driver, car as passenger, public transport, walking, and cycling, however, the latter two are not calibrated or assigned to the network. It represents an average weekday. In the following subsections, we describe our method to implement and calibrate c-bike and e-bike throughout all sub-models (*differentiated model*). For comparison, we also develop an equivalent *simplified model* that treats cycling as a single mode of transport. Both models are calibrated using the same procedures and data to allow for insight into whether a differentiated modeling of bicycle traffic impacts model quality. Figure 5.5 shows the structure of the model.

5.3.1 Network Model and Bicycle Impedance

The network model remains unchanged for car and public transport compared to the base model. There are 89 link types that represent combinations of permitted transport modes, number of lanes, maximum speed, and capacity. For example, they differentiate between a four-lane motorway with a 120km/h speed limit and a single-lane residential road with a 30km/h speed limit. Capacity-restraint functions are applied to account for congestion effects by increasing car travel time as capacity utilization increases. For public transport, the model uses the actual schedule of the local

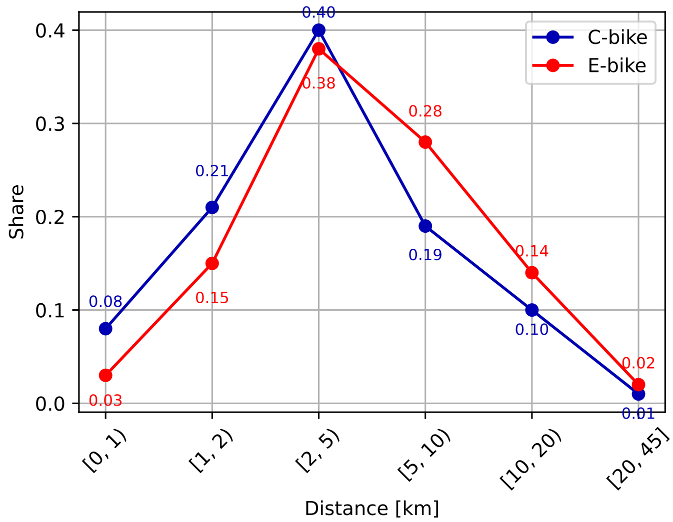

Figure 5.4: Target c-bike and e-bike trip distance distributions

public transport system on a normal weekday. The study area is subdivided into 572 traffic zones, which serve as the basis for demand modeling and the computation of indicator matrices.

To represent bicycle infrastructure, we introduce the link attribute bicycle infrastructure, which can take the values: none, stairs, pedestrian zone, forest/service road, bicycle lane, bicycle path, bicycle road, or rail-trail (specifically the Nordbahntrasse). Stairs are generally blocked and one-way streets are made accessible for bicycles in both directions to reflect actual usage. Figure 5.10 shows a graph of the bicycle infrastructure network. No capacity-restraint functions are applied to bicycle traffic. Elevation is written to each node using a digital terrain model (Bezirksregierung Köln, 2025), allowing the computation of a directional link attribute *gradient*. Figure 5.6 illustrates the city's challenging topography.

C-bike and e-bike impedance are indicator matrices in VoD space, each containing values for all OD pairs. They are used in destination, mode, and route choice. VoD is chosen for its readily available empirical parameters (see Section 5.1.2) and avoids distinguishing between objective and subjective influences on travel time. When calculating the impedance for an OD pair, the route with the lowest impedance is considered.

Based on Section 5.1.2, we consider distance, bicycle infrastructure, turns, gradient, and motor vehicle speed limit in the two impedance functions. For bicycle type b, the impedance I of a route r consisting of links L and turns T is

$$I_{r,b} = \sum_{l \in L} dist_l * (1 + f_{infra,l} + f_{gradient,l,b} + f_{vmax,l}) + \sum_{t \in T} \theta_t, \tag{5.1}$$

where $dist_l$ is the length of each link, f_{infra}, $f_{gradient}$, and f_{vmax} are factors reducing or increasing each link's impedance in VoD space, and θ_t is a penalty for some types of turns. In the following paragraphs, we explain how we arrived at the VoD values for our model.

Some sources (Arning & Kaths, 2025a; Meister et al., 2023) find e-bikes to be less sensitive to **infrastructure** provision than c-bikes, while others (Hardinghaus & Weschke, 2023) find the opposite. Similarly, there is no conclusive insight into whether there is a difference between c-bikes and e-bikes regarding motor vehicle speed in mixed traffic or turns at intersections. For this reason, only the impact of gradient is differentiated by bicycle type. Table 5.4 reports VoD values extracted from the literature for different types of bicycle infrastructure. Sources where VoD was not explicitly reported are marked with * and the values presented are estimates based on reported parameter

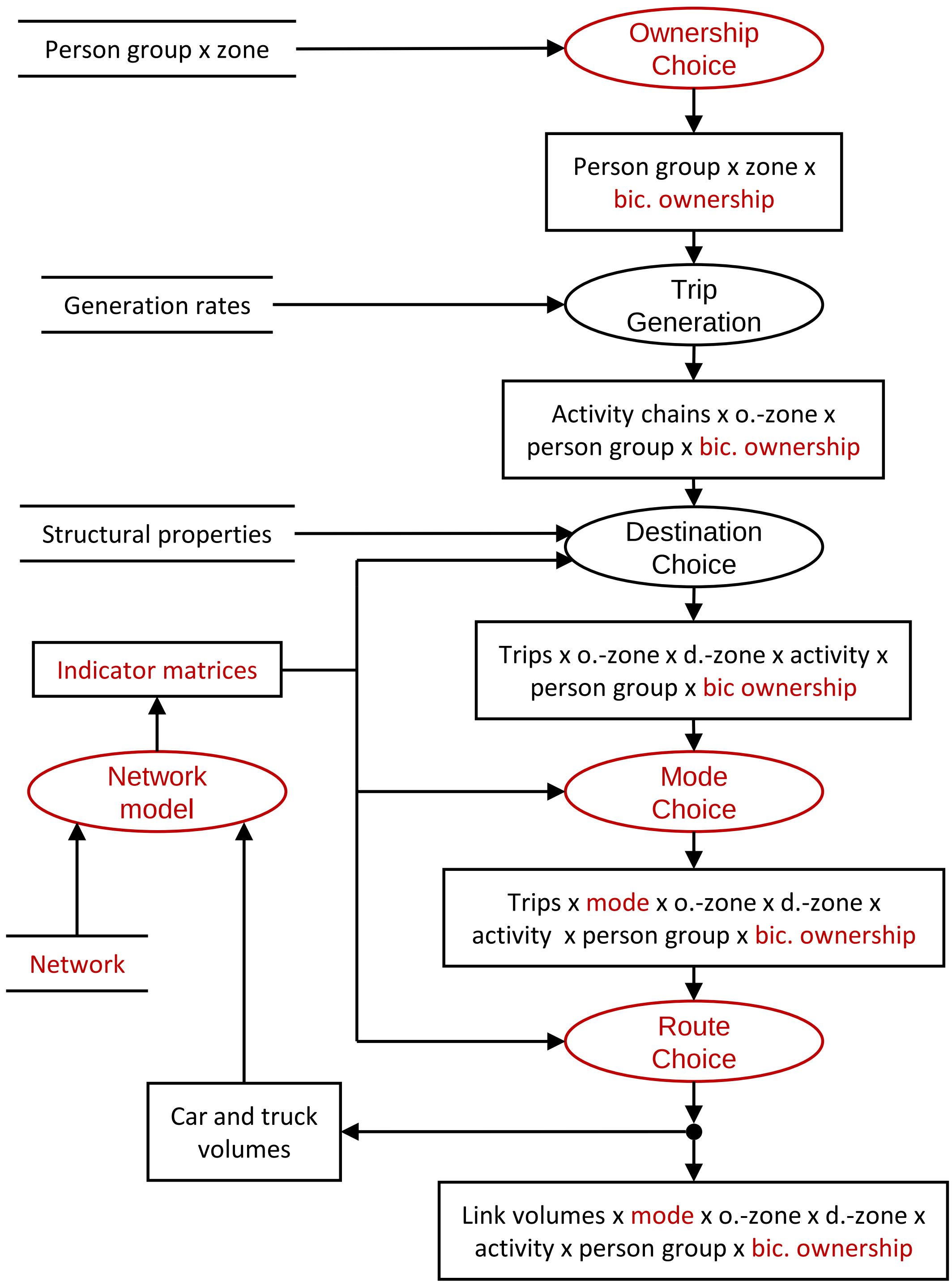

Figure 5.5: Data-flow diagram of the differentiated model. Changes and additions to the base model highlighted in red. "x" separates the dimensions of demand matrices.

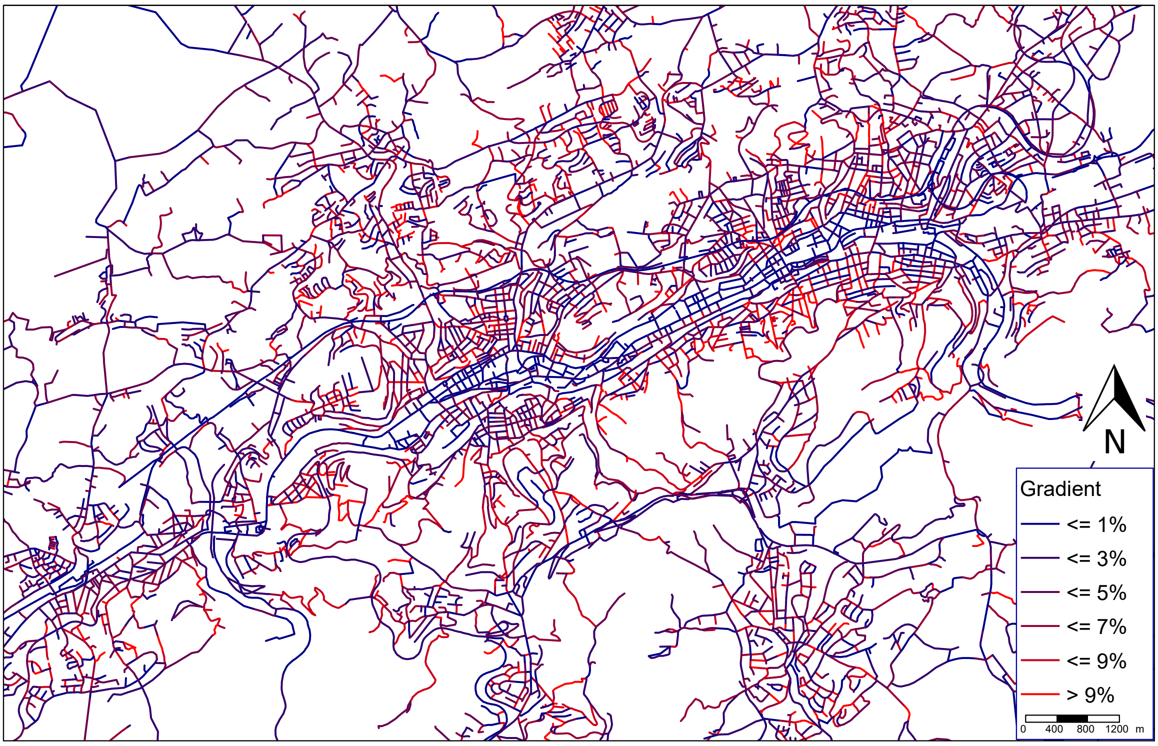

Figure 5.6: Positive gradient of bicycle permissible links in the network model

Table 5.4: Literature VoD values for bicycle infrastructure

Source	Bic. path	Bic. lane	Bic. track	Other
Broach et al. (2012)	-0.16			-0.11 (Bicycle boulevard)
Prato et al. (2018)	-0.20			2.17 (Foot path)
Huber et al. (2021)*		-1.12	-0.92	
Cho and Shin (2022)*		-1.32		
Łukawska et al. (2023)		-0.06	-0.11	-0.13 (Cycle-superhighway)
Meister et al. (2023) (c-bike)	-0.23	-1.00		
Meister et al. (2023) (e-bike)	-0.12	-1.12		

Table 5.5: VoD values for bicycle infrastructure used in the model

Bicycle infrastructure	**Initial** f_{infra}	**Final** f_{infra}
rail-trail	-0.50	-0.60
bicycle road	-0.50	-0.50
forest/service road, bicycle lane, bicycle path	-0.35	-0.35
pedestrian zone, stairs, none	0.00	0.00

values and average trip lengths. We normalize against riding in mixed traffic. The values vary strongly, from one source indicating that riding 1000m on a bicycle lane is still equivalent to riding 937m in mixed traffic (Łukawska et al., 2023) to other sources that find infrastructure to more than completely outweigh the objective link distance (e.g., Meister et al. (2023)). As a result, we choose medium initial values for f_{infra}, as reported in Table 5.5. These values are later calibrated (see Section 5.3.5).

Four references report VoD values for link **gradient**, either for categories (Broach et al., 2012; Meister et al., 2023, 2024) or as a linear increase in VoD for every % of added gradient (Cho & Shin, 2022). Figure 5.7 visualizes the wide range of values for c-bikes. It should be noted that the two extreme cases are both from the same publication in which the authors compare two different models using the same data (Meister et al., 2024). In order not to overestimate the role of e-bikes in transport modeling, we assume modest VoD values for link slope. Namely, we assume that gradients below 2%, including downhill slopes, have no impact on impedance, and that for every %-point of gradient above 2%, $f_{gradient,c-bike}$ increases by 0.25. In other words, at 6% gradient a VoD of 1 is reached, meaning cyclists would view 2km of cycling below 2% gradient equivalent to 1km at 6%. For e-bikes, several studies find that e-bikes are less but not unaffected by gradient (Arning & Kaths, 2025a; Khavarian et al., 2024; Meister et al., 2023). To again not overstate the relevance of differentiated e-bike modeling, we therefore assume that e-bike impedance is still affected half as strongly as c-bike, i.e. with a VoD increase of 0.125 for every %-point in gradient above 2%. During model calibration (see Section 5.3.5), these values are slightly increased to 0.28 and 0.14, respectively. For the simplified model, we end up with a value of 0.27 after calibration.

Cyclists dislike riding near fast-moving traffic. Table 5.6 presents **speed limit** VoD values from the literature. When differentiating between c-bikes and e-bikes in a Swiss study, e-bike VoD values for 30km/h road speed limits were positive, likely due to regulatory differences: Swiss e-bikes provide assistance up to 45 km/h, whereas German e-bikes are limited to 25 km/h (Meister et al., 2023). Lacking quantitative data on preference differences between conventional and 25 km/h e-bikes, we do not distinguish between them. Based on available VoD values, we set f_{vmax} to -0.1 for links with speed limits of 30 km/h or lower or where cyclists are unaffected by motor traffic, namely rail-trails and pedestrian zones, and 0 otherwise.

Lastly, we take into account **turns**. Due to the wide variety of intersection designs and types of turns, the VoD values reported in Table 5.7 are difficult to compare. For traffic signals in particular,

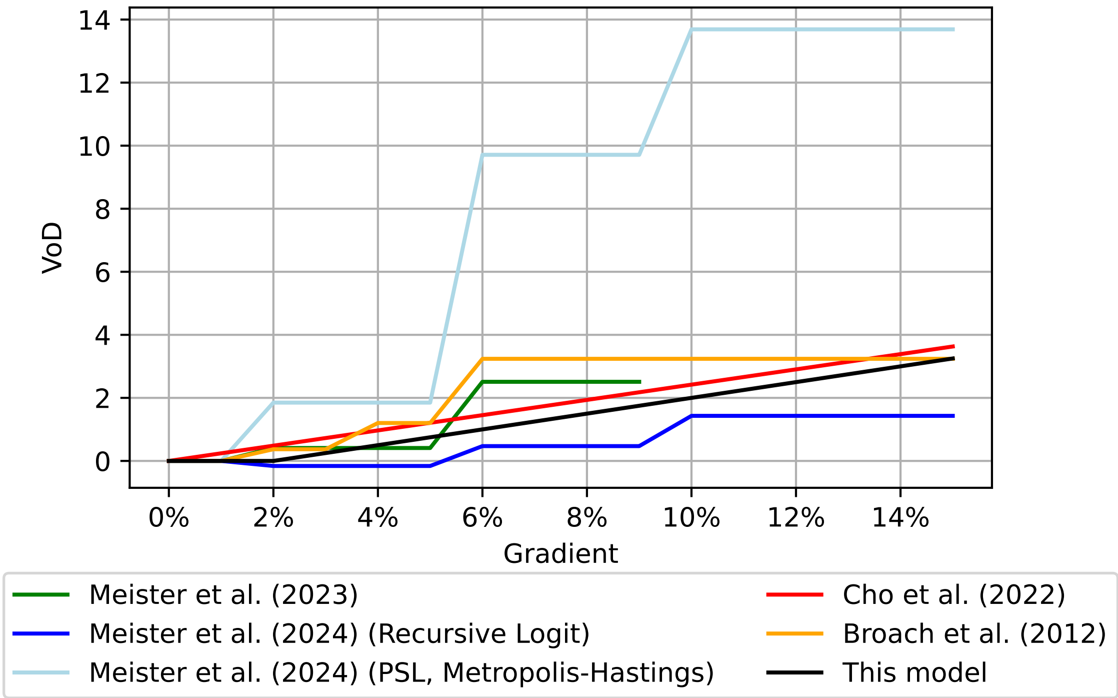

Figure 5.7: VoD values for the impact of link gradient on c-bike impedance from the literature and the values chosen for the differentiated model

Table 5.6: Literature VoD values for a motor vehicle speed limit of 30km/h compared to 50km/h

Source	**VoD**
Huber et al. (2021)*	-0.043
Hardinghaus and Weschke (2022)*	-0.062
Meister et al. (2023)	-0.16
Meister et al. (2024)	-0.09, -0.12, -0.14

Table 5.7: Literature VoD values for turns and intersections

Source	Type of turn or intersection	VoD value [m]
Broach et al. (2012)	turn	42
Prato et al. (2018)	left turn right turn	423 221
Huber et al. (2021)*	intersection	insig.
Shah and Cherry (2021)*	left turn traffic signal	50 -33
Cho and Shin (2022)*	traffic signal intersection	-1870 740
Meister et al. (2023)	traffic signal	190
Łukawska et al. (2023)*	turn road hierarchy down turn road hierarchy up roundabout traffic signal	24 44 18 4
Khavarian et al. (2024)*	traffic signal	545

the findings are conflicting: some sources report a high aversion of cyclists (Khavarian et al., 2024; Meister et al., 2023), some report values that are close to 0 (Łukawska et al., 2023), insignificant (Huber et al., 2021), or changing signs depending on the model used (Meister et al., 2024), and some report negative VoD values, meaning cyclists prefer routes with more signalized intersections (Cho & Shin, 2022; Shah & Cherry, 2021). For turns, values range from 22m (Łukawska et al., 2023) to 423m (Prato et al., 2018). In relative terms, there is little difference between c-bikes and e-bikes (Khavarian et al., 2024), prompting us to again not differentiate between the two. In light of these contradicting findings, we do not differentiate by intersection type. For left turns, we set θ to 0.05km, close to two sources (Broach et al., 2012; Shah & Cherry, 2021) in-between more extremes values (Łukawska et al., 2023; Prato et al., 2018), and 0 otherwise.

5.3.2 Ownership Model

C-bikes are inexpensive, so it is typically assumed in transport modeling that anyone who would regularly choose to cycle owns one. In contrast, the higher acquisition and maintenance costs of an e-bike make it essential to model ownership and mode choice separately, as many potential users do not own one. While the 2020 mobility survey includes data on c-bike and e-bike ownership, the sample size is insufficient to attain person-group-specific ownership rates. Therefore, we use an existing ownership model to model ownership rates for each person group (Arning & Kaths, 2025b). The person groups used in this model do not account for income-related differences beyond differences in mobility tool ownership and occupational status, because beyond these, income was found to have a negligible impact on e-bike use (Arning & Kaths, 2025a). We calibrate the alternative specific constants (ASC) for "only c-bike", "only e-bike" and "both" in such a way that the share of each ownership type across the whole population matches the results of the mobility survey. The resulting ownership rates for each person group are depicted in Table 5.8. Across all zones, each person group is then subdivided into four subgroups, one for each ownership type. For example, our calibrated ownership model predicts that 41% of unemployed individuals with car own only a c-bike, so a zone with a population of 100 unemployed individuals with car in the base model will have 41 unemployed individuals with car and only a c-bike in the differentiated model. For the simplified model, the same approach is used. However, "only c-bike", "only e-bike" and "both" are collapsed to "owns bicycle".

Table 5.8: Calibrated ownership rates for model person groups

Person group	**only c-bike**	**only e-bike**	**both**	**none**
Employed individuals with car	54.1%	3.8%	14.1%	28.0%
Employed individuals without car	54.1%	3.8%	14.1%	28.0%
Unemployed individuals with car	41.2%	6.5%	16.6%	35.8%
Unemployed individuals without car	41.2%	6.5%	16.6%	35.8%
Retirees	22.9%	13.1%	25.0%	39.0%
Children	65.8%	0.0%	4.2%	30.0%
Elementary school students	65.8%	0.0%	4.2%	30.0%
Secondary school students	65.8%	0.0%	4.2%	30.0%
Vocational school students	50.1%	0.7%	3.4%	45.8%
University students	51.7%	0.5%	3.0%	44.9%
Inbound commuters	54.1%	3.8%	14.1%	28.0%
Inbound leisure travelers	54.1%	3.8%	14.1%	28.0%
Inbound shoppers	54.1%	3.8%	14.1%	28.0%
Inbound university students	50.3%	0.7%	3.6%	45.3%
original ASC	1.75	-3.15	-1.82	0
calibrated ASC	1.46	-2.4	-0.15	0
Total model population	46.9%	5.4%	14.7%	33.0%
Total survey population	46.9%	5.5%	14.5%	32.9%

This differentiation of person group-specific and thereby also zone-level c-bike and e-bike ownership enables the model to capture spatial variation in c-bike and e-bike ownership across the urban area. As a result, it supports more detailed analyses of changes in bicycle use among population subgroups and zones than is possible with more aggregate approaches commonly found in the literature.

5.3.3 Trip Generation and Destination Choice Models

Trip generation and destination choice remain consistent with the base model. Visum's VISEM procedure is used across trip generation, destination, and mode choice. For each person group (see Table 5.9 for a complete list) and origin zone, it generates activity chains based on generation rates. For instance, a Home-Work-Errand-Home x University student generation rate of 0.0051 means that a zone with 100 university students generates 0.51 Home-Work-Errand-Home activity chains per day. Generation rates remain unchanged compared to the base model and are independent of bicycle ownership.

For destination choice, the model accounts for the relevant structural property of all potential destination zones (e.g., number of workplaces for the trip purpose work) and a cross-modal, OD-pair-specific utility. Destination choice then takes place step-wise along each activity chain for every origin zone and person group using a Logit model. The number of trips T between origin zone i and destination zone j for each step is computed as:

$$T_{ij} = O_i * \frac{S_j * exp(u_{ij})}{\sum_{j'=1}^{Z} S_{j'} * exp(u_{ij'})}, \tag{5.2}$$

where O denotes the number of originating trips, S the relevant structural property, and Z the number of zones. Utility is defined by

$$u_{ij} = a_{pg,purp} * ModeLogSum_{ij} + b_{pg,purp} * CarDist_{ij}. \tag{5.3}$$

Here, $CarDist$ is the car travel distance matrix between all zones, while $ModeLogSum$ aggregates

Table 5.9: Person groups

Person group	**Abbreviation**
Employed individuals with car	EMPwC
Employed individuals without car	EMPwoC
Unemployed individuals with car	UEMPwC
Unemployed individuals without car	UEMPwoC
Retirees (age 65 and above)	Retirees
Children	Child
Elementary school students	ElemStud
Secondary school students	SecStud
Vocational school students	VocStud
University students	UniStud
Inbound commuters	InbW
Inbound leisure travellers	InbL
Inbound shoppers	InbB
Inbound university students	InbU

the mode-specific mode choice utilities (see Section 5.3.4) in a log-sum formulation. The parameters a and b are specific to trip purpose ($purp$, see Table 5.10 for a complete list) and person group (pg) and remain unchanged compared to the base model.

5.3.4 Mode Choice Model

The mode choice utility functions for walking, car as driver, car as passenger, and public transport remain unchanged from the base model and are given in Equations 5.4, 5.5, 5.6, and 5.7, respectively. The term $c_{mode,pg}$ represents both person group-specific and mode-specific constants, capturing differences in mode choice preference between person groups. Indicator matrices TT, DIS, AET, RT, TF, and DWT denote travel time, distance, access/egress time, ride time, transfers, and departure waiting time, respectively.

$$u_{foot,i,j,pg} = -0.12 * TT_{foot,i,j} - 1.2 * ln(DIS_{foot,i,j}) + c_{foot,pg} \tag{5.4}$$

$$u_{card,i,j,pg} = -0.08 * TT_{car,i,j} - 0.12 * AET_{car,i,j} + 0.6 * ln(DIS_{car,i,j}) + c_{card,pg} \tag{5.5}$$

$$u_{carp,i,j,pg} = -0.08 * TT_{car,i,j} - 0.12 * AET_{car,i,j} + 0.6 * ln(DIS_{car,i,j}) + c_{carp,pg} \tag{5.6}$$

$$u_{pt,i,j,pg} = -0.06 * RT_{pt,i,j} - 0.09 * AET_{pt,i,j} - 1 * TF_{pt,i,j} - 0.12 * DWT_{pt,i,j} + 0.8 * ln(DIS_{pt,i,j}) + c_{pt,pg} \tag{5.7}$$

To introduce c-bike and e-bike, we build on findings from an existing mode choice model (Arning & Kaths, 2025a). As nesting c-bike and e-bike was rejected in that work, they are treated independently. The utility functions for c-bike and e-bike are given in Equations 5.8 and 5.9, respectively. Beyond the factors already captured in c-bike and e-bike impedance I (see Section 5.3.1), p captures person-group-specific preferences, q accounts for trip-purpose-specific preferences, and n reflects each bicycle type's distance sensitivity. In the simplified model, a single bicycle utility function of the same structure is used.

$$u_{cbike,i,j,pg,purp} = n_{cbike} * ln(I_{cbike,i,j}) + p_{cbike,pg} + q_{cbike,purp} \tag{5.8}$$

Table 5.10: Trip purposes

Trip purpose	**Abbreviation**
Home	H
Work	W
Leisure	L
Errands	E
Shopping daily needs	S
Shopping occasional needs	B
Elementary School	Se
Secondary School	Ss
Vocational School	Sv
University	U
Escort	C
Kindergarten	K
Outbound work	Wx
Outbound leisure	Lx
Outbound shopping	Bx
Outbound university	Ux

$$u_{ebike,i,j,pg,purp} = n_{ebike} * ln(I_{ebike,i,j}) + p_{ebike,pg} + q_{ebike,purp} \tag{5.9}$$

Like in destination choice, mode choice also occurs along a chain of activities for each person group and origin zone. For each trip from i to j, the share P of mode m is given by:

$$P_{ijm} = \frac{exp(u_{mij})}{\sum_{m'}^{M} exp(u_{m'ij})}. \tag{5.10}$$

The VISEM procedure has two important features: car, c-bike, and e-bike are not included in the choice sets of person groups without access to the respective vehicle. Consequently, car, c-bike and e-bike ownership is not considered in the utility functions. Additionally, if the first trip in a chain uses a car or bicycle, the same mode is used for the subsequent trips in the chain to bring the vehicle home. Conversely, if the first trip occurs without a car or bicycle, these modes remain unavailable. Bike and car-sharing in Wuppertal are negligible.

The two parameters n are calibrated to match c-bike and e-bike trip distance distributions (Figure 5.4), while p and q are calibrated to mode shares by person group and trip purpose (Figure 5.3). The model includes 56 person groups (four bicycle ownership types per person group in the base model), six modes, and 16 trip purposes, resulting in 2,280 utility functions requiring calibration. Additionally, n, p, and q must be iteratively adjusted due to their interdependent effects. Calibration was semi-automated using the Visum COM-API and Python. The code is available on GitHub (`https://github.com/buw-bicycle-traffic/ebike-transport-model`).

To ensure comparability between the differentiated and simplified model, we define a common calibration stop-point: parameters p and q are adjusted to one decimal place of accuracy until the scalable quality value (SQV, see 5.4.1) of the mode share for the respective person group or trip purpose mode no longer improves. For n, the coincidence ratio (CR, see 5.4.1) of the observed and modeled bicycle-type-specific trip distance distribution is used. Calibrating bicycle mode choice required several hundred iterations and weeks of computation on a 3GHz processor with 16GB RAM. Initial values for parameter n were -1 (c-bike), -0.5 (e-bike), and -0.9 (bicycle, simplified model), with final calibrated values of -0.9, -0.4, and -0.7, respectively. Table 5.11 lists equivalent values for parameters p and q. The resulting distance distributions are presented in Section 5.4.1 and mode shares by person group and trip purpose in Table 5.12. Mode shares for originating traffic

Table 5.11: Values for bicycle mode choice parameter p (person groups) and q (trip purposes) before and after calibration

Person group, trip purpose	**C-bike** Initial	**C-bike** Final	**E-bike** Initial	**E-bike** Final	**Bicycle** Initial	**Bicycle** Final
EMPwC	0	1.9	0	-0.9	3.2	2.6
EmpwoC	0	2.6	0	-1.6	3.9	2.8
UEMPwC	0	0.9	0	-1.9	2.3	1.9
UEMPwoC	0	0.9	0	-15.0	2.1	0.6
VocStud	2	1.1	0	-25.0	2.5	1.2
ElemStud, SecStud	4	1.9	-4	-2.0	3.2	2.1
UnivStud	4	2.2	-2	-1.0	3.8	2.5
Retirees	-2	1.0	4	-3.1	2.8	1.8
Child	2	3.9	-4	-35.0	5.0	3.5
InbW, InbL, InbB, InbU	0	3.7	0	0.1	5.0	4.1
W, Wx, H	0	0.1	0	0.2	0.7	0.5
L, Lx	1	0.2	1	0.4	0.7	0.6
E, S, B, Bx	-4	-0.1	-2	0.3	0.2	0.2
Se, Sv, Ss, U, Ux	1	0.2	-6	0.7	0.7	0.5
C, K	-6	-0.9	-2	0	-0.5	-0.3

are visualized spatially in Figure 5.8. These are mainly influenced by local bicycle ownership and structural properties, with relation-specific mode shares more strongly influenced by gradient and bicycle infrastructure.

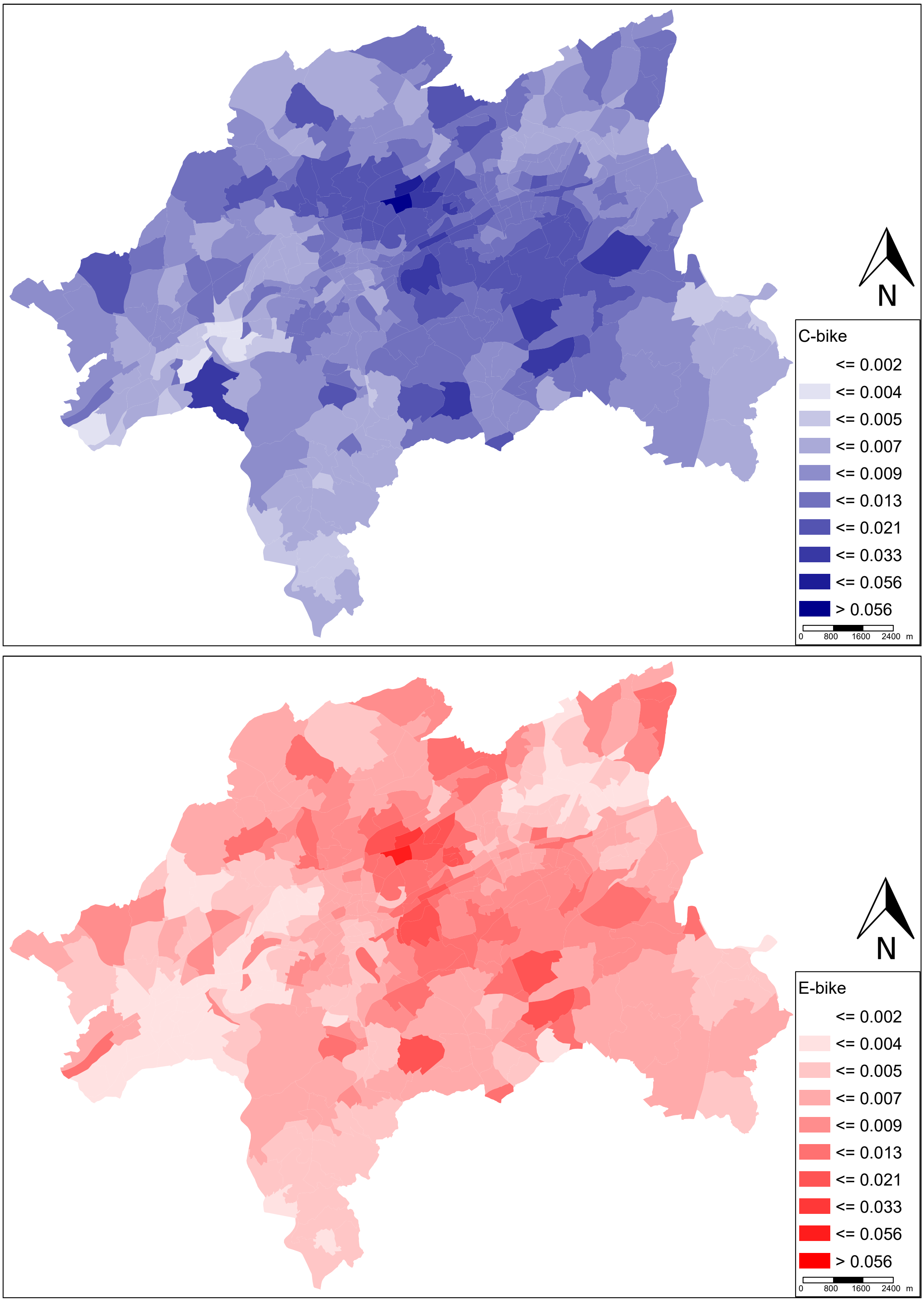

Figure 5.8: C-bike (top) and e-bike (bottom) mode share among all trips originating in each zone in Wuppertal

Table 5.12: Mode shares by person group and trip purpose in the observed data and the calibrated differentiated and simplified model

Person group,	**Observed**			**Diff. model**			**Simp. model**
trip purpose	c-bike	e-bike	bicycle	c-bike	e-bike	bicycle	bicycle
EMPwC	0.9%	0.9%	1.8%	0.9%	0.9%	1.8%	1.8%
EMPwoC	3.6%	1.1%	4.7%	3.5%	1.1%	4.6%	4.7%
UEMPwC	0.3%	0.6%	0.9%	0.3%	0.5%	0.8%	0.9%
UEMPwoC	0.6%	0.0%	0.6%	0.6%	0.0%	0.6%	0.6%
VocStud	0.6%	0.0%	0.6%	0.5%	0.0%	0.5%	0.6%
ElemStud, SecStud	1.6%	0.2%	1.8%	1.5%	0.1%	1.6%	1.8%
UniStud	1.1%	0.2%	1.3%	1.0%	0.2%	1.2%	1.3%
Retirees	0.3%	0.3%	0.7%	0.2%	0.3%	0.5%	0.7%
W, Wx, H	1.1%	0.8%	1.9%	1.1%	0.7%	1.8%	1.9%
L, Lx	1.2%	0.8%	2.0%	1.1%	0.8%	1.9%	2.0%
E, S, B, Bx	0.8%	0.6%	1.4%	0.7%	0.6%	1.3%	1.4%
Se, Sv, Ss, U, Ux	1.2%	0.3%	1.5%	1.1%	0.4%	1.5%	1.6%
C, K	0.7%	0.5%	1.2%	0.7%	0.5%	1.2%	1.1%

5.3.5 Route Choice Model

C-bike and e-bike impedance from Section 5.3.1 are used as the utility for c-bike and e-bike route choice, respectively. Unlike in mode choice, no distinction is made between person groups or trip purposes. For each bicycle type and OD pair, Visum's bicycle assignment procedure first identifies the route with the lowest impedance. Additional viable routes are then generated in ten iterations by randomly varying segment impedances of the original optimal route to find new routes. Routes with meshes posing a large detour to the ideal route are removed. For each OD pair ij and bicycle type b, trips T are then assigned to a specific route r among all N viable routes s using a PSL model:

$$T_{ijbr} = T_{ijb} * \frac{exp(I_{rb}) * PS_r}{\sum_{s=1}^{N}(exp(I_{sb}) * PS_s)} \tag{5.11}$$

This stochastic assignment accounts for random variance in cyclists' preferences. The Path-size factor PS for route r is determined by the shared length of routes r and s, $dist_{rs}$, relative to their respective total lengths $dist_r$ and $dist_s$:

$$PS_r = \frac{1}{\sum_{s=1}^{N} \frac{dist_{rs}}{\sqrt{dist_r * dist_s}}}. \tag{5.12}$$

As indicated by the splitting arrow below route choice in Figure 5.5, the model iterates between route, destination, and mode choice because car traffic volumes influence car travel times, affecting not only route but also destination and mode choice. Iterations continue until car traffic volume changes by fewer than 10 vehicles on every link.

C-bike and e-bike route choice was calibrated using the extrapolated count data presented in Section 5.2. Preliminary results showed that target mode shares from the mobility survey were unrealistically high compared to recent count data. To align total modeled bicycle counts with reality, target mode shares were scaled down by a factor of 4.34. After recalibrating mode choice accordingly, total bicycle counts matched well. Individual count deviations that remained were then addressed by calibrating the parameters of c-bike and e-bike impedance (see Section 5.3.1. Specifically, we adjusted the VoD factor for rail-trail from -0.5 to -0.6 and increased the gradient VoD from 0.25% and 0.125% to 0.28% and 0.14% for c-bikes and e-bikes, respectively. We also corrected some infrastructure attribution errors and added missing zone connectors. Since adjustments to

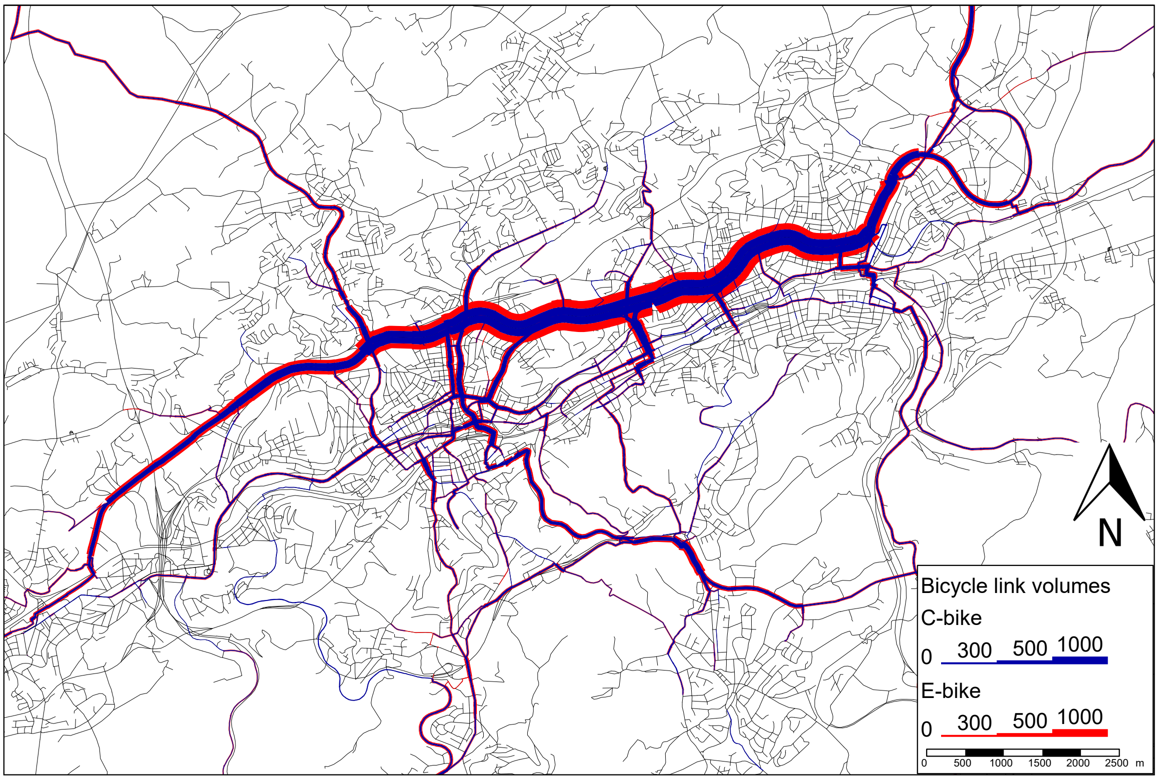

Figure 5.9: C-bike and e-bike AWT in Wuppertal in the differentiated model after calibration

impedance also affects mode choice, mode choice was calibrated a third time. This final calibration had negligible impact on route choice results, requiring no further adjustments. The same calibration procedure was applied to the simplified model. Figure 5.9 shows modeled AWT bicycle traffic volumes with the Nordbahntrasse clearly visible. For observed and modeled values at counting locations before and after calibration, see Table 5.13. During count 14, we differentiated manually between c-bikes and e-bikes. 52.8% of bicycles were identified as e-bikes on that day, confirming the general plausibility of the model's results on that link (43.5%) in that regard. Part of that difference might be due to a higher seasonality of e-bike travel compared to c-bike travel (Arning & Kaths, 2025a), resulting in counting location 14's e-bike share in May being higher than the true yearly average.

5.3.6 Scenarios

All scenarios build on the differentiated model, which also denotes the *Reference Scenario*, to allow for e-bike-specific interventions and analyses. For *Scenario A*, we implement all main routes envisioned in the 2019 Bicycle Traffic Concept of the City of Wuppertal, roughly doubling the length of both rail-trail and other bicycle infrastructure. Added segments are always coded as bicycle path or, when continuing the Nordbahntrasse, rail-trail. Figure 5.10 compares the bicycle infrastructure in the Reference Scenario and Scenario A.

In *Scenario B* we model the impact of doubling e-bike availability in Wuppertal. To attain new person-group-specific ownership rates, we recalibrate the ASCs from Table 5.8 to new total target shares of 32.3%, 10.9%, 29.1%, and 27.5% for only c-bike, only e-bike, both, and none, respectively. Lastly, in *Scenario C* we combine the changes of Scenarios A and B.

Table 5.13: Observed and modeled bicycle average weekday traffic (AWT) and scalable quality value (SQV) at the 17 counting locations

Counting	**Observed**	**Diff. Model**				**Simp. Model**	
location	bicycle	c-bike	e-bike	bicycle	SQV	bicycle	SQV
1	236	141	111	252	99%	249	99%
2	439	97	74	171	89%	175	89%
3	238	167	151	317	95%	311	95%
4	882	292	203	496	88%	543	90%
5	974	543	459	1003	99%	913	98%
6	509	294	193	487	99%	706	92%
7	868	438	415	852	99%	710	95%
8	1439	526	501	1028	90%	837	86%
9	234	82	73	154	95%	164	96%
10	295	58	81	139	92%	99	90%
11	106	15	8	23	93%	27	93%
12	159	44	17	61	93%	102	96%
13	2150	1697	1359	3055	84%	2961	85%
14	3191	2079	1602	3681	92%	3521	94%
15	1187	1157	914	2071	80%	1840	84%
16	385	157	80	238	93%	394	100%
17	722	12	5	18	79%	22	79%

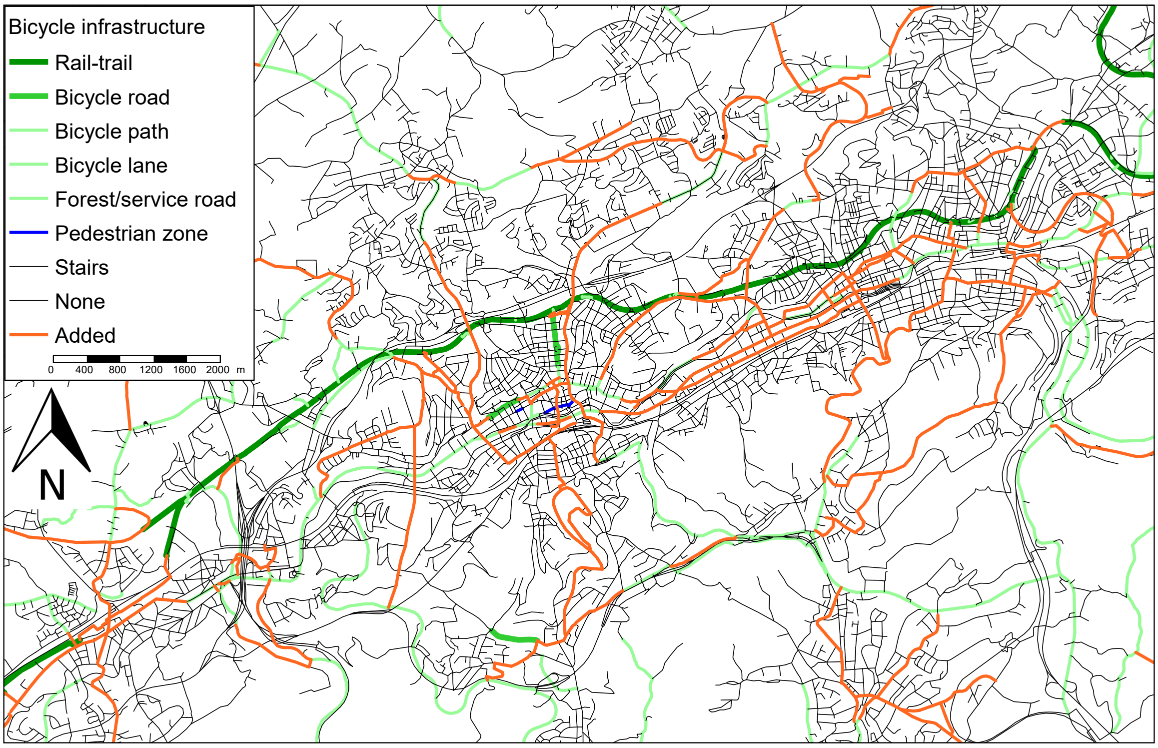

Figure 5.10: Bicycle infrastructure in the Reference Scenario and sections added in Scenario A

5.4 Results

5.4.1 Model Quality

In this subsection, we evaluate whether the differentiated model not only enables more detailed analyses but also achieves higher quality after calibration. Pestel (2021) differentiates two categories of quantitative quality measures: those evaluating differences between model results and reality and those assessing model behavior through realism, sensitivity, and scenario analyses. The latter category is less applicable here due to limited empirical knowledge about reasonable model behavior regarding e-bikes. For the first category, Friedrich et al. (2019) compile model results relevant for quality assessment and appropriate quality measures and thresholds.

To investigate mode choice validity, we apply the Scalable Quality Value (SQV) to average trip distance and average travel time per mode and the Coincidence Ratio (CR) to trip distance and trip travel time distributions per mode. Modeled trip-purpose and person-group-specific mode shares match the target mode shares almost perfectly in both the differentiated and the simplified model (Table 5.12). To investigate route choice validity, we apply the SQV to bicycle AWT counts. To facilitate comparison between the differentiated and simplified models, c-bike and e-bike results are aggregated. The CR is computed according to Equation 5.13, where PM_c and PO_c denote the modeled and observed shares of distance or travel time class c, using ten equiquantile classes (Pestel, 2021) based on the Wuppertal mobility survey. A CR>0.7 is deemed sufficient (Cambridge Systematics, Inc., 2010; Friedrich et al., 2019). The SQV, calculated via Equation 5.14, measures deviations between modeled (M) and observed (O) values, with a scaling factor f allowing the quality measure to be applied to model results of different magnitudes. Appropriate scaling factors are 10,000 for daily bicycle counts, 5 for average travel distance, and 18 for travel time (Pestel, 2021). An SQV>0.75 is considered acceptable (Friedrich et al., 2019).

$$CR = \frac{\sum_{c=1}^{C}(min(PM_c, PO_c))}{\sum_{c=1}^{C}(max(PM_c, PO_c))} \tag{5.13}$$

$$SQV = \frac{1}{1 + \sqrt{\frac{(M-O)^2}{f*O}}} \tag{5.14}$$

The differentiated model shows a slightly better fit for average bicycle trip distance (SQV of 94% and 90%) but performs slightly worse for average travel time (84% and 86%). Note that bicycle travel time is less critical, as it was not the primary focus of the model. All other modes remain nearly unchanged. For the distributions, the differentiated model also slightly outperforms the simplified model, with CRs of 73% and 72% for bicycle trip distance and 78% and 77% for bicycle travel time. Again, other modes show even less variation. Table 5.14 presents the results in more detail. The complete distributions are provided in Tables 5.15 and 5.16. Finally, we evaluate route choice validity. Despite recalibration in the simplified model and substantial changes in traffic volumes at individual counting locations, overall bicycle route choice validity remains largely unaffected, with an average weighted SQV across all locations of 0.90 for both models. Individual counting location values are listed in Table 5.13. In summary, validation shows that we achieved acceptable model quality for bicycle traffic and that the differentiated model is only marginally better than the simplified model.

5.4.2 Scenario Impacts

We expect bicycle infrastructure expansion to increase c-bike and e-bike mode share and mileage, while additional e-bikes should increase e-bike usage, partially at the expense of c-bikes. The overall cycling mode shift in Scenario C may exceed the sum of A and B due to synergy or fall short due to saturation effects. Tables 5.17 and 5.18 present the model results for each scenario and the changes compared to the Reference Scenario. Synergy represents the difference between Scenario C's change

Table 5.14: Average trip travel distance and time per mode and SQV. Internal travel only.

Indicator	**Mode**	**Observed**	**Diff. model**	**SQV**	**Simp. model**	**SQV**
Travel distance [km]	total	4.58	4.43	97%	4.43	97%
	walking	1.29	1.05	91%	1.05	91%
	bicycle	4.81	4.50	94%	4.29	90%
	car driver	5.99	5.44	91%	5.44	91%
	car passenger	5.21	5.17	99%	5.17	99%
	public transport	5.88	5.28	90%	5.27	90%
Travel time [min]	total	19.62	21.79	90%	21.72	90%
	walking	18.13	16.29	91%	16.26	91%
	bicycle	20.87	17.18	84%	17.73	86%
	car driver	17.19	16.37	96%	16.34	95%
	car passenger	16.18	14.09	89%	14.06	89%
	public transport	34.02	46.26	67%	46.17	67%

and the sum of A's and B's change, e.g., $-0.006\%p = -0.14\%p - (-0.12\%p) - (-0.02\%p)$. Car modal split includes both car drivers and passengers, while mileage considers only drivers.

Table 5.15: Travel distance distributions in the mobility survey, differentiated model and simplified model. Internal travel only.

Mode	Class [km]	Observed	Diff. model	CR	Simp. model	CR
Total	(0, 0.7)	10.0%	8.3%		8.3%	
	[0.7, 1)	10.0%	5.3%		5.3%	
	[1, 1.8)	10.0%	12.8%		12.8%	
	[1.8, 2.2)	10.0%	5.6%		5.6%	
	[2.2, 3)	10.0%	10.3%		10.3%	
	[3, 4)	10.0%	11.6%		11.6%	
	[4, 5)	10.0%	9.9%		9.9%	
	[5, 7)	10.0%	15.3%		15.3%	
	[7, 10)	10.0%	13.6%		13.6%	
	[10, 657]	10.0%	7.3%	76%	7.3%	76%
walking	(0, 0.3)	10.0%	11.8%		11.8%	
	[0.3, 0.5)	10.0%	9.8%		9.8%	
	[0.5, 0.6)	10.0%	6.3%		6.3%	
	[0.6, 0.9)	10.0%	19.1%		19.1%	
	[0.9, 1)	10.0%	6.6%		6.6%	
	[1, 1)	10.0%	0.0%		0.0%	
	[1, 1.5)	10.0%	23.5%		23.5%	
	[1.5, 2)	10.0%	12.9%		12.9%	
	[2, 2.6)	10.0%	6.6%		6.5%	
	[2.7, 12]	10.1%	3.5%	57%	3.4%	57%
bicycle	(0.07, 1)	10.0%	11.6%		10.3%	
	[1, 1.5)	9.9%	6.8%		6.1%	
	[1.5, 2)	10.0%	7.2%		6.7%	
	[2, 2.5)	10.0%	6.5%		6.2%	
	[2.5, 3.3)	10.0%	10.6%		10.3%	
	[3.3, 4)	10.1%	9.7%		9.6%	
	[4, 5)	10.0%	12.0%		12.2%	
	[5, 7.4)	9.9%	21.5%		22.7%	
	[7.5, 10)	10.1%	10.1%		11.0%	
	[10, 45)]	9.9%	4.2%	73%	4.8%	72%
car driver	(0, 1.5)	10.0%	6.8%		6.8%	
	[1.5, 2)	10.0%	5.5%		5.5%	
	[2, 3)	10.0%	14.2%		14.2%	
	[3, 3.6)	10.0%	8.8%		8.8%	
	[3.6, 4.5)	10.0%	11.8%		11.8%	
	[4.5, 5.3)	10.0%	9.2%		9.2%	
	[5.3, 7)	10.0%	15.9%		15.9%	
	[7, 9)	10.0%	13.8%		13.8%	
	[9, 12)	10.0%	9.2%		9.2%	
	[12, 300]	10.0%	4.9%	73%	4.9%	73%
car passenger	(0.1, 1.3)	9.9%	4.3%		4.3%	
	[1.3, 2)	10.0%	8.7%		8.7%	
	[2, 2.8)	10.1%	13.2%		13.2%	
	[2.8, 3)	10.0%	3.3%		3.3%	
	[3, 4)	10.1%	15.0%		15.0%	
	[4, 5)	9.9%	12.6%		12.6%	
	[5, 6)	10.0%	9.9%		9.9%	
	[6, 8)	9.9%	15.1%		15.1%	
	[8, 10)	10.1%	9.6%		9.6%	
	[10, 70]	10.1%	8.3%	72%	8.3%	72%
public transport	(0.1, 1.7)	9.9%	8.0%		8.0%	
	[1.8, 2)	10.0%	3.7%		3.7%	
	[2, 3)	9.9%	15.0%		15.1%	
	[3, 3.5)	10.1%	7.1%		7.2%	
	[3.5, 4)	10.1%	7.5%		7.5%	
	[4, 5)	10.0%	12.7%		12.7%	
	[5, 6)	9.9%	11.9%		11.9%	
	[6, 7.1)	10.1%	10.1%		10.1%	
	[7.2, 10)	10.0%	15.7%		15.6%	
	[10, 657]	10.1%	8.4%	73%	8.3%	73%

Table 5.16: Travel time distributions in the mobility survey, differentiated model and simplified model. Internal travel only. Classes with zero-width intervals (e.g., 20 to 20 minutes) due to survey methodology were merged with the next-higher class.

Mode	**Class [min]**	**Observed**	**Diff. model**	**CR**	**Simp. model**	**CR**
Total	(0.0, 5.0)	10.0%	10.2%		10.2%	
	[5.0, 10.0)	20.0%	20.0%		20.0%	
	[10.0, 15.0)	20.0%	20.0%		20.0%	
	[15.0, 20)	20.0%	20.0%		20.0%	
	[20.0, 35.0)	20.0%	23.3%		23.3%	
	[35.0, 690.0)	10.0%	15.8%	83%	15.7%	83%
walking	(0.0, 5.0)	10.0%	6.7%		6.7%	
	[5.0, 7.0)	10.0%	10.2%		10.2%	
	[7.0, 10.0)	20.0%	15.1%		15.1%	
	[10.0, 15.0)	20.0%	21.3%		21.3%	
	[15.0, 20.0)	10.0%	17.3%		17.3%	
	[20.0, 25.0)	10.0%	12.4%		12.4%	
	[25.0, 30.0)	10.0%	7.5%		7.5%	
	[30.0, 325.0]	10.0%	9.4%	80%	9.4%	80%
bicycle	(0.0, 5.0)	10.0%	14.3%		13.9%	
	[5.0, 10.0)	20.0%	16.4%		16.8%	
	[10.0, 15.0)	19.9%	16.4%		17.4%	
	[15.0, 20.0)	10.2%	15.1%		15.5%	
	[20.0, 25.0)	10.0%	11.9%		13.1%	
	[25.0, 30.0)	9.9%	10.8%		10.8%	
	[30.0, 40.0)	10.0%	10.2%		8.5%	
	[40.0, 120.0]	10.0%	4.9%	78%	3.9%	77%
car driver	(0.0, 5.0)	10.0%	14.0%		14.0%	
	[5.0, 10.0)	20.0%	20.9%		20.9%	
	[10.0, 13.0)	10.0%	13.1%		13.0%	
	[13.0, 15.0)	10.0%	7.8%		7.9%	
	[15.0, 20.0)	20.0%	16.1%		16.1%	
	[20.0, 30.0)	20.0%	18.2%		18.3%	
	[30.0, 615.0]	10.0%	10.0%	85%	9.9%	85%
car passenger	(0.0, 5.0)	10.0%	17.4%		17.4%	
	[5.0, 10.0)	19.9%	23.8%		23.8%	
	[10.0, 12.0)	9.9%	8.9%		8.8%	
	[12.0, 15.0)	10.1%	12.1%		12.2%	
	[15.0, 20.0)	20.1%	15.4%		15.3%	
	[20.0, 30.0)	20.1%	15.8%		15.8%	
	[30.0, 155.0]	10.1%	6.7%	77%	6.6%	76%
public transport	(0.0, 14.0)	9.9%	4.5%		4.5%	
	[14.0, 20.0)	10.0%	9.2%		9.2%	
	[20.0, 22.0)	10.0%	2.9%		2.9%	
	[22.0, 25.0)	10.0%	4.6%		4.6%	
	[25.0, 30.0)	10.0%	8.6%		8.6%	
	[30.0, 35.0)	10.1%	9.6%		9.7%	
	[35.0, 40.0)	10.0%	7.5%		7.5%	
	[40.0, 45.0)	10.0%	6.4%		6.4%	
	[46.0, 60.0)	9.9%	17.4%		17.4%	
	[60.0, 590.0]	10.1%	29.3%	58%	29.1%	58%

Table 5.17: Modal split across scenarios and modes of transport

Scenario	walk	c-bike	e-bike	c-bike+e-bike	car	public transport
Reference	20.50%	1.14%	0.77%	1.91%	58.36%	19.23%
A	20.49%	1.23%	0.79%	2.02%	58.28%	19.21%
Change	-0.02%p	0.09%p	0.02%p	0.12%p	-0.07%p	-0.03%p
B	20.39%	1.09%	1.53%	2.62%	57.96%	19.03%
Change	-0.12%p	-0.05%p	0.76%p	0.71%p	-0.39%p	-0.20%p
C	20.36%	1.17%	1.57%	2.74%	57.91%	18.99%
Change	-0.14%p	0.03%p	0.80%p	0.84%p	-0.45%p	-0.24%p
Synergy	-0.006%p	-0.012%p	0.018%p	0.006%p	0.015%p	-0.015%p

Table 5.18: Mileage across scenarios and modes of transport

Scenario	walk	c-bike	e-bike	c-bike+e-bike	car	public transport
Reference	205280	79630	69887	149516	2389371	1312280
A	205076	84988	71564	156552	2393810	1311608
Change	-204	5359	1677	7035	4438	-671
B	204098	76391	139820	216210	2376031	1300699
Change	-1182	-3239	69933	66694	-13341	-11580
C	203783	80620	142549	223169	2380900	1298739
Change	-1497	991	72662	73653	-8471	-13540
Synergy	-111	-1129	1052	-77	431	-1289

As expected, Scenario A increases both bicycle types' modal split and daily mileage, albeit only very modestly by 0.12%p and 7035km, respectively. The greater increase for c-bikes suggests e-bike travel is constrained by ownership rates. Notably, while the increase in bicycle trips mostly replaces car trips (-0.07%p), total car mileage rises (4438 km). This is due to the inclusion of bicycle impedance in the log-sum term of destination choice, which increases trip lengths across all modes. In Scenario B, doubling e-bike availability roughly doubles e-bike modal share and mileage. 58% of new e-bike mileage is induced traffic. Among the replaced modes, car mileage declines the most (-13341km), accounting for 19% of e-bike mode shift. Scenario B generates not just more mileage but also new trips: while Scenario A adds only 301 trips (+0.03%), Scenarios B and C increase trips by 2212 (+0.23%) and 2470 (+0.26%), respectively.

Scenario C combines both previous scenarios, leading to a greater increase in cycling. Synergy effects show that the combined impact on bicycle modal share and mileage closely matches the sum of the individual scenarios, differing by only 0.006%p and -77 km, respectively. When differentiating between bicycle types, however, it is revealed that the two measures in combination lead to a stronger decrease in c-bike travel and increase in e-bike travel than if the two measures are evaluated separately. Additionally, public transport substitution is more pronounced when both measures are implemented together.

Beyond mode shift, we examine bicycle impedance reduction as a key benefit of infrastructure expansion. While travel time savings are typically prioritized in analysis (Argyros et al., 2024; Hallberg et al., 2021; Rich et al., 2021), our model operates in VoD rather than VoT space and does not explicitly model speed. However, our approach allows to quantify the improvement of "soft" factors beyond speed. We first compute total encountered c-bike and e-bike impedance across all trips in the Reference Scenario and then recalculate using the same trip matrices but Scenario A's impedance matrices. To account for partial impedance reductions for new bicycle trips, we apply the Rule of Half, assuming each added trip benefits from half the average impedance reduction of Reference Scenario trips. Table 5.19 presents our results: Scenario A reduces total impedance by

Table 5.19: Impedance reduction due to infrastructure expansion

	C-bike	E-bike
Trips Reference	10830	7301
Impedance Reference [km]	91479	72490
Impedance A [km]	84776	67289
Diff. A-Reference [km]	-6704	-5201
New trips	876	228
Diff. A-Reference Rule of Half [km]	-271	-81
Total Impedance reduction [km]	-6975	-5282

12,257km per day. Monetizing this reduction in VoD space is less straightforward than for travel time, as e.g. willingness-to-pay values are not readily available. We can, however, make some analogies to visualize its magnitude: cautiously assuming a value of time of 10€/h and an average speed of 15km/h yields a daily benefit of 8171€ or nearly 3 million € annually.

5.5 Discussion and Conclusion

5.5.1 Impacts of Bicycle Ownership and Infrastructure on Cycling

Promoting active mobility while reducing car dependency is key to livable cities. Our model confirms that expanding bicycle infrastructure increases cycling, although the mode shift may be smaller than expected given the ambition of the modeled network additions. This aligns with other studies on large-scale infrastructure expansion (Hallberg et al., 2021; Liu et al., 2021; Oskarbski et al., 2021), although some report stronger increases (Paulsen & Rich, 2024; Rich et al., 2021). Our differentiated modeling approach reveals that infrastructure expansion primarily boosts c-bike mode share, as low e-bike ownership limits e-bike use. In contrast, promoting e-bike ownership drastically increases e-bike use, with the car being the most strongly substituted mode after induced travel–an important factor for assessing environmental impact. This finding aligns with meta-analyses on e-bike substitution rates (Bigazzi & Wong, 2020; Bourne et al., 2020).

Our findings show negligible synergies between Scenarios A and B in terms of modal split and mileage. We conclude that the combined impact of infrastructure expansion and e-bike promotion depends on the nature of the improvements. If infrastructure expansion mainly reduces gradients, such as the added bridge part of our Scenario A, additional benefits from increased e-bike adoption are likely smaller. However, if the infrastructure is designed to minimize riding in mixed traffic, which both c-bikes and e-bikes profit off equally, positive synergies can be expected.

While we do not explicitly quantify travel time savings, which have been identified in previous studies as a key benefit of infrastructure expansion (Argyros et al., 2024; Hallberg et al., 2021; Liu et al., 2021; Oskarbski et al., 2021; Paulsen & Rich, 2024; Rich et al., 2021), our model allows quantifying the change in the overall attractiveness of cycling, incorporating distance, infrastructure, gradient, motor vehicle speed, and turns within VoD space. By quantifying this impedance reduction for both existing and new trips, we show that infrastructure expansion not only increases cycling, but also considerably improves conditions for current cyclists, highlighting broader benefits beyond travel time savings. These additional benefits should be considered in infrastructure appraisal, with further work needed to appropriately monetize them.

5.5.2 Modeling Electric Bicycle Traffic

Differentiating c-bikes from e-bikes enables analyzing e-bike-specific policies, measures, and impacts. However, it did not meaningfully improve model quality, even when focusing on the validity of cycling-related model results and despite high shares of e-bike travel among cycling and hilly terrain in our case study. This suggests that unless the focus is on e-bike-related policies or model results, treating bicycle traffic as a uniform mode remains a valid and efficient approach.

For cities aiming to use e-bike-specific transport models to guide decisions on sustainable mobility, infrastructure planning, and policy development, several recommendations can be made. First, collecting detailed travel behavior and ownership data, segmented by bicycle type and user demographics, is crucial for accurately modeling c-bike and e-bike usage. Given the relatively uniform distribution of e-bike use across the network and a low relevance of link-specific e-bike shares for infrastructure design, unsegmented bicycle count data are sufficient, even for assessments in very hilly contexts like ours. However, this may be inadequate in contexts involving higher-speed e-bikes, such as in Switzerland or other regulatory environments.

From a mathematical perspective, VoT and VoD impedance are interchangeable–all factors can be included in either formulation, and parameters can be transformed from VoD to VoT space and reverse. Because travel time, unlike distance, is objectively affected by factors such as gradient or infrastructure, VoT space has so far been preferred in other modeling studies. This introduces challenges, as some factors affect objective travel time (e.g., bicycle speed limits), some need to be included even though they do not affect objective travel time (e.g., motor vehicle speed), and some impact both (e.g., infrastructure). These complexities make it difficult to separate objective and subjective effects in impedance formulation and to gather appropriate VoT values. The VoD approach, on the other hand, is simpler to implement, as all factors can be treated as fully subjective in relation to travel distance. If travel time savings are of analytical concern, more sophisticated speed modeling is required. This does not mean the model itself must operate in VoT space: Travel time can be computed solely as an indicator matrix for impact analysis, while impedance still operates in VoD space. In this case, it is crucial to consider that improving bicycle conditions (e.g., adding infrastructure) may increase travel time (e.g., due to cyclists taking detours). The subjective improvements captured in the VoD impedance should then also be included in the policy appraisal.

5.5.3 Limitations

Several limitations apply to the interpretations of our scenario impacts. The ownership model does not account for infrastructure expansion increasing bicycle ownership, thus slightly underestimating additional bicycle travel in Scenario A. New e-bike owners would likely use their e-bikes less than early adopters, leading to an overestimation of additional e-bike travel in Scenario B. Lastly, since c-bike and e-bike mode choice utilities are included in the log-sum terms of destination choice despite their low overall share, induced mileage from improved bicycle accessibility is likely overstated.

Further limitations apply to our model in general. While the expansion of bicycle count data to AWT accounted for daily, weekly, and seasonal variations, it did not consider weather or dominant trip purposes at each location. In some cases, only a few hours were counted. Thus, comparing route choice validity between the differentiated and simplified model might not be limited by model quality but by consistency between counting locations. Similarly, adjusting 2020 travel survey data to match observed count volumes may skew person-group-specific target mode shares, as some groups, such as former public transport commuters, likely increased their cycling more during the COVID pandemic than others, such as schoolchildren who already cycled to school at considerable rates before the pandemic. Although Wuppertal provides a strong example for e-bike modeling, further case studies are needed to confirm the impact of differentiated modeling on model quality, especially in areas with higher levels of cycling and better data.

Some limitations of our model stem from its macroscopic nature. In contrast, agent-based approaches (Hebenstreit, 2021; Jafari et al., 2022; Kaziyeva et al., 2021) enable a more disaggregated and behaviorally rich representation of individual travelers and their activity patterns. For instance, intra-household dynamics, such as the constraint that a single e-bike in a two-person household cannot be used by both members simultaneously, cannot be represented in our modeling framework. Similarly, adaptive changes in individuals' activity schedules in response to the availability of new mobility options cannot be captured.

Lastly, and most importantly, our model does not capture the effects of cultural change: bicycle traffic is not only influenced by factors such as infrastructure, travel time, or gradient. Local mobility cultures can lead to significant differences in bicycle use between places and times with otherwise similar characteristics. Improving bicycle infrastructure may signal to the city society that cycling is desirable, especially when paired with soft measures like campaigns. Additionally, there is evidence that increased bicycle traffic can in turn lead to even more cycling through normalization (den Hoed, 2025) and safety in numbers effects (Elvik & Goel, 2019). Future research should incorporate these societal dynamics into transport models to more accurately assess the impact of policies promoting active mobility.

5.5.4 Conclusion

We developed the first macroscopic transport model that dynamically differentiates between electric and conventional bicycle traffic across all sub-models, demonstrating its analytical advantages over traditional approaches. Our study revealed that while bicycle infrastructure expansion increases cycling, improvements for existing bicycle travel beyond mere travel time benefits are of high relevance. To promote e-bike use, increasing e-bike availability is key. Most of the new e-bike travel is induced or replaces car usage, highlighting e-bikes' potential to not just replace other active modes or public transport, but reduce car dependence and greenhouse gas emissions. Synergies between infrastructure expansion and e-bike ownership promotion were negligible in our case study.

For cities evaluating e-bike-specific measures or impacts, such as e-bike subsidies or electric and conventional cycling rates, differentiating between the two types of bicycles in transport modeling is essential. This requires sufficient data on c-bike and e-bike ownership and use as well as bicycle count data, which can be a practical challenge. We recommend using route choice bicycle impedance as the foundation for mode and destination choice, with additional factors considered in the latter sub-models where relevant. While both value of distance and value of time formulations are feasible, we suggest using value of distance due to easier availability of appropriate parameter values and simpler impedance formulation. If accurate travel time is of interest for analysis, it can be computed as an additional model output. While offering more analytical possibilities, the differentiated modeling approach did not improve model quality, even though our study area is very hilly. For use cases not specifically focused on e-bike traffic, undifferentiated bicycle modeling therefore remains an effective solution.

The electrification of bicycle traffic is a revolution of active mobility–and it is ongoing. To integrate e-bikes into smart, clean, and healthy transportation systems, cities have to truthfully represent this revolution in their transport models and policy evaluations.

Chapter 6

Discussion and Conclusion

Contents

6.1 Discussion

The findings of this study offer insights into whether and how e-bikes should be represented in travel demand models. The travel demand model presented in Chapter 5 is the first that treats c-bikes and e-bikes as distinct, dynamic choice alternatives across all relevant sub-models and takes into account differences in preferences between the two bicycle types. It thereby demonstrates the feasibility of such an approach. Differentiating between c-bikes and e-bikes is not only possible but also yields plausible results and enhances the model's practical value. However, it does not lead to a meaningful improvement in model quality. The following subsection discusses these findings in greater detail.

The first main research question is: **"How can the electrification of bicycle traffic be accounted for in travel demand models?"** When modelling e-bike route choice, the same principles that apply to bicycle route choice in general must be followed, such as checking the network model for bicycle shortcuts, using a stochastic route choice procedure, and accounting for route similarities. Although research on e-bike route choice is limited (see Section 5.1.2), an impedance function for both c-bike and e-bike traffic was developed based on five key factors (Łukawska, 2024): distance, bicycle infrastructure, turns, gradient, and motor vehicle speed. Differences between the two bicycle types are reflected in the treatment of distance (via separate sensitivities in mode choice utility) and gradient. This approach produced plausible route assignment results for total bicycle traffic and plausible link-specific e-bike shares, although the latter can be validated at only one counting location due to the lack of e-bike-specific count data elsewhere.

In empirical bicycle route choice research, models almost always operate in value of distance (VoD) space (see Broach et al. (2012); Cho and Shin (2022); Łukawska et al. (2023); Meister et al. (2024); Prato et al. (2018); Shah and Cherry (2021) for examples). In contrast, impedance functions in travel demand models more commonly operate in value of time (VoT) space (de Melo & Isler, 2023; Hallberg et al., 2021; Liu et al., 2020; Oskarbski et al., 2021). Drawing on practical experience, it is recommended to construct bicycle impedance functions for travel demand models in VoD space rather than VoT space, for two main reasons. First, VoD values for route attributes are easier to obtain from the literature, as most GPS-based studies use VoD space. Second, and somewhat counterintuitively, VoD simplifies impedance formulation. While many route attributes, such as intersections or gradient, clearly influence travel time but not the physical distance of a route, this does not mean VoT is the more effective modelling space. A route's travel time alone may more accurately capture the route's attractiveness than a route's distance, leading many modellers to adopt VoT model formulatiosn. But that reasoning overlooks that factors affecting travel time can just as easily be expressed in VoD space and that many factors affect both objective travel time and subjective cycling experience. For instance, cyclists avoid steep gradients not only because they slow them down but also due to physical exertion. Given two routes with equal travel time but different slopes, cyclists will likely choose the flatter one. Capturing this effect in a VoT framework would require accounting for gradient twice: once for its effect on speed, and again for its additional disutility due to exhaustion. While the former can be well-informed by literature on gradient-speed relationships, empirical VoT values for the latter are rare. VoD modelling avoids this issue. Empirical route choice studies in VoD space inherently capture both objective and subjective impacts (e.g., safety, comfort, and effort), allowing impedance functions to reflect total perceived disutility without needing to disentangle overlapping effects.

In the mode choice model presented in this thesis, the utility of both c-bikes and e-bikes depends on bicycle-type-specific impedance, impedance sensitivity, person group, and trip purpose. This structure allows to calibrate mode shares by person group and trip purpose, as well as trip distance distributions. These calibration measures are commonly used for other modes due to data availability and the importance of such model outputs (Friedrich et al., 2019). During calibration of c-bike and e-bike trip distance distributions, a challenge arose: matching observed trip distances purely by adjusting the impedance sensitivity parameter would have led to setting it to a positive value. This would imply that higher impedance increases utility and mode share, which would be an implausible result. To resolve this, all trip-purpose-specific constants instead were increased by the same amount for each bicycle type, effectively adding a modal constant. This raised the base utility, resulting in longer c-bike and e-bike trips, while maintaining negative impedance sensitivities. However, this solution demonstrates a degree of arbitrariness about the impedance sensitivity parameter, which is critical for modelling mode shifts due to improvements in bicycle infrastructure. For future modelling efforts, it is therefore recommended to not adjust the utility functions of c-bikes and e-bikes in isolation from the other modes, but instead to set up a completely new mode choice model for all modes based on a coherently estimated empirical model.

Regarding ownership choice, it proved effective to model person-group-specific ownership separately from mode choice, using a discrete choice model to predict ownership rates by group. This approach allowed defining overall e-bike ownership as a scenario parameter while still generating more realistic person-group-specific ownership rates, avoiding the oversimplification of applying a uniform adjustment factor across all groups.

Several data needs arise from these recommendations for modelling e-bike traffic. First, accurately differentiating between c-bike and e-bike traffic requires a network model that includes data necessary for impedance calculation, most notably gradient. This information is typically publicly available and trivial to integrate. Access to accurate, up-to-date data on bicycle infrastructure varies by region and administration, a challenge affecting bicycle traffic modelling in general. For model calibration and validation, data on c-bike and e-bike ownership by person group, as well as mode shares segmented by trip purpose and person group, are essential and should be recorded in travel surveys. Calibrating and validating differentiated route choice models further requires segmented count data. However, no reliable automated method currently exists for distinguishing between c-bikes and e-bikes. Some researchers have investigated using GPS data from crowdsourcing campaigns or sports and routing smartphone applications to generate total bicycle traffic volumes, highlighting both the potential (E. Richter, Raudszus, & Lißner, 2025) and limitations (Bhowmick et al., 2023; Huber, Lißner, & Francke, 2019) of such approaches. Thus, e-bike count data availability is currently still limited to local manual counts. These counts are conducted only sporadically in practice and are becoming increasingly unreliable, as advancements in e-bike technology make it progressively more difficult for counting personnel to visually distinguish between c-bikes and e-bikes.

The second main research question was: **"Does accounting for the electrification of bicycle traffic in travel demand models improve model quality and usefulness?"** The work presented in this thesis confirms that model usefulness is enhanced. The differentiated model offers greater analytical flexibility than an undifferentiated one. For example, it showed that expanding bicycle infrastructure leads to a larger increase in c-bike use than in e-bike use. It also revealed that rising e-bike ownership not only boosts e-bike usage but also reduces car usage.

Assessing model quality, in other words validation, is a complex task, especially when introducing a new mode of transport. According to Pestel (2021), validation should involve checking model parameters, results, and behaviour. For model parameters, the reasonableness (i.e., sign and magnitude) of each newly introduced parameter was ensured by drawing on empirical studies of cyclists' preferences, such as in the ownership model and impedance function. An exception is the mode choice utility function, where the signs of impedance sensitivity parameters were prescribed as negative to ensure plausible model behaviour, but no established guidance exists on reasonable magnitudes. Typically, one would assess marginal rates of substitution; however, since the model presented in this thesis operates in VoD space, these values are not directly comparable to those in the literature, which usually use monetary or VoT terms. Assessing model behaviour, that is how results respond to changes in input data (Pestel, 2021), is similarly challenging. Given the relatively recent rise in e-bike adoption, there is limited precedent for expected model behaviour, such as mode shifts. Nonetheless, the model exhibits generally plausible behaviour, with substitutions broadly aligning with findings from relevant meta-studies (Bigazzi & Wong, 2020; Bourne et al., 2020).

To rigorously assess whether the differentiated modelling approach improved model quality, the study presented in this thesis therefore mostly relied on validating base-year model results against observed data. Both the differentiated and undifferentiated models were calibrated using the same procedure, ensuring that any differences in model quality stemmed from model specification rather than calibration rigour. After comparing modelled and observed mode shares, trip distance distributions, and bicycle counts, no meaningful differences in model quality were found (see Section 5.4.1). It is important to point out that in order to be able to compare model quality between the differentiated and the undifferentiated model, model quality was only quantified at the aggregate level common to both model variants. The main advantage of the differentiated model, i.e., providing differentiated model results such as traffic volumes, modal splits, or trip distance distributions for both types of bicycle, therefore does not reflect in model quality appraisal. This study is the first to systematically evaluate the impact of differentiating c-bike and e-bike modelling on overall model quality. While several limitations, in particular limited data availability for calibration and validation, may partly explain this outcome, the results suggest that caution is warranted in assuming that more detailed bicycle modelling will necessarily lead to substantial improvements in model quality.

6.2 Limitations

This section first discusses fundamental limitations of the overall research approach in understanding and predicting e-bike traffic, followed by key practical shortcomings in the implementation of the study.

As outlined in the introduction of this thesis, e-bike technology has existed for well over a century (Bolton, 1895). While advances in battery technology have only enabled e-bikes as we know them today since the early 2000s (Jamerson & Benjamin, 2012), the variation in adoption timelines and usage patterns across countries suggests that cultural factors also play a major role in shaping which population groups use e-bikes, to what extent, and why. Choice modelling cannot explain why battery technology advanced when it did, or why e-bikes suddenly became fashionable among senior citizens in Europe at a particular point in time. Even less can it predict how such trends will evolve in the future. That task lies with other disciplines, such as electrical engineering, sociology, or futures studies. Any attempt at looking into the future using transport models is ultimately based on assumptions about the broader trajectory of technological and societal trends. Neither this thesis nor other works in the field can accurately predict how important e-bikes will become, but we can explore how different scenarios of e-bike uptake would impact transportation systems.

In a similar but more specific vein, any kind of choice modelling can only investigate and reflect the preferences of people in the past or, at best, the present. Given the rapid growth in e-bike usage, most current users can still be considered early adopters. In other words, we need to consider that a female 30-year-old living in a suburban and hilly area who owns an e-bike in 2025 might have had specific motives for purchasing an e-bike, which she likely does not share with all other persons from the same demographic who might acquire an e-bike only some years in the future or maybe never. This means modelling may, for example, fundamentally overestimate future e-bike mode share when extrapolating current e-bike owners' behaviour and preferences to the broader population. One methodological workaround would be to survey current non-e-bike users about their hypothetical preferences and travel patterns if they had an e-bike. However, this approach brings the typical drawbacks of stated preference methods; most notably, that respondents lack experience with what owning and using an e-bike actually feels like. Related to this, Section 6.1 already addresses the challenge of assessing the quality of a travel demand model for a relatively new mode of transport: there is little historical data or prior experience to benchmark model parameters and behaviour against. Again, this underscores a broader issue: in theory, travel demand models can predict the future, but only if we also know the behavioural parameters of the future.

While Chapters 2, 3, 4, and 5 each include detailed discussions of their specific limitations, some of these are important to recontextualise at the conclusion of this thesis, beginning with data limitations. The analyses in Chapters 3 and 4 are based on survey data from 2017 (Nobis & Kuhnimhof, 2019). While aggregate results from the more recent Mobilität in Deutschland 2023 survey have been published recently, its raw data is expected to become available only after the submission of this thesis. A future replication study would be valuable to assess how preferences regarding ownership and mode choice have shifted in these six years. Due to the revealed preference nature of the survey, the mode choice model presented in this thesis cannot account for induced demand. Capturing such effects would require, for example, a stated preference survey that includes an option such as "no trip undertaken under these circumstances." Additionally, non-transport trips, which comprise a large share of total bicycle use (Bostanara et al., 2025), are not accurately represented in the data used in this study. It also omits several emerging modes of transport that have gained importance in Germany in recent years, including bicycle and e-bike sharing systems as well as private and shared e-scooters. Due to the inability to include monetary variables in the models, monetary marginal rates of substitution, such as values of time, could not be calculated, limiting the ease of comparison with other studies. The gradient variable used in Chapter 4 is zonal rather than specific to origin-destination relations. This was primarily due to the insufficient spatial precision of trip origin and destination data. Even if precise coordinates had been available, computing a route-based gradient measure retrospectively would have required behavioural assumptions, such as gradient aversion, that this work was aiming to investigate empirically. Moreover, this study does not include a dedicated empirical e-bike route choice model. Instead, it relies on VoD values from the literature. This decision was based on the fact that appropriate VoD values were sufficiently available and that e-bike-specific count data to validate such a model is lacking, making additional modelling effort ineffective in this context.

Lastly, three limitations are highlighted that are neither rooted in fundamental research methodology nor in data availability, but relate to implementation choices that would be approached differently in hindsight. First, when modelling c-bike and e-bike ownership, other important mobility tools were neglected, most notably cars and public transport season tickets. As a result, the model can only account for substitution effects between the two bicycle types, but not, for instance, between e-bike and car ownership. This limitation likely led to an underestimation of car substitution effects resulting from increased e-bike ownership. Second, the utility function for destination choice contains a log-sum term aggregating all modes' utilities without weighting. In the differentiated model, reducing c-bike or e-bike impedance therefore has a disproportionately large impact on destination choice utility, despite the two bicycle modes accounting for only a small share of total travel in the case study. This led to implausible model behaviour, namely an increase in car mileage resulting from improvements in bicycle infrastructure. Ideally, the log-sum term should be revised to apply weights that reflect the relative significance of each mode. However, this issue only became apparent in the later stages of the project, when re-specifying and recalibrating the model was no longer feasible within the remaining time frame. Future work should prioritise correcting this structural limitation to improve behavioural realism. Third, while the finding that model quality does not meaningfully improve by differentiating between c-bikes and e-bikes is an important contribution, as this question had not previously been examined, it cannot be ruled out that a more thorough recalibration of mode choice could have produced different results. Due to time constraints, only the 32 parameters of the c-bike and e-bike utility functions (or 16 parameters in the undifferentiated model) were calibrated. If additionally, the 51 parameters for the other modes' utility functions had been calibrated in both models, further improvements in model quality might have been achieved, potentially a greater one in the differentiated model. However, because calibration effort increases not linearly but approximately exponentially with the number of parameters, doing so was beyond the scope of this thesis.

6.3 Future Research

Based on the discussion of the findings and limitations of this work, several directions for future research are proposed, starting with modelling bicycle traffic in general and ending with e-bike traffic in particular. Researchers studying bicycle mode choice need to pay more attention to route-specific attributes, that is which route was chosen for a trip in the first place and its characteristics. To increase data availability, GPS-assisted travel surveys are an obvious solution. Despite already being an established survey method (Heinonen et al., 2024; Nguyen, Armoogum, Madre, & Garcia, 2020), GPS tracking is not commonly employed in large-scale European travel surveys due to concerns about higher non-response rates (Svaboe, Tørset, & Lohne, 2024). Similarly, personal attitudes and perceptions are not commonly recorded in large-scale travel surveys (Kagerbauer & Magdolen, 2024), even though bicycle use at the individual level is strongly influenced by such factors (Haustein & Møller, 2016; Piatkowski & Bopp, 2021), and including these variables in discrete choice models for bicycle mode choice enhances their explanatory power (Ding, Chen, Duan, Lu, & Cui, 2017; O'Reilly et al., 2024; Ramezani et al., 2021). Therefore, for survey data to capture more relevant influencing factors on bicycle use, GPS-assisted methods and the inclusion of relevant attitudinal variables should be considered. Subsequently, attitudinal and route-specific factors should be given more attention in modelling bicycle mode choice.

Another general challenge for modelling bicycle traffic is the issue of non-transport trips, i.e., trips not undertaken to move from one place to another, but rather as a "joyride". These recreational trips constitute a large share of bicycle traffic, especially in places with low levels of cycling (Bostanara et al., 2025). Most travel surveys do not accurately capture such trips. However, the problem extends beyond data availability: both trip-based and activity-based travel demand modelling approaches operate on the fundamental assumption that movement occurs to travel between distinct locations. Integrating non-transport, and specifically non-transport round trips, into travel demand models therefore poses a fundamental methodological challenge that should be addressed.

Appropriately including shared mobility or Mobility as a Service in travel demand models is challenging, both for bicycle traffic and for other modes. In this research field, agent-based modelling frameworks such as MATSim (Hebenstreit, 2021; Horni, Nagel, & Axhausen, 2016; Meyer de Freitas et al., in press), NetLogo (Barrios & Godier, 2014; Wilensky & Rand, 2015), and mobiTopp (Mallig, Kagerbauer, & Vortisch, 2013; Zwick et al., 2022) have proven particularly useful. As bicycle sharing continues to grow steadily in Germany (Statista, 2025), further research is needed on how to integrate such systems into travel demand modelling practice.

Many works identify important differences between c-bikes and e-bikes regarding mode and route choice preferences (see Section 5.1.2). However, findings were often inconclusive or contradictory between studies, especially regarding aversion to turns, intersections, or bicycle infrastructure. More research in this field is needed to enable more robust modelling of electric and conventional bicycle traffic. In particular, differences in preferences regarding bicycle infrastructure between c-bike and e-bike users would have considerable implications for the future appraisal of bicycle infrastructure. For both c-bike and e-bike route choice, preferences also vary considerably between person groups (Hardinghaus & Weschke, 2022; Meister et al., 2023; Rupi et al., 2023; Shah & Cherry, 2021), but it is unclear to what degree these differences are relevant for the application of route choice models in travel demand models. In current practice, bicycle traffic assignment in travel demand models often relies on the preferences of an average cyclist, and the variance in preferences between person groups is accounted for by random variations in utility. In other words, demand of an origin-destination relation is distributed relatively evenly across several plausible routes (FGSV, 2022; Friedrich et al., 2019; Oskarbski et al., 2021; van Dulmen & Fellendorf, 2021). This pragmatic approach may be viable, as decisions about infrastructure design in practice rarely depend on link-specific shares of person groups or bicycle types, which therefore do not need to be as accurate as the overall bicycle traffic volume. However, accurately modelling bicycle route choice for specific person groups or bicycle types may be more relevant for equity analysis or in light of the electrification of bicycle traffic, which further increases the variance in route choice preferences and may require differentiated considerations in future infrastructure design. Therefore, beyond investigating differences in preferences between person groups and bicycle types through route choice modelling, future research should also examine whether and when these differences necessitate more differentiated traffic assignment procedures in travel demand models.

Travel demand models in practice usually have a forecast horizon of five to 20 years. As the first models considering the electrification of bicycle traffic begin to approach or reach their forecast years, it would be valuable to retrospectively assess the validity of these model forecasts. Evaluating past modelling efforts can provide important insights to inform and improve future model development.

As already pointed out throughout this thesis, a relatively simple yet central limitation of this work was the unavailability of large-scale e-bike count data. This represents a fundamental constraint for any future e-bike travel modelling efforts. Therefore, in addition to recording chosen routes in representative travel surveys, the development of automated e-bike counting technology should be given high priority if future modelling efforts are to advance. To conclude this subsection, it is argued that data availability is the most critical bottleneck for bicycle modelling efforts in general and for e-bike modelling in particular, rather than model theory. Future research should put more emphasis on establishing a robust data foundation for the study of bicycle traffic.

6.4 Conclusion

When riding a bicycle, we are more exposed to our surroundings than when driving a car or sitting on a bus, and we also rely on our own physical effort to move. As a result, modelling bicycle traffic is more challenging than, e.g., car traffic, because subjective factors, such as perceived safety when riding in mixed traffic or physical exhaustion from steep gradients, are more difficult to account for than objective factors like travel time or fuel costs. In this regard, electric bicycles (e-bikes) are not fundamentally different from conventional bicycles (c-bikes); rather, they introduce an additional layer of complexity. The experience of stress in mixed traffic or the ability to overcome steep hills differs on an e-bike compared to a c-bike. In other words, when modelling e-bike traffic, we must consider the same broad range of hard-to-quantify influencing factors required for c-bike traffic, with the added challenge of distinguishing which factors affect c-bike and e-bike traffic similarly, and which do not. Simply thinking of e-bikes as faster bicycles is an obvious starting point, but it is insufficient if we aim to develop travel demand models capable of capturing how the electrification of bicycle traffic will shape our transportation systems in the future.

This thesis presented the first macroscopic travel demand model that dynamically differentiates between electric and conventional bicycle traffic across all sub-models and accounts for differences in preferences between the two. Its analytical advantages over undifferentiated modelling approaches were demonstrated. Additionally, this work represents the first rigorous assessment of the impact of differentiated e-bike modelling on overall model quality, revealing that the improvement was only marginal. Based on these findings, several recommendations can be made regarding when and how to model e-bikes in travel demand models:

In general, the ongoing and rapid electrification of bicycle traffic should not be overlooked in travel demand modelling. It was demonstrated that increasing e-bike availability leads to higher overall cycling levels, particularly in areas with currently low cycling activity, and that neglecting this effect may result in underestimating the benefits of bicycle infrastructure and similar interventions in project appraisal. At the current forefront of macroscopic travel demand models, the electrification of bicycle traffic is typically represented through scenario parameters, either explicitly in speed functions or as e-bike market shares, that effectively reduce the impedance of bicycle traffic uniformly across all model segments. In developing a more differentiated modelling approach, drawing on both the findings of this study and existing research, gradient was identified as the only attribute beyond distance or speed that could be confidently distinguished between c-bikes and e-bikes in mode and route choice impedance. For mode choice, differences between person groups and trip purposes are also relevant when distinguishing between the two types of bicycle, however these differences are not relevant for an undifferentiated modelling approach where separation between the two types of bicycles is not of interest. Therefore, undifferentiated yet e-bike-aware modelling approaches remain valid, particularly in flat areas.

There are two circumstances in which these e-bike-aware yet undifferentiated modelling approaches are insufficient. The first is when a travel demand model must address e-bike-specific questions, such as modelling shares of e-bike versus c-bike traffic on individual network elements, or predicting how increasing e-bike ownership would affect mode shares, mileage, or the appraisal of bicycle infrastructure. The second is when the model area is particularly hilly. For such use cases, the differentiated modelling approach presents a practical solution for how to account for e-bikes in travel demand models in practice. It generates valid model results and plausible model behaviour. An empirical ownership model combined with scenario-setting for an overall target e-bike ownership rate is well suitable to operationalise growing e-bikes market shares. E-bikes as a distinct alternative in mode choice allow for person group and trip purpose specific mode shares, reflecting the large variance of e-bike usage patterns in the real world. While the limited availability of e-bike count data prevents rigorously validating differentiated c-bike and e-bike traffic assignment, its results are plausible.

The challenges for future e-bike modelling research largely align with that of modelling bicycle traffic in general. To more confidently understand what drives, shapes, or prevents cycling, be it electric or not, we need more and better data on cyclists' attitudes and perceptions, the actual routes they choose, as well as their number. Lastly, especially in areas with low levels of cycling, we need to develop new modelling approaches to capture non-transport trips in our so far very utilitarian model architecture.

The future is unknown; models cannot change that. Still, they help us discern what we do and do not know, and how we can use our understanding of the world to make informed guesses about the best way forward. That might be less than what transport modellers sometimes hope for. But like maps, models help us navigate this uncertainty. Not by telling us exactly where to go, but by helping us understand where we are and what paths might lie ahead.

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