

A Review of Current Practice and Research on E-Bikes in Transport Models



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BICYCLE
TRAFFIC

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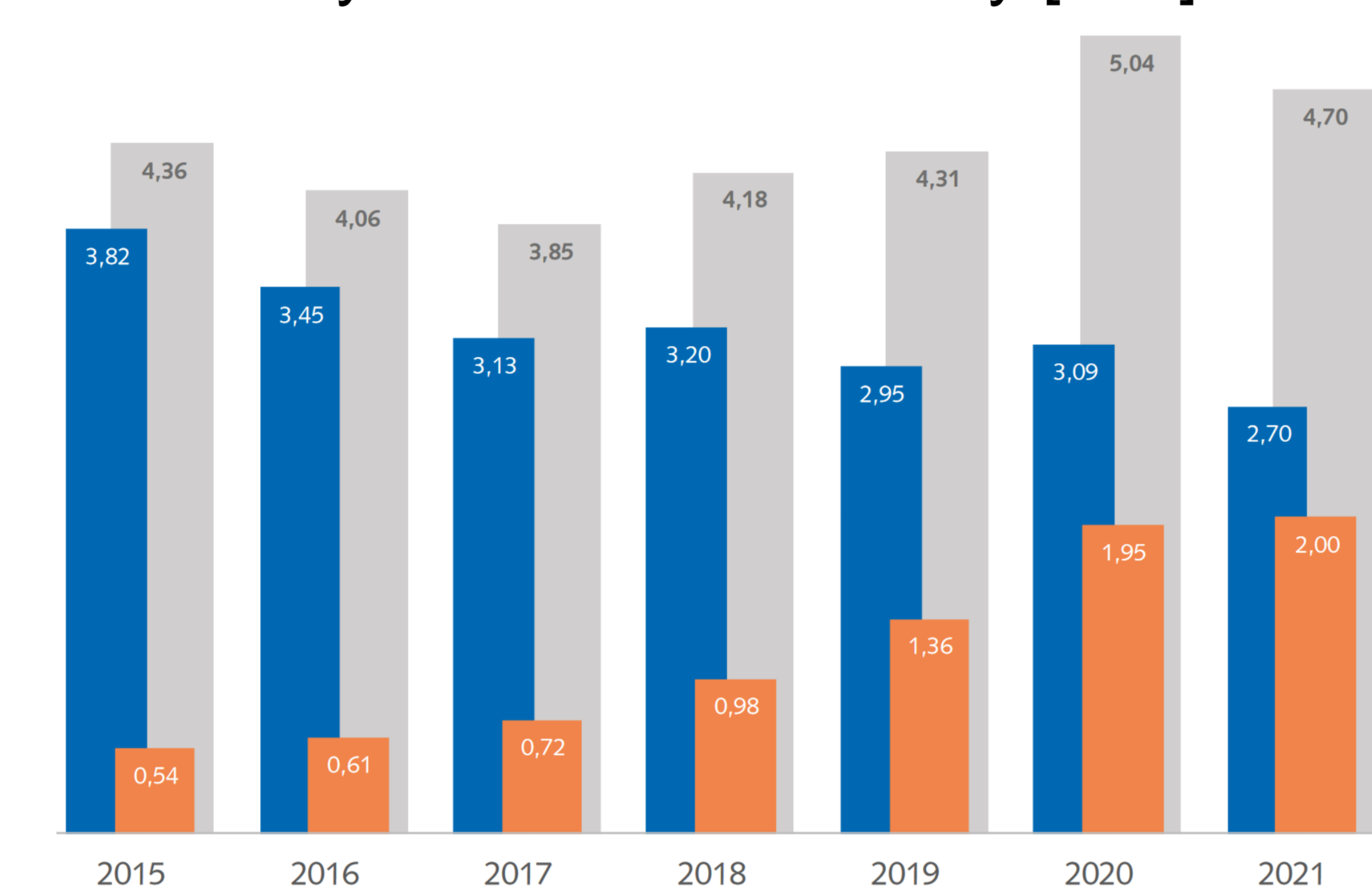
INTRODUCTION

Despite **differences between e-bikes and conventional bicycles** regarding for example speed, exhaustion, user groups, price, and safety, **macroscopic transport models rarely differentiate** between c-bikes and e-bikes in practice.

When changes in the transportation system affect the choices its users (can) make, it is **necessary to include these new options** in transport models to ensure that their outcomes continue to be accurate. The **neglect of e-bikes in contemporary transport models poses a risk to the models' predictive accuracy**. Additionally, such models might not fully capture the future benefits of bicycle infrastructure investments and do not allow for the analysis of measures directed at e-bikes, such as subsidies or dedicated infrastructure.

This research synthesizes findings regarding how e-bikes are currently considered in transport models and what e-bike mode and route choice research suggest for appropriate modeling approaches.

Number of **conventional**, **electrical** and all bicycles sold in Germany [mn.]

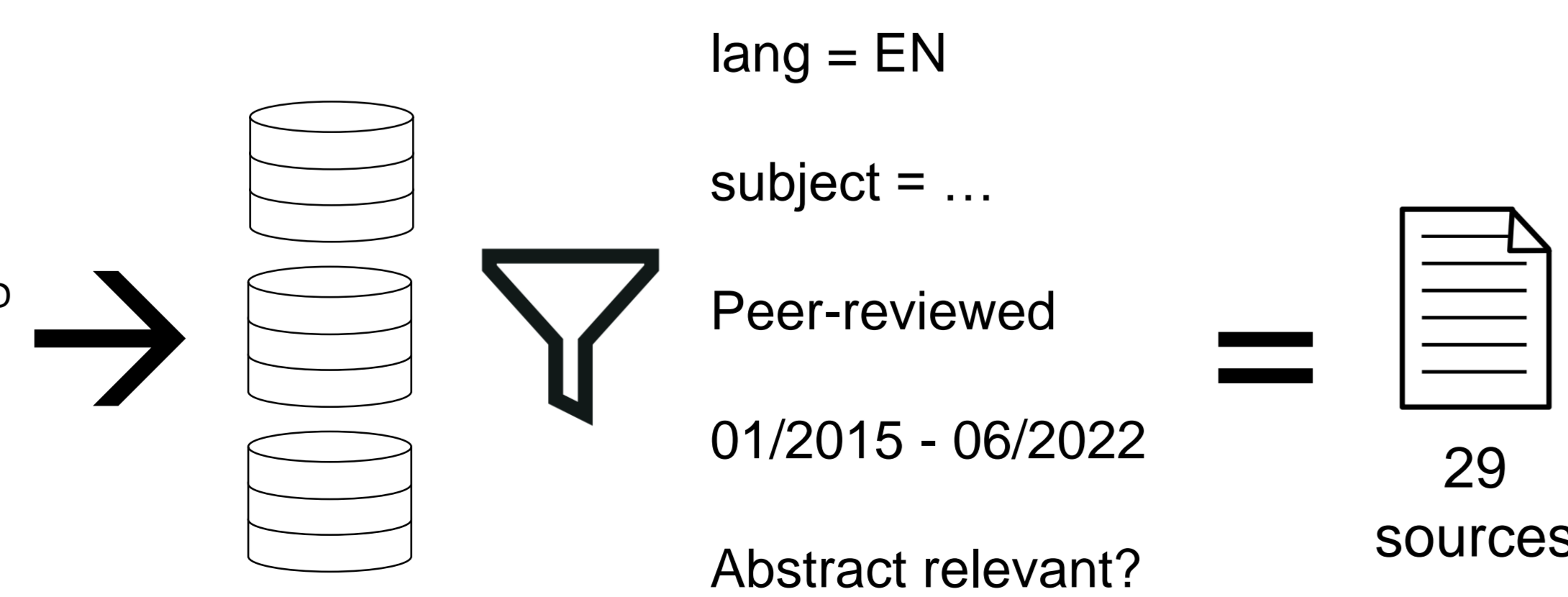


Existing transport models and their considerations regarding e-bikes

Model	Area	Model Specification
GM4	Netherlands	Distinct e-bike mode . E-bike LOS (travel time, distance...) same as c-bike, but separate estimation of mode and route choice coefficients.
COMPASS (Under development)	Copenhagen	Explicit 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. No differentiation between c- and e-bikes.
Verkehrsmodell 2030	Berlin	
OTM 7	Copenhagen	
Cynemon	London	
NTM6/RTM	Norway	Conventional cycling mode
MODUS 3.1	Paris	
LuTRANS	Stockholm	
NPVM	Switzerland	
Landstrafikmodellen	Denmark	Combined conventional cycling and walking mode
2016 Travel Demand Model	Los Angeles	Combined conventional cycling mode, no trip assignment
NYBPM	New York City	
Regional Travel Demand Model	Chicago	No cycling mode
VENOM	Amsterdam	No cycling mode (new models to be derived from GM4)

METHOD

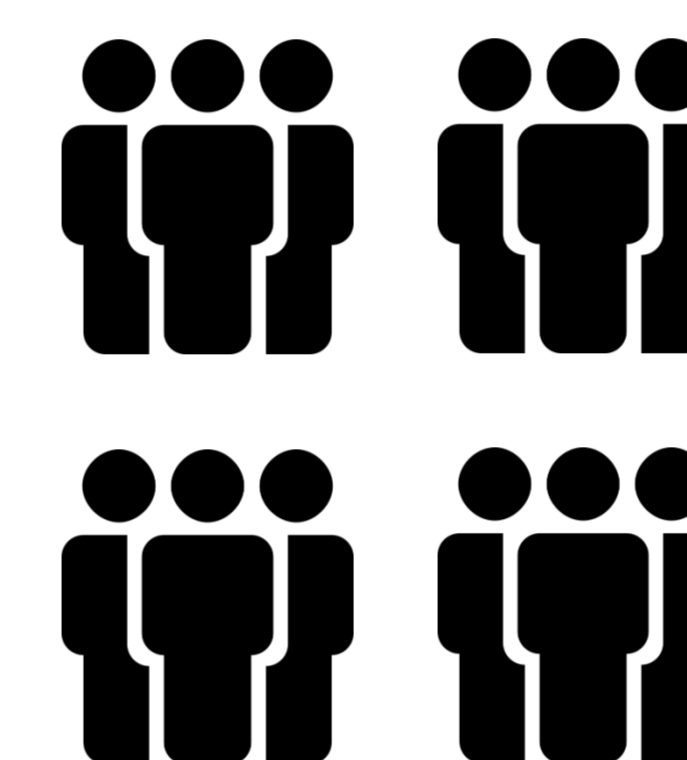
- 1) (infrastructure OR locale OR topography OR demograph* OR "user groups") AND (ebike OR "electric bicycle" OR pedelec) AND (ownership OR purchase OR acquisition)
- 2) (subsid* OR campaign OR incentive) AND (e-bike OR "electric bicycle" OR pedelec) AND (ownership OR purchase OR acquisition)
- 3) (e-bike OR "electric bicycle" OR pedelec) AND ("mode choice" OR modal)
- 4) (e-bike OR "electric bicycle" OR pedelec) AND ("route choice" OR path)



Within a **systematic literature review** we searched for sources that either directly contribute to the research on modeling e-bikes in transport models (of which there are few) or that investigate factors affecting e-bike ownership and use and how e-bikes might differ from c-bikes in mode and route choice.

RESULTS

In this section, we present the **three most important learnings about how to model e-bikes** in macroscopic transport models. For a more detailed report on all findings, we invite you to take along a print version of the manuscript.

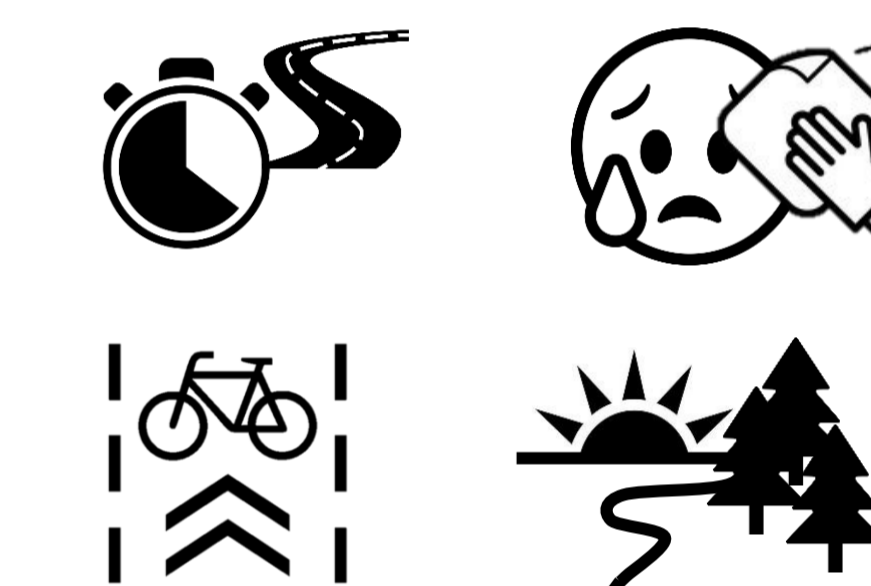


E-bike model parameters must be differentiated by person groups

In many advanced transport models, parameters such as VOT, weights of generalized costs components or mode specific constants, are estimated separately for the different homogeneous person groups. Because **attitudinal factors and personal fitness are especially relevant** to active mobility, this is even more so relevant for bicycle mode and route choice. Because of these specific motivations behind e-bike (non-)use it might be useful to partition the population into **different groups than commonly done for other modes** (elderly leisure cyclists, non-cyclists, bicycle commuters, bicycle enthusiasts). Only by doing so, the different rates of e-bike adoption and mode substitution can be modelled adequately.

Utility in mode and route choice must include more than just travel time

There is evidence from qualitative and quantitative research that besides travel time, **physical exhaustion** (e.g. due to slope or wind), **safety** (mostly influenced by motor traffic and infrastructure) and the perceived **beauty** of the surroundings (land use) are highly relevant for accurate route choice and to a certain degree mode choice modeling. Those factors therefore need to be included in the utility of e- and c-bikes, such as through Multinomial Logit models.



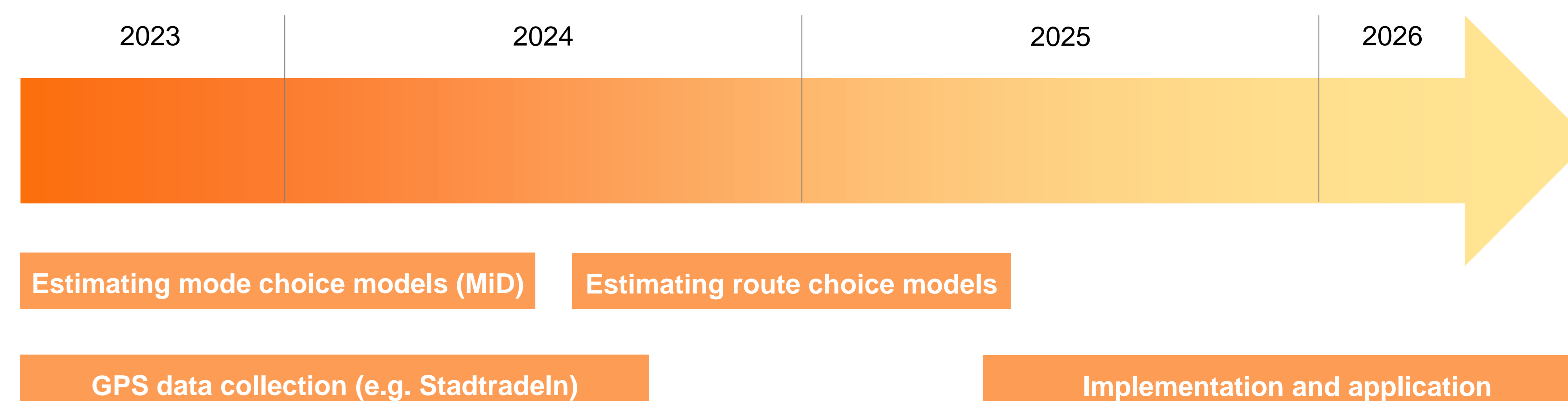
Models must allow for scenario-setting regarding e-bike propagation

Due to the **dynamic development** of technological and attitudinal factors around e-bikes, mode choice parameters estimated on today's data cannot be assumed to hold true in the future. However, simply assuming a fixed share of e-bike travel among cycling in transport models would mean that the model is insensitive to measures affecting e-bike utility such as dedicated infrastructure or subsidies. As a compromise, we propose that 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. This allows for both **scenario-setting and dynamic e-bike share**.



OUTLOOK

PLUG-IN: First project to fully model e-bike mode and route choice in municipal transport models



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Sources
Bicycle sales diagram: https://www.ziv-zweirad.de/fileadmin/redakteure/Downloads/Marktdaten/ZIV_Marktdatenpraesentation_2022_fuer_Geschaftsjahr_2021.pdf
Icons: <https://www.creativefabrica.com/de/product/e-bike-line-art-logo-design-icon-vector/>

TRB Annual Meeting 2023 TRBAM-23-00801 Tuesday, Jan 10, 6:00PM – 7:30PM