Comprehensive spatial and cost assessment of urban transport options in Munich

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ABSTRACT

The constant introduction of new mobility options in urban transportation complexifies the mode choice of individual users. Relevant indicators have to give users a reliable guideline for mode choice as well as giving municipalities and industry a reasonable guideline for strategic orientation. Therefore, in this paper, a comprehensive assessment of transport options is conducted for indicators such as travel time, costs, CO2 emissions and external costs. The main added value of this paper is the method employed: Trips with origin-destination (OD) coordinates are routed for different transport modes using Open Trip Planner (OTP). In the next step, a cost model calculates these indicators for all transport modes. The presented method can compare privately-owned vehicles with different propulsion types with conventional as well as new public mobility services from a spatial perspective within the Munich area as a case study. The comprehensive information provided by these results helps mobility stakeholders in the decision-making process. The thematic analysis potential of the method is shown in figures which present the efficiency and sustainability of transport modes in different contexts. Recommendations for individual users, the mobility industry, and political decision-makers can be derived from these figures to implement measures for more sustainable and efficient mobility. Results include, that i) Individual users are more cost-efficient when using shared mobility services depending on the annual mileage (below 5,000 km for cars); ii) electric vehicles will be the most cost-efficient propulsion type and, at the same time, have the lowest CO2 emissions. The visualized interdependencies between the guiding principles for transport planners and transport modes allow providers of mobility-as-a-service (MaaS) platforms to integrate a variable pricing system according to these principles. Pricing models will be investigated in further studies.

1. Introduction

The number and impact of new transport options in urban mobility is continuously increasing (Kamargianni et al., 2016). Therefore, the number of different choices to be made for a simple trip in the city area is high. The lack of transparency regarding travel time, costs, emissions, and the external (social) costs of these options lead to uncertainty amongst users and highly complex mode choice behavior (Kamargianni et al., 2016). At the same time, these indicators are relevant for the formation of guiding principles and measures in municipalities' city planning efforts, as well as for the strategic orientation of the mobility industry.

Recent literature is not able to manage the comparison of costs and emissions between privately-owned vehicles and public services, although this is a key information for private users in order to shift from privately-owned vehicles to public services and thus reduce car usage in the inner cities. Most of the relevant studies are focused on specific indicators (cost or emissions), transport modes (private or public) or locations (inner city or regional), and are not able to draw a larger picture showing a comprehensive comparison of all urban transport options (Table 1).

The comprehensive nature and uniform comparison of private and public transport modes are primary added values of this paper. In the context of this study, "comprehensive" is used to describe the wide scope of the comparison and data analysis in terms of target values (cost and emissions), locations (inner city and regional) and number of transport modes (private and public). Conventional (public transport, taxi) as well as new (ridesharing, ride-hailing) mobility services are considered in this study. At the same time, the illustration of full travel costs including consumer-facing monetary costs as well as CO_2 emissions and external costs is another novel feature. The results presented can be used as decision-making support by mobility stakeholders like individual users, political entities, and industry. Additionally, the study's method shows further application potential for subsequent tools that can implement decision-makers' strategies such a Mobility-as-a-Service (MaaS) plat-

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Table 1
Overview of relevant thematically related studies.

Author	Included factors				Method
	Time	Cost	Emissions	Other	
Focus on sustainability and social benefit					
König, Nicoletti et al. (König et al., 2021)		X	X	X	Calculation / Simulation
Bugiel et al. (Anita Bugiel; Anne Vonderstein; Chrstina Denz 2010)	X	X	X		Experiment / simulation
Wachotsch et al. (Wachotsch et al., 2021)	X	X	X	X	Calculations
Pomykala (Pomykala, 2018)		X	X	X	Evaluation of secondary lit.
Condon (Condon & Dow, 2020)	X	X	X	X	Calculation / analysis
Saighani and Leonhäuser (2017)		X			Calculation / analysis
Skrucany et al. (Skrúcaný et al., 2018)			X	X	Calculation / analysis
Sommer et al. (SOMMER et al., 2021)		X			Calculation / analysis
Focus on individual benefit					
Pez (Wilde et al., 2017)	X			X	Experiment
Müller-Görnert (Müller-Görnert, 2021)	X	X	X		Evaluation of secondary lit.

forms with a corresponding pricing system. MaaS describes digital services or smartphone apps which enable access to public, shared and private transport modes. The platform integrates planning, booking and paying for the journey.

However, the TUM Accessibility Atlas and related tools (Büttner et al., 2018; Pajares, 2021) as well as GIS-APIs for mobility data analysis tasks (Adenaw et al., 2019; Pajares, 2021) also provide a comprehensive overview and comparison of urban mobility and can take city-specific and social aspects into account. The visualization and evaluation methods differ from the approach used in this study because the results are linked rather to the geographic position (accessibility), whereas results in this paper are related more to the specific transport modes, and compare a larger quantity of different transport mode characteristics. This paper builds upon recent work in (König et al., 2021) and puts the parameters presented for the calculation of consumer-facing costs, CO_2 emissions and external costs in the spatial perspective of the Munich area as a case study.

The goal of this study is to present and test a new method (Section 3) and to demonstrate the method's application potential. Section 4 shows the first thematic applications and analysis potentials by comparing privately-owned vehicles and public services in terms of costs and emissions. It also shows the efficiency and sustainability of these transport modes in different contexts.

2. State of the art

In the following sections, the current status of literature assessing urban transport options is investigated. First, we concisely summarize general methodologies of mobility research. In the subsequent paragraph, a brief overview of studies on the analysis of transport options in recent literature is given. This allows for a comparison of the method used to calculate similar or related indicators in the present study with approaches utilized in existing literature. Finally, the method of this study is put in context with current focus areas of urban mobility research.

Collection and analysis of mobility data plays a major role in transportation research. A variety of methods can be applied in order to gather data. Classic approaches include questionnaires, experiments, (expert) interviews, traffic census, focus groups or observations (Kim et al., 2017; Yu et al., 2021). While working with an extensive amount of data in the past often meant elaborate survey procedures, circumstantial agreements for proprietary data and sophisticated analysis software, progressing digitalization, as in many other domains, opens new possibilities especially regarding data availability. An increasing number of governmental but also private institutions either publish data directly or set up application programming interfaces (APIs) which enable third party developers to access certain data. Data sources used in this paper as well as general advantages of data publication will be discussed later on in this section. Tools like smartphones and corresponding applications, GPS-Loggers as well as powerful simulation tools mutually increase researchers' possibilities regarding collection, processing and analysis of data. In the following paragraph, existing studies are categorized, inter alia, according to the aforementioned methodologies.

König, Nicoletti et al. (König et al., 2021) give an overview of parameters and costs for mobility options in general and focus on battery electric vehicles. They include innovative mobility scenarios such as shared mobility and automated driving services as well as conventional mobility services such as public transport and taxi. Additionally, König, Nicoletti et al. (König et al., 2021) consider energy consumption and total costs of ownership for different vehicles, vehicle segments and propulsion types. Publications from various authors likewise deal with the analysis and evaluation of urban transport modes. Table 1 provides an overview of relevant, thematically related studies. It categorizes the publications according to their focus and shows which of the indicators were used and which methodology was applied.

Opposing to most of the studies presented in Table 1, this study uses a simulative approach based on Open Trip Planner (OTP) and the APIs of mobility service providers. Identified as "the most promising open-source trip planning software" (OpenTripPlanner 2013) as early as 2013, OTP still is a popular tool when it comes to traffic and/or spatial analysis. Wessel and Farber (Wessel & Farber, 2019) for example analyze the impact of time dependency when estimating travel times on public transport. They use OTP as an instrument for calculating the shortest paths between origins and corresponding destinations at multiple times during a day. Tenkanen and Toivonen (Tenkanen & Toivonen, 2020) present a longitudinal dataset on spatial accessibility by different travel modes in order to understand how city regions function. Following the door-to-door principle, they compute travel time and distance during different hours of the day using OTP. The results support spatial planning and decision-making on a regional level. Their basic findings and approaches obtained with data from Helsinki can be transferred to every city providing comparable data. Poelman et al (Poelman et al., 2020) utilize the route planner in their working paper to measure urban accessibility for low-carbon modes of transport in various cities. The results of the paper include an in-depth analysis of multiple cities' public transport (PT) efficiency as well as general indicators giving hints on city characteristics influencing the performance of environmentally friendly modes of transport.

Based on OpenStreetMap as well as General Transit Feed Specification (GTFS) feeds, OTP strongly relies on the previously mentioned open data. Open data, meaning e.g. spatial, environmental, or mobility data being generated and publicized in accordance with applicable privacy guidelines by private companies or governmental agencies, possesses enormous potential as a basis for new mobility products (Löhrer et al., 2021). Besides establishing transparency, it allows companies to draw on its potential by aggregating and processing it. The concept of open data defines the free usage and dissemination of

Individual
- Mode choice models
- Use of AI methods for prediction of travel demand and behavior, etc. (e.g. neural network)
- **Routing models and algorithms for different modes**

Spatial
- Accessibility analysis
- Agent-based simulations
- **Origin-destination (OD) matrices**

Planning
- Impact analysis of city planning measures
- Indicator analysis for e.g. sustainability in urban transport
- Multi-Criteria-Decision-Making models
- **Recommendations of measures for society, industry and politics**

Mode specific
- **Total-cost-of-ownership (TCO), consumer-facing costs**
- **Energy consumption, emission model**
- Lifecycle
- **External costs**

Fig. 1. Schematic overview of general aspects or levels in urban transport research.

machine-readable, structured data through the application of open utilization rights (Binzen & Termer, 2017).

The significance of open data, especially from public transport agencies as an enabler for GIS-based analyses is recognized by Gidam & Kalasek (2020). Machine-readable timetable information offers new possibilities and is crucial for understanding PT as the key element of an eco-friendly mobility system. To obtain realistic results, this paper utilizes programming interfaces from various mobility providers. These allow the collection of fundamental data, such as the location of rentable vehicles. An overview of the used APIs is given in Table 3 (Section 3.1).

As the comparison of previous studies assessing urban mobility options in Table 1 shows, different metrics are employed in current research. However, it is apparent that objective indicators are needed in order to validly evaluate various mobility options. Understanding the user's choice behavior is crucial when determining the right factors. Theoretical approaches describing the process of transport mode choice deliver scientific frameworks based on objective metrics and therefore build the foundation for the indicators used in this paper. Theories on transport mode choice can be classified into two major groups (Juschten & Hössinger, 2020):

- Economic theories focusing on objective properties of all disposable options and the decision-makers themselves
- Psychological or behavioral approaches, emphasizing the influence of subjective habits, attitudes, values or norms which affect individual behavior

Economic theories are mainly based around the idea that mode choice is primarily driven by the maximization of individual utility (Juschten & Hössinger, 2020). An introduction to decision-making models derived from the field of economics, like the principle of maximizing utility or a variants of logit models can e.g. be found in (Javeed et al., 2019). König (König, 2005) further describes how such models can be developed and which factors are most relevant. A well-established theory, belonging to the latter of the two aforementioned groups, for understanding mode choice (Ajzen, 2020; Juschten & Hössinger, 2020) is Ajzen's theory of planned behavior (Ajzen, 1991). While the basic theory itself isn't novel, it keeps being adapted and/or extended (e.g.

(Ahmed et al., 2020; Ibrahim et al., 2020)) to consider the most recent developments in research and allow for optimal analysis of transport behavior. Focusing rather on objective, quantifiable indicators, multiple studies consider costs and travel time as especially relevant factors when choosing between modes of transport (Ahmed et al., 2020; Dällenbach, 2020; Jin et al., 2020; König, 2005; Wilde et al., 2017). Furthermore, personal norms such as environmental awareness have been identified as deciding factors by other authors (Ababio-Donkor et al., 2020). These findings in literature lead to the choice of indicators presented in Section 3.

In accordance with the comprehensive approach described in Section 1, we derive methods from multiple directions of urban transport research in order to quantify the indicators described above. During the field research for this study, four different focus areas or levels in urban transport analysis were identified (Fig. 1).

There is an individual level where the behavior of transport mode users is investigated and modelled. This can be done by examining the aspects that influence people's mode choice, or by predicting behavior and travel demand. Measurement data and new AI methods (Nam & Cho, 2020) are used to make predictions. Most recent papers try to assess and analyze the effects of travel behavior by examining the factors that influence people's mode choice (Kim et al., 2017; Li et al., 2020; Witchayaphong et al., 2020). With information about origin and destination, routing algorithms can create trips for different transport modes with specific priorities (shortest, fastest, eco-friendliest, etc.). Recent studies focus on routing in combination with new mobility trends such as ridesharing (Yu et al., 2021) and MaaS (Georgakis et al., 2019), as well as sustainability and emissions reduction (Tirkolaee et al., 2018).

At the spatial level, infrastructural information and inputs from the individual level are used to simulate traffic flows (agent-based) or accessibilities within a city. Accessibility analyses for specific areas and transport modes (Büttner et al., 2018; Pajares, 2021) can be used for transportation network design, management and city planning (Büttner et al., 2018; Di et al., 2018). New approaches also consider user perception in accessibility measurements (Lättman et al., 2018) to create more realistic results and precise recommendations for network design. Agent-based simulations can model the actions and inter-

Table 2
Overview of transport modes, vehicle segments, and propulsion types included.

Criteria	Characteristics					
Private vehicles	Cars	Motorcycle[1]	Motorized scooters[1]	Bicycles	Pedelecs	E-scooters
Public services	Taxi	Ride-hailing	Car sharing[2]	Bike sharing	E-scooter sharing	Public transport
Car segments	Small car	Medium car	Large car	Small SUV		
Propulsion types for cars	Gasoline	Diesel	Electric (BEV[4])	Hybrid[3] (charged)	Hybrid[3] (empty)	Fuel cell (FCEV[5])

[1] (electric / gasoline)
[2] free-floating (FF) and station-based (SB)
[3] Plug-in hybrid (PHEV)
[4] Battery Electric Vehicle
[5] Fuel Cell Electric Vehicle

actions of transport mode users on a spatial scale. This delivers very detailed results on traffic performance and users' travel behavior for a specific city (Martínez et al., 2017) or mobility service (Liyanage & Dia, 2020).

Urban transport is analyzed on a more abstract level when coming from a planning perspective. Here, outputs from the spatial and individual analysis are used to create or assess indicators, measures and recommendations for mobility and city planning efforts. A popular measure undertaken in urban transport management is the implementation of pricing policies (Fowri & Seyedabrishami, 2020). Fostering sustainable mobility is another common scope. Before corresponding steps can be taken, indicators for sustainable urban transport systems must be investigated (Buzási & Csete, 2015). Another more abstract method to work out decisions and measures for sustainable transport is the usage of multi-criteria-decision-making models (Kizielewicz & Dobryakova, 2020; Sałabun, Palczewski, & Wątróbski, 2019; Zapolskytė et al., 2020).

Finally, the transport mode-specific level considers models that describe the technical properties of machines and services used for transport. Their technical and economic characteristics are summarized for cost, energy consumption, and emission models (life cycle (Mitropoulos & Prevedouros, 2015)). Costs can be analyzed in different ways such as total-cost-of-ownership (Mitropoulos et al., 2017), life-cycle costs (Qiao et al., 2020), and service pricing, depending on the transport mode and scope of the study.

Fig. 1 shows the aspects examined by this study (in bold) by putting them in the general context of transport research. The field investigating individual user behavior provides fundamental insights when identifying significant indicators that allow an objective assessment of different well-established or emerging mobility options. In order to quantify those indicators, different techniques of spatial mobility analysis are applied. Origin-destination (OD) matrices are processed by routing algorithms for different transport modes. The obtained results, like travel time or distance, are subsequently extended through the combination of cost and emission models partially derived from mode specific research approaches. Finally, using elements from planning level concepts, concrete measures and recommendations can be formulated (Section 5). By combining approaches from all of the identified research areas described above, this paper presents a novel, comprehensive view on mobility analysis. However, the specific approaches used in this paper only constitute a limited subset of their respective field. The main contribution of this work lies in the development of a framework that takes major parameters of urban mobility into account and allows for the derivation of specific recommendations backed up by numerical indicators.

Although preceding studies achieve assessments of specific modes of transport based on methodologies of their respective research field, the preceding section substantiates a need for a comprehensive analysis that combines multiple approaches and produces results that are directly comparable and transferable to city planning. This leads to the research question of the present study: How can the full travel costs of private and public means of transport be uniformly compared with the goal of deriving a pricing system for sustainable and efficient mobility?
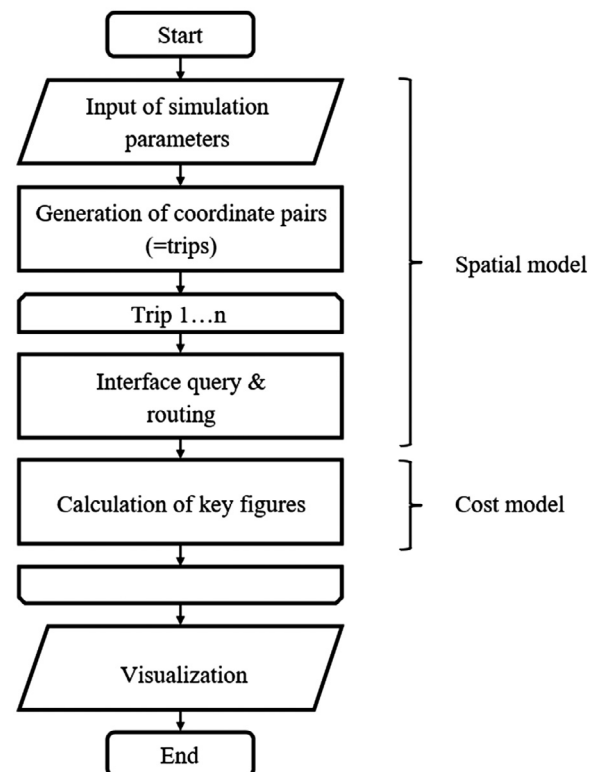

Fig. 2. Simplified program sequence of the spatial and cost model.

The hypothesis of the paper claims that the method presented can fulfill the research question and offer an adequate comparison of travel costs between public and private transport modes.

3. Methodology and data

This study harnesses two approaches of assessing transport modes. First, the spatial aspects of trips are analyzed for specific transport modes (spatial model). Subsequently, costs, emissions, and external costs are calculated for all transport modes (cost model). Both are combined within one comprehensive model. The simplified program sequence is shown in Fig. 2.

3.1. Transport modes in Munich

Transport modes covered in this study can be divided into three categories:

- Privately owned vehicles
- Public mobility services
- Walking

Table 3
List of APIs used in this paper.

Provider	Information used	Source
MVG	Route planning, estimation of travel time, identification of tariff zone of start and end location	(Schneider, 2021)
Flinkster	Location of the closest rental vehicle	(DB Connect GmbH 2021)
Call a Bike	Location of the closest rental vehicle	(DB Connect GmbH 2021)
Tier	Location of all available rental vehicles within a given radius	(TIER Mobility GmbH 2021)
Emmy	Location of the closest rental vehicle	(Cornelius Müller 2020)
Google Maps	Route planning / Travel time estimation including traffic	(Google LLC 2021)
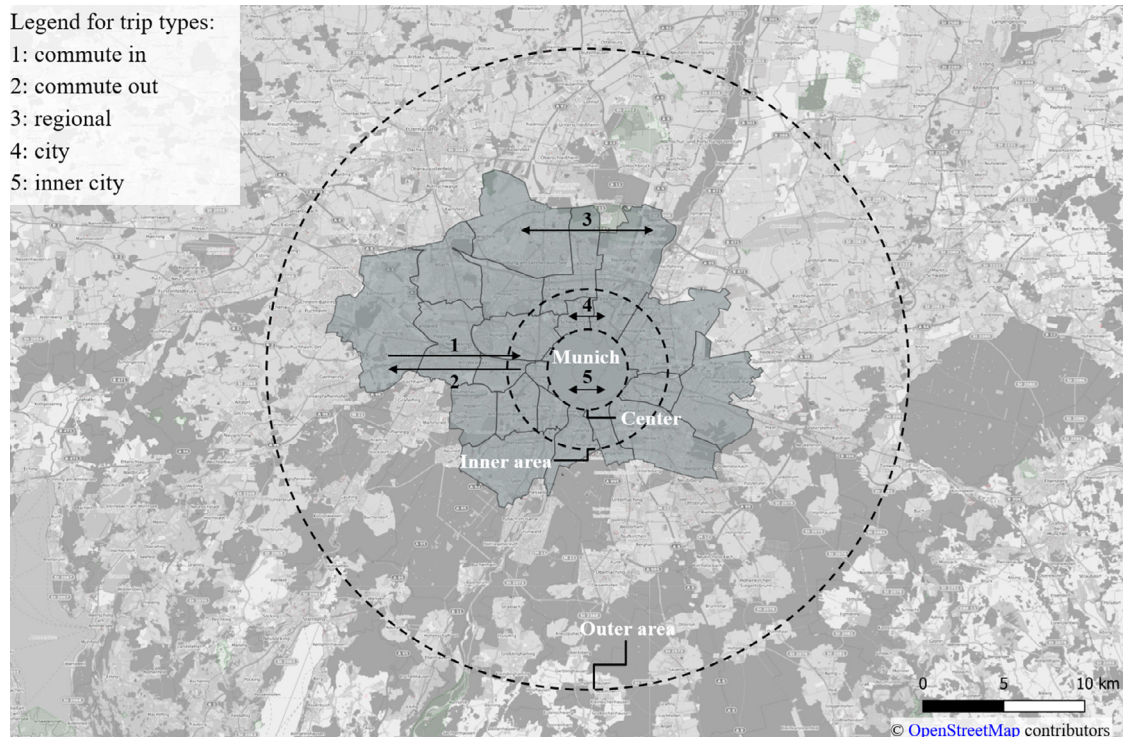
Fig. 3. Munich area with city districts and definition of trip types; map tile from openstreetmap.org (OSM 2021).

All transport modes, vehicle segments and propulsion types included in the model (Section 3.2 and 3.3) are available within the city of Munich and summarized in Table 2. Cars are categorized into the bestselling vehicle segments in Germany (Statista GmbH 2021). Different consumer behavior was added for plug-in hybrids (charged and empty battery) due to the significant difference in costs and emissions (Chakraborty et al., 2020).

In Order to obtain information on e.g. public transport schedules or pricing or positions of shared vehicles and public mobility services, APIs were utilized. Table 3 lists the APIs used in this paper and summarizes their respective usage within the analysis.

Access with documentation was provided for all listed APIs, and substantially contributed to the calculation method (Section 3.3) and transport mode comparisons (Section 4). However, access to the API of floating car sharing providers (e.g. ShareNow) was not available.

3.2. Spatial model

A spatial simulation model was developed in order to compare private vehicles with public mobility services. The goal of the spatial model is to calculate the distance and duration for trips between arbitrary geographic points in the region of Munich. APIs from different mobility service providers (Table 3) are combined with OTP (Marcus Young 2021). For the analysis, 5.000 coordinate pairs are randomly generated and classified into trip types according to Fig. 3 based on the location of the start and destination points, resulting in slightly different numbers

for each trip type. The number of trips is greater than 500 for all trip types, so that the significance of the statements is constant and the required minimum sample size is always exceeded, while ensuring that the required computational effort does not exceed the capacity of common hardware. The minimum sample size is calculated in the case of an infinite population, as represented by the trips within an urban area, according to the equation presented by Mossig in (Mossig, 2021).

$$n = Z^2 \cdot \frac{P \cdot Q}{\varepsilon^2} \tag{1}$$

The minimum required sample size n is therefore 385 for a safety probability Z of 95% and a tolerated error ε of 5% and is thus clearly exceeded for all trip types. The actual mean value of the population P is unknown in the present case and is assumed to be 0.5, which means that the product $P \cdot Q$ is maximized ($Q = 1 - P$) and thus the worst case is assumed (Mossig, 2021).

An arbitrary daytime between 8 am and 6 pm during weekdays is set for each trip (Table 4). During that time period, the PT plan is most consistent and unrealistic waiting times are avoided. Random times of day with a high number of samples are chosen to equalize the advantages and disadvantages of schedule-dependent transport modes. Trips by cars, bicycle, and on foot are directly routed by OTP using the A*-algorithm with Euclidean heuristics, and the results are received via HTTP-query (Barbeau et al., 2020). For sharing service providers such as Flinkster (car-sharing station-based), Call a Bike (bike sharing), Emmy (scooter sharing) and Tier (e-scooter sharing), the position of the near-

Table 4
Query start time.

Program sequence	Weekday	Date	Time of day CET
Sequence 1	Monday	2020-04-20	2:43 pm
Sequence 2	Monday	2020-04-20	5:22 pm
Sequence 3	Tuesday	2020-04-21	5:18 pm
Sequence 4	Wednesday	2020-04-22	1:06 pm
Sequence 5	Thursday	2020-04-23	8:36 am
Sequence 6	Thursday	2020-04-23	9:04 am

est vehicle must first be determined. Subsequently, the trip is composed of walking to the vehicle and driving to the destination, and both again routed by OTP. E-scooter trips are approximated by bike rides with walking to the scooter first and adapted average speeds (König et al., 2021). The routes for public transport can be queried directly over the API using the MVG app (Munich's PT provider).

All API data is only available for the moment of the query, historical data cannot be obtained. In this study, API data is queried once per trip. The exact time slots of the program sequence start time with a lead time of around two hours are listed in Table 4.

For each sequence around 200 to 800 trips were queried. The trip queries are separated in order to cover different times of day and weekdays for the analysis. In the second step, the data is cleaned from erroneous values. A common method in data mining is to remove the trips for which at least one API does not produce a result (Runkler, 2015). This occurs, for example, when the randomly generated coordinates are located in poorly accessible places such as forests. Around 500 trips were eliminated according to this method.

The model configurations and results are restricted to the area of Munich shown in Fig. 3. Different trip types and three zones with concentric circles around the geographical center of Munich (Northern Tower of Frauenkirche) (Statistisches Amt München und Landeshauptstadt München, 2021) have been defined. The first zone has a radius of 2.5 km and defines the center of Munich. The radius was chosen to represent an area where all sharing services are available. The inner area with a radius of 5 km approximates to MVG zone M with constant pricing for public transport tickets. For the outer area, a radius of 25 km was chosen, because the majority (82%) of commuters resides within the specified area (Statistisches Bundesamt. Berufspendler - Erwerbstätige nach Stellung im Beruf, 2021). Trip type "commute in" describes commuting trips from the outer area to the inner area, trip type "commute out" the opposite direction. Trip type "regional" includes all trips within the outer area, trip type "city" within the inner area, and trip type "inner city" within the center. In addition, compass directions (given by OTP) for each calculated trip are saved in the result dataset.

After the distances and durations for all trips and transport modes have been calculated, these values are given to the cost model to calculate costs and emissions for these trips (Section 3.3). Spatial model outputs are the linear distance D_{linear}, traveled distance D_{traveled} and travel time T_{traveled} which, at the same time, represent inputs for the cost model.

3.3. Cost model

To assess and compare different transport modes regarding consumer costs, emissions and external costs, a model for these indicators was developed. All input parameters for the model were gathered from (König et al., 2021).

In the context of this study, two different cost types are defined. Firstly, consumer-facing costs include all costs directly passed on to the user of the transport mode. For services and public transport, these are defined by the prices a costumer has to pay. For private vehicles, consumer-facing costs are defined by the total cost of ownership (TCO). Secondly, external and social costs describe all costs that are caused by the usage of the specific transport mode. This includes, for example, production costs, costs by environmental damage, costs in the health care

system due to accidents or noise, costs by land usage and many more factors. The detailed definition and determination of parameter in the field of external costs will be objective of future studies. The actual calculation of the two types of costs is explained in detail in the following paragraph.

The model for consumer-facing costs can be divided into two different approaches. For privately-owned vehicles a total-cost-of-ownership (TCO) approach with cost factors according to German regulatory frameworks, and for mobility services a price-based approach depending on the provider price model is chosen. The total costs-of-ownership for a trip of a privately-owned vehicle is calculated using the following equation

$$c_{\text{TCO}\_i\_j} = D_{\text{traveled}}$$
$$\cdot \left(\frac{C_{\text{depreciation}} + C_{\text{tax}} + C_{\text{T-V}} + C_{\text{tires}} + C_{\text{repair}} + C_{\text{inspection}} + C_{\text{care}} + C_{\text{insurance}} + C_{\text{park}}}{D_{\text{annual}}} + c_{\text{energy}} \right)$$

$$(2)$$

using $i \in = \{5, 10, 15\}$ thousand kilometers annual mileage for cars and $j \in = \{1, 2, 5\}$ thousand kilometers annual mileage for other vehicles (scooter, bicycle, etc.). The energy costs per kilometer,

$$C_{\text{energy}} = \frac{f_{\text{cons}}}{100} \cdot C_{\text{fuel}} \qquad (3)$$

are dependent on the average fuel or electric energy consumption f_{cons} and the average fuel or electric energy costs C_{fuel}. Considering the complex tariff structure, public transport costs were calculated assuming two opposing usage patterns, single tickets and a subscription ("Isar Card Abo"). Single ticket prices were directly queried from the MVG API while per-trip-prices in case of a subscription are calculated under the assumption that the ticket is used on 20 days per month and two times per day, which resembles commuting. Ridesharing service costs, as well as ridehailing and taxi costs, were calculated according to the provider's price model. These cost models are summarized in (König et al., 2021) and adapted to the presented cost model. For the calculations of final travel costs of each trip C_{service}, minimum prices C_{min}, base prices C_{base}, price per travel time $C_{\text{T\_rate}}$ and price per travel distance $C_{\text{D\_rate}}$ are considered using

$$C_{\text{service}} = \begin{cases} C_{\text{rate}} = C_{\text{base}} + D_{\text{traveled}} \cdot C_{\text{D\_rate}} + T_{\text{traveled}} \cdot C_{\text{T\_rate}}; \ \forall \ C_{\text{min}} < C_{\text{rate}} \\ C_{\text{min}}; \ \forall \ C_{\text{min}} \geq C_{\text{rate}} \end{cases} \qquad (4)$$

according to the mobility service provider's specific price rates. For the calculation of emissions per kilometer, well-to-tank emissions,

$$CO2_{\text{wt}} = D_{\text{traveled}} \cdot \frac{f_{\text{av,cons}}}{100} \cdot CO2_{\text{prod}} \qquad (5)$$

and tank-to-wheel emissions,

$$CO2_{\text{tw}} = D_{\text{traveled}} \cdot \frac{f_{\text{av,cons}}}{100} \cdot CO2_{\text{veh}} \qquad (6)$$

as well as total emissions,

$$CO2_{\text{sum}} = CO2_{\text{wt}} + CO2_{\text{tw}} \qquad (7)$$

are considered depending on the energy consumption of the specific vehicle. External costs for a trip,

$$C_{\text{external}} = D_{\text{traveled}} \cdot C_{\text{ext,lit}} \qquad (8)$$

depend on literature values summarized in (König et al., 2021). Emissions and external costs for taxis and ride-hailing services have to be adapted due to an additional percentage of empty rides (Komanduri et al., 2018; Wittmann et al., 2020). Life-cycle emissions for production and recycling are not included but will be further investigated in subsequent studies. CO_2 emissions per kilometer for public transport are taken directly from an analysis by the municipality of Munich (Landeshauptstadt München, 2021).

For simplification purposes, the following assumptions are made. OTP can route a limited number of transport modes: cars, bicycles and walking. To represent a more realistic routing for additional transport
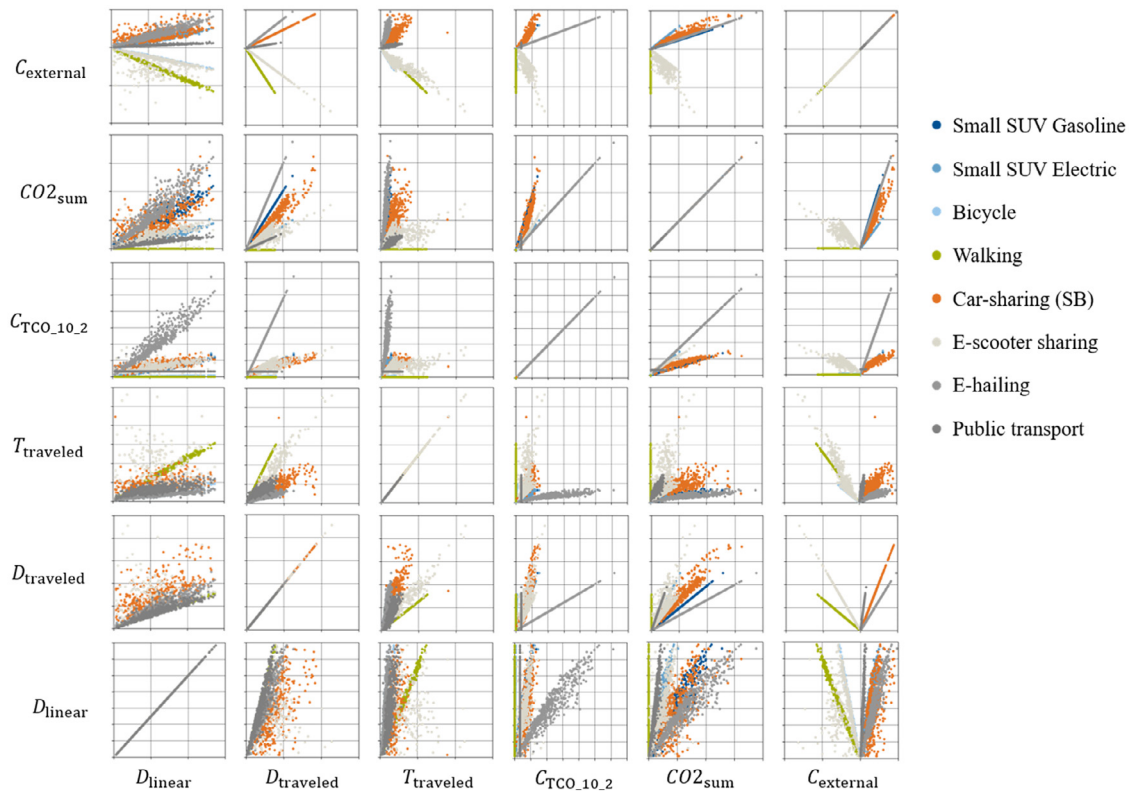
Fig. 4. Data set overview with selected result dimensions.

modes such as pedelecs and e-scooter, the average speed for cycling assumed by OTP was adjusted to more realistic speed values (König et al., 2021). For car sharing, e-hailing and taxi emission calculations, the equivalent emissions of a medium car with a gasoline powertrain were assumed.

4. Results

To comprehend the full extent of the results, an overview of the dataset created by the described model (Section 3) is given in Section 4.1. After that, the data is further analyzed regarding questions that address social, industrial and political challenges and opportunities.

4.1. Data set overview

The data set has the following characteristics:
Fig. 4 visualizes a part of the data set by plotting key results against each other. Linear dependencies between costs, emissions and traveled distance are illustrated. A significant spread in the results between costs, emissions and linear distance is observed, especially for public transport (PT) and sharing services. This is due to the fact, that walking distances to shared vehicles and PT stations as well as waiting times at the stations are taken into account and vary significantly for each trip.

Table 5
Data set characteristics.

Characteristics	
Number of trips	$N_{trips} = 4500$
Number of trip types	$N_{types} = 5$
Number of transport modes	$N_{trans} = 13$
Linear distance, longest trip	$D_{long} = 40.5$ km
Linear distance, shortest trip	$D_{short} = 100$ m
Number of result dimensions	$N_{result} = 11$

This provides an opportunity to draw conclusions regarding optimal geographical conditions and mode choice. The calculation method chosen causes the linear dependency between distance traveled and costs, emissions and external costs for private vehicles and all non-sharing services. The second box on the bottom of Fig. 4 shows the correlation between travelled and linear distance of all calculated trips. The trips or points are shown in different colors for each transportation mode listed in the legend on the right side. Public transport in dark grey on the left side of the graph indicates the most direct correlation between linear and travelled distance. On the other side, station based car-sharing in orange points out a very spreaded correlation between linear and travelled distance due to the additional travel distances to the car sharing stations in combination with the low density of stations within the city and region.

4.2. Data analysis

The data set presented offers a numerous different analysis options and shows the implications for transportation system stakeholders. Due to the possibility of comparing privately-owned vehicles with public mobility services of all kinds, highly diverse and informative graphs can be created. In the following section, a variety of topics such as shared mobility, micromobility, sustainable transport, vehicle propulsion systems and external costs are analyzed. This variety represents the added value of this method, which will be further discussed in Section 5.

The first case examined deals with a comparison of monetary costs for private and shared vehicles. A prominent question in this case is: Does it makes sense to buy a car, or just use new sharing services? This depends strongly on the annual mileage traveled and the region in which one resides (Fig. 5).

The graphs in Fig. 5 show that sharing services for outer regions (trip type regional) with longer distances are more cost-efficient than inner-city trips (trip type inner city), especially in comparison to private vehicles. However, the difference in average trip duration between private vehicles and sharing services increases significantly for regional trips
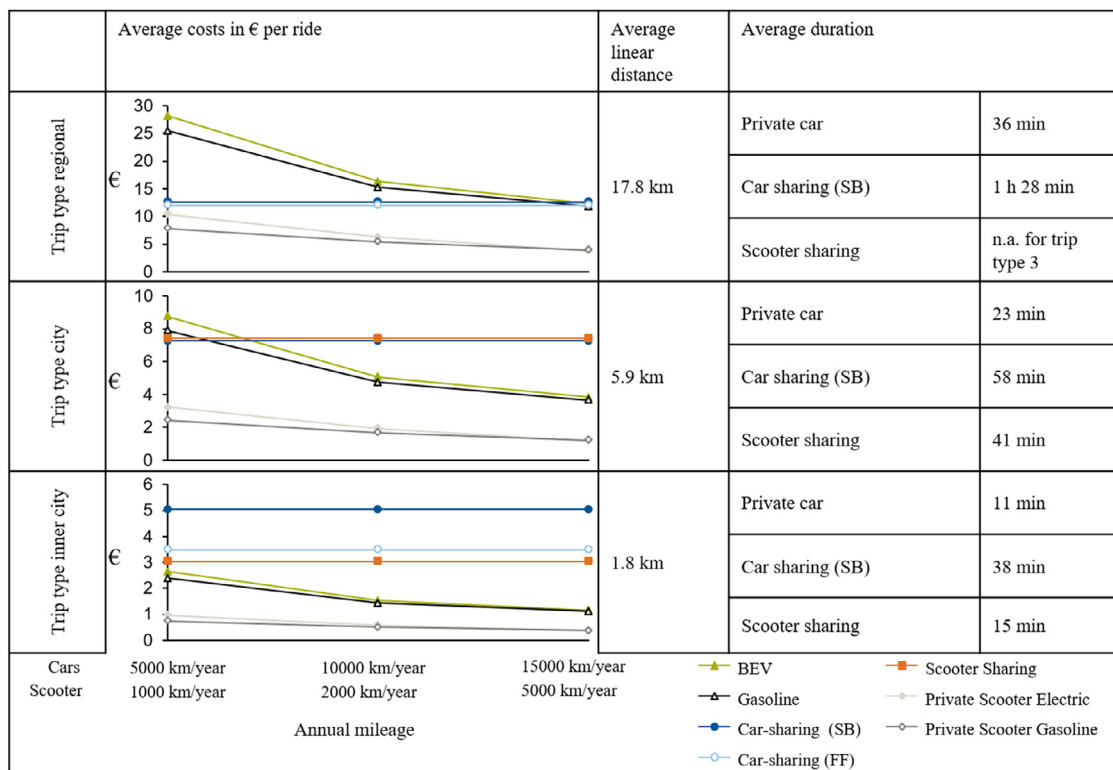
Fig. 5. Comparison of privately-owned vehicles and sharing services (car segment small SUV and holding period of 5 years for all private vehicles).

due to the lower coverage of sharing vehicles and stations in outer regions. Free-floating car sharing is more cost-efficient than station-based services in the city area. For outer regions the costs deviate less. However, car sharing performs significantly worse compared to the other modes in regards of total travel times. This is due to the additional time needed to reach the vehicle, which is assumed to be done on foot in this study. Better coverage or other sharing systems (which were not considered in this study due to unavailability of data) could mitigate the observed effect. Compared to gasoline propulsion, electric propulsion becomes more cost-efficient the lower the trip distance and the higher the annual mileage. The break-even point for buying a car in the inner city (trip type inner city) is at around 4500 km annual mileage, and around 300 km for a motorized scooter. In the city area (trip type city), it is around 6000 km for cars. Below these minimum total travel distances, it is more cost-efficient to use sharing services than invest in privately-owned vehicles.

Another common question regarding micromobility options in the city area is: When should I use a bike or an e-scooter for my trips, and should I buy one for myself (Fig. 6)?

Looking at the micro and active mobility options, all of these options can compete with cars in the inner-city area (trip type inner city) in terms of average duration. Pedelecs and e-scooters can even compete with cars in the outer city (trip type city), but all of these options become less worthwile for longer trips in the regional area (trip type regional). For low annual mileages below 5000 km per year it is more cost-efficient to use an e-scooter sharing service than a private car for trips within the city area. The break-even point for buying a bike or e-scooter is below 50 km per year. Above that limit, it is more cost-efficient for an individual to buy a bike or e-scooter.

Environmental sustainability is becoming more important for private users as well as industrial and political stakeholders, and CO_2 emissions are one of the key indicators for sustainable transportation (Buzási & Csete, 2015). In Fig. 7, the CO_2 emissions for well-to-tank and tank-to-wheel are aggregated and ranked for various transport modes in 2020.

CO_2 emissions for active and micromobility options are the lowest. Due to the current EU energy mix (European Environment Agency 2021), electric vehicles are less sustainable in terms of CO_2 emissions than public transport, but comparable to motorized scooters with gasoline propulsion systems. Individual and privately-owned mobility options with high percentages of tank-to-wheel emissions have the highest CO_2 emissions in total. In particular, hailing services such as e-hailing and taxis emit the most CO_2 due to the empty rides that are needed to operate these services. 59% more rides for e-hailing (Komanduri et al., 2018) and around 80% more rides for taxis (Wittmann et al., 2020) are expected per occupied ride.

The urban mobility market is undergoing disruption by services. This is why conventional public transport providers and taxi companies are competing with new services such as e-hailing and any kind of sharing service. Fig. 8 shows the competitiveness of the services in the specific region.

It is clear that among hailing services, e-hailing (Uber, FreeNow, etc.) is significantly more cost-efficient than conventional taxi services. Comparing only sharing services requiring a street license and reaching speeds above 40 km/h, scooter sharing (e.g. Emmy) has the lowest costs for inner-city use. In the outer city area, however, all three services incur about the same costs for consumers. E-Scooter sharing (Tier, etc.) has higher consumer-facing costs than bike sharing for all regions, but is more cost-efficient than public transport in the inner city. In the outer city and regional areas, conventional public transport is the most efficient transport mode of all public services.

In addition to new mobility services, conventional car manufacturers have to adapt to changing emissions limits, and must choose more sustainable and cost-efficient propulsion types. Fig. 9 compares the CO_2 emissions and TCO for different vehicle segments and propulsion types. BEVs have by far the lowest CO_2 emissions compared to all other propulsion types, while gasoline car segments have the highest emissions in terms of CO_2. Comparing that to the total cost of ownership for vehicles with these propulsion types, BEVs are only slightly more expensive
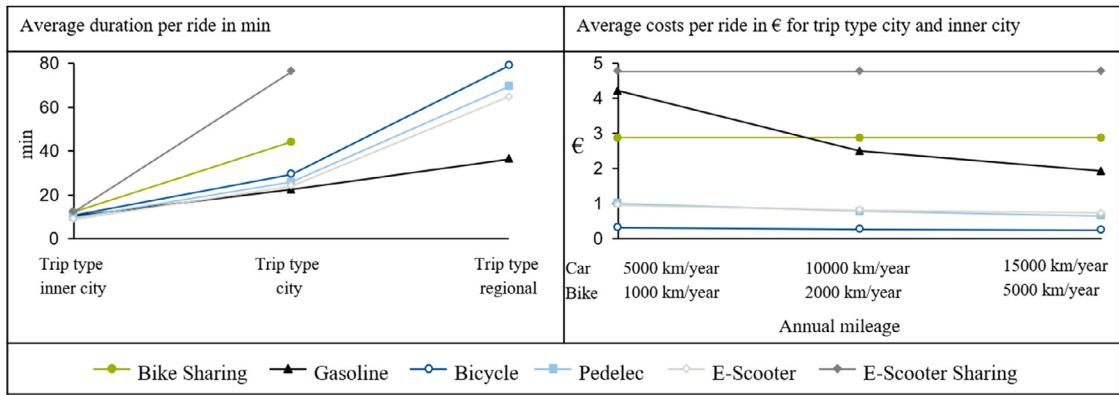
Fig. 6. Comparison of private and shared micromobility options (car segment small SUV and holding period of 5 years for all private vehicles).
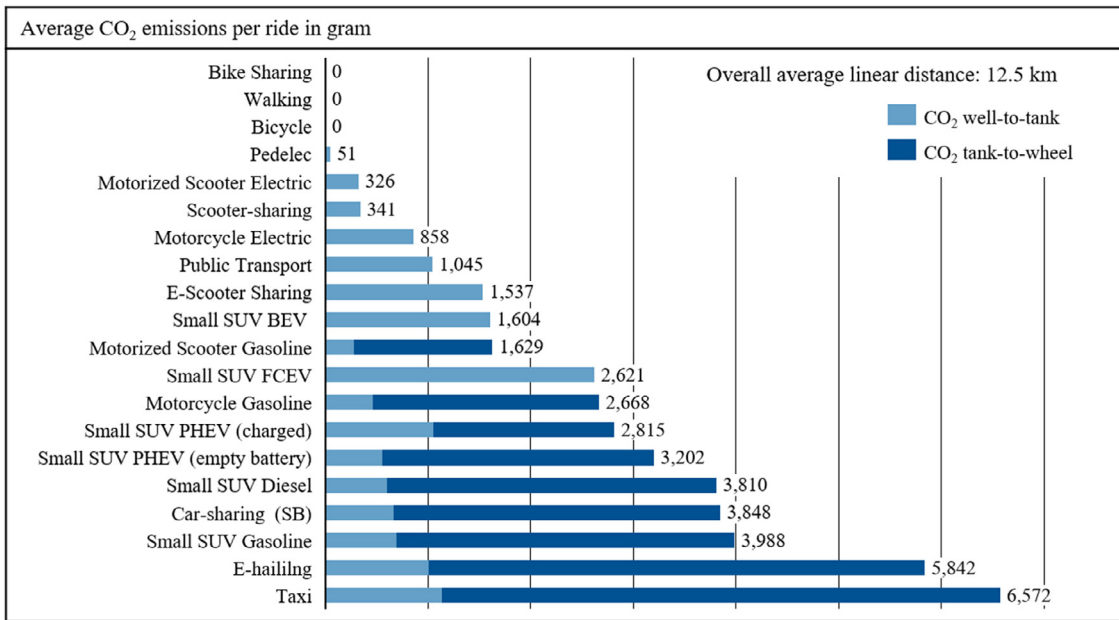

Fig. 7. Average CO_2 emissions per ride for all transport modes.
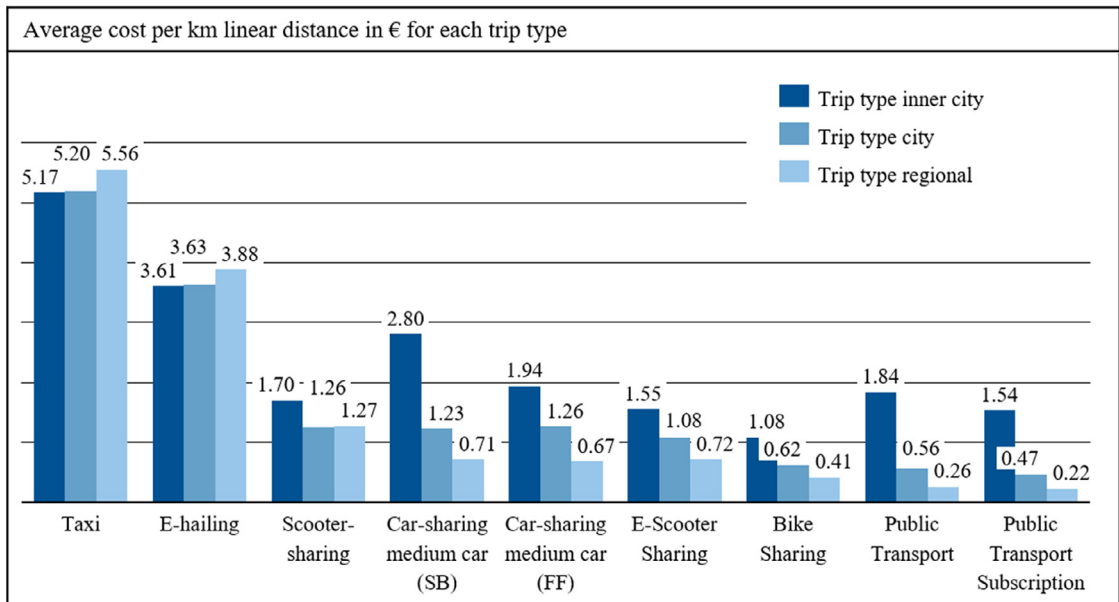

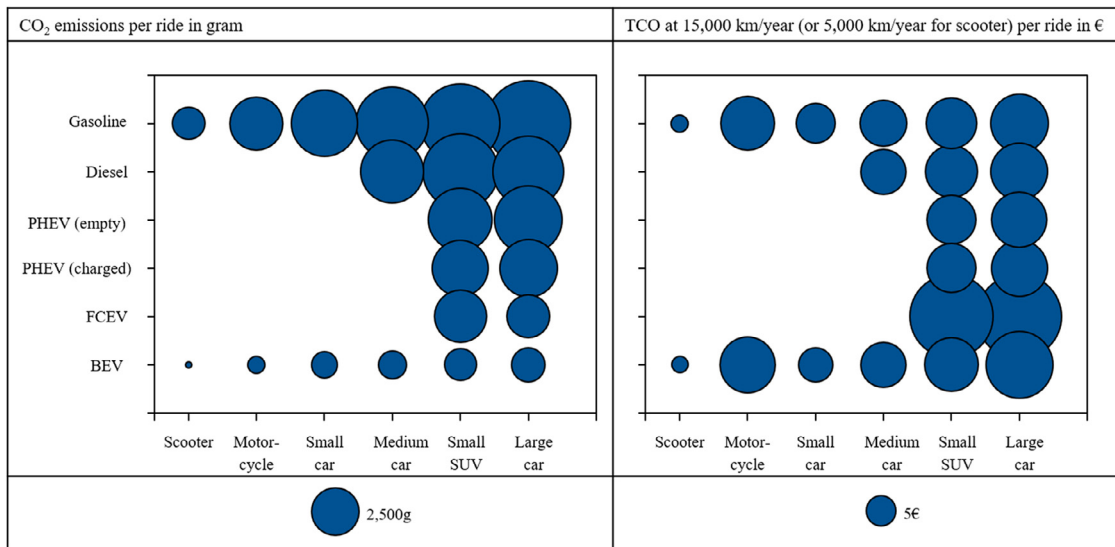**Fig. 8.** Average cost comparison for urban public mobility services.

Fig. 9. CO_2 emissions and TCO for different propulsion types and vehicle segments.
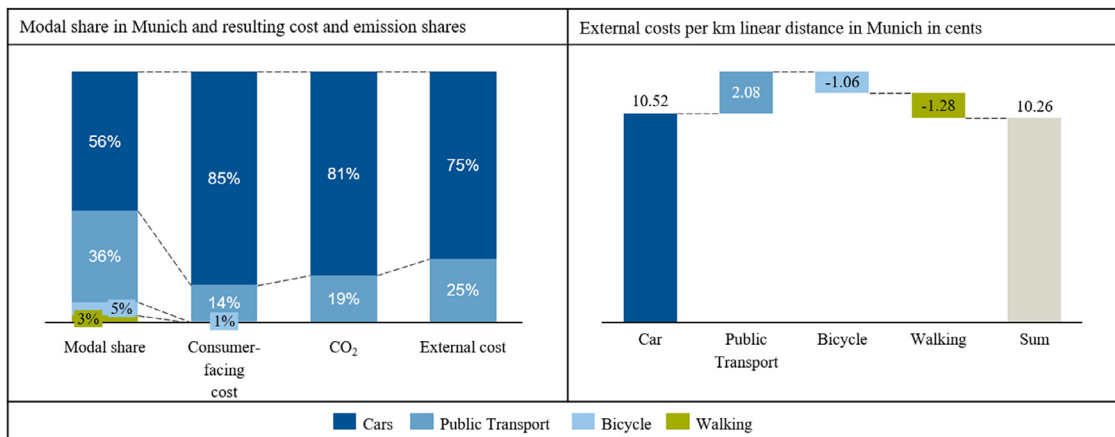

Fig. 10. Modal share and external costs per km in Munich.

than gasoline or diesel cars. Both CO_2 emissions and TCO increase with vehicle size. Large gasoline cars emit around 30% more CO_2 than small gasoline cars, and around 300% more than small BEVs. In TCO terms, small BEVs are already cheaper than small gasoline cars in Germany due to the significant environmental subsidy program of the German government, though larger BEVs are more expensive than their gasoline equivalents. Electric scooter emissions are a quarter of small BEV emissions.

Political decision-makers try to act in the best interest of society. Due to the complexity of society these decisions cannot be made based on single factors such as costs or emissions. For this case, a new dimension is introduced to represent costs for the society (König et al., 2021). These costs are hereinafter called "external costs". Fig. 10 shows the mobility behavior of citizens in Munich's metropolitan region, and which transport modes are responsible for most external costs.

Figure 10 visualizes the percentage of consumer-facing-costs, CO_2 emissions, and external costs calculated by the presented model based on the modal split of trips being taken in the Munich area (Follmer & Belz, 2017). It can be seen that only 56% of all trips are taken by cars, but these cause 85% of consumer-facing costs, 81% of CO_2 emissions, and 75% of all external costs. The right-hand portion of the graph shows the external costs per km linear distance, which were multiplied with the modal shares for Munich to show the average external costs caused by a one-kilometer linear distance traveled for each transport mode. For each kilometer traveled, cars produce around 10.5 cents of social costs,

while PT produces 2 cents. Biking and walking can only reduce these costs by around 2 cents, due to the positive health and environmental effects.

Fig. 11 shows the difference between distance traveled and linear distance. It can be seen that walking trips have the most direct connection, while sharing services have the most inefficient routing due to detours to free vehicles or stations. The PT network in the city is quite dense, and can accomplish more direct routes than cars. However, in the outer region, the difference between PT and car routes is smaller.

5. Discussion

The following discussion includes interpretations of results, recommendations for mobility stakeholders and a critical discussion of method and results.

5.1. Interpretation of results and recommendations

In the following section, the results obtained (Section 4.2) are discussed and interpreted. Also, specific recommendations are drafted for actions in the specific areas of society, industry, and political sphere.

For citizens living in the city of Munich some basic recommendations regarding the usage of sharing services can be made (Figs. 5, 6, 8). Sharing services could be used for trips longer than 2 km within the city
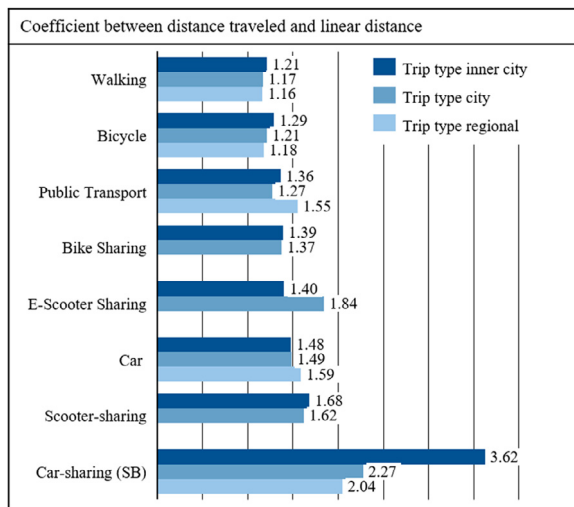
Fig. 11. Coefficient between distance traveled and linear distance for each transport mode.

region, but not in the outer region due to the low coverage. The presented method can indicate recommendations for the minimum annual mileage above which buying a car is cost efficient. The results show, that an annual mileage of around 5.000 km or higher is recommended in order to buy a car. Another learning from the results is that buying an electric vehicle is more cost-efficient than a gasoline-driven vehicle for a total of around more than 15.000 km per year. Bike and e-scooter sharing is recommended for touristic or short visits only, otherwise, the annual mileage of 50 km per year will be exceeded and a private vehicle would be more cost-efficient. Other convenience aspects such as free parking and leaving sharing vehicles at arbitrary places can raise the reasonable annual mileage for bike or e-scooter sharing.

To be environmentally sustainable in terms of CO_2 emissions, citizens of Munich could use active and micromobility for short trips in the inner-city area, and can save more than 90% emissions compared to gasoline-powered cars (Fig. 7) without losing time on their trips. If weather conditions are bad or other circumstances exclude these options, public transport could be used, and up to 75% of emissions can be saved compared to gasoline cars (Fig. 7). For sustainable transport also offering individual usage and a higher comfort level, electric vehicles are recommended, saving around 60% of emissions compared to gasoline cars (Fig. 7).

New mobility services have to compete with conventional services and competitors within their own markets. To be successful, the following recommendations can be made. Due to the high consumer-facing costs compared to other options, taxis must become at least 30% more cost-efficient to be able to compete with e-hailing services. This is possible by reducing the number of taxis and using more efficient fleet management strategies (Wittmann et al., 2020). Sharing services in general have to find the best trade-off between coverage in outer regions and utilization or profitability of the services. The method presented in this study can optimize these regional and cost aspects by implementing synthetic sharing vehicle distributions instead of using the API and evaluating each combination. Station-based car sharing could focus more on outer regions and leave business in the inner city to free-floating services, due to the detours to stations necessary for short trips in the city center. Also, the ratio of distance traveled to linear trip distance is high for station-based car sharing in the city area (Fig. 11). Public transport is most cost-efficient for longer trips, but expensive compared to other options for shorter trips. The PT provider in Munich could offer lower prices for short trip tickets and establish a new ticket price section for mid-range trips within the M Zone area (Fig. 8).

The recommendations for the automotive industry derived from the results presented above all point into one direction: Investment in BEV technology. Smaller cars or electric scooters are preferable for the city area due to their low emissions and costs. FCEVs are currently too expensive for private ownership and are not competitive. PHEVs could be considered as a transition technology for short-term or specific use cases with longer trip distances (e.g. vacation). In the long run, electric vehicles will account for the majority of individual transport in metropolitan areas.

To reduce social costs, an increase in investment in active mobility is needed. This could include several different measures such as improving cycling paths, banning cars from specific streets or districts, and many more (Nieuwenhuijsen & Khreis, 2016; Sallis et al., 2016). Additionally, external costs of cars and PT must be reduced at the same time as reducing the percentage of car trips in general. In other European cities such as Copenhagen, the city government provides more support for active mobility, which leads to lower costs for society as a whole (Fig. 12). Compared to Munich, Copenhagen has a substantially different city structure, history, culture, industry and many other factors which lead to a different traffic system and modal share. However, Copenhagen was chosen as one case example in order to demonstrate the impact of modal share on external costs.

Copenhagen has around 20% fewer car rides, around 25% more cycling and around 15% more walking trips than Munich (City of Copenhagen 2021), and thereby achieves significant negative external costs per km traveled (detours are not considered because the model including routing only works for Munich so far). External cost values are based on a cost-benefit-analysis where negative external costs represent positive effects on society and thereby a reduction of costs for society. Copenhagen is a smaller city with less population, so it is easier to walk short distances within the city. However, the exemplary calculation shows that it does not need much change in the modal split to at least equalize the external costs to zero.

5.2. Limitations of method and results

The presented method achieves a comprehensive assessment of diverse mobility options in terms of manifold research directions. However, due to the complexity of the topic, simplifications and assumptions possibly distorting the results had to be made. Those are discussed in the following section. Results for free-floating car-sharing are not accurate because of the missing API access, and thus missing position of available vehicles. In addition, motorized scooter trip duration and distance are approximated by the values used for cars, which is mostly accurate for inner-city streets but not for regional roads and highways. External costs are generalized and must be approximated by categories such as car, bicycle, walking and public transport. The external cost issue and other areas for improvement will be further investigated in future studies to optimize the model shown.

On the other hand, the evaluation of existing data offers further potential. For example, the spatial and geographical information (GPS coordinates) of the trips can offer more information that can be analyzed accordingly (e.g. distance to next PT station, distance and walking duration to next sharing vehicle, etc.). Another option is a higher resolution of the chosen zones, compass directions, and trip types, which would offer a more detailed analysis of the city infrastructure and traffic network. Additionally, only multimodal but not intermodal trips are considered in this study. A combination of different transport modes for one trip has not been taken into account yet, except for the combination with walking when using public transport or sharing services.

A critical aspect of this method is the use of randomly generated coordinates. It can only reflect the current status of the urban transport system but is not able to make any statements about the travel demand of citizens in that area. Many results of infrastructural impacts are based on the urban settlement structure and the historically developed land use of a region. However, the presented method provides the opportunity
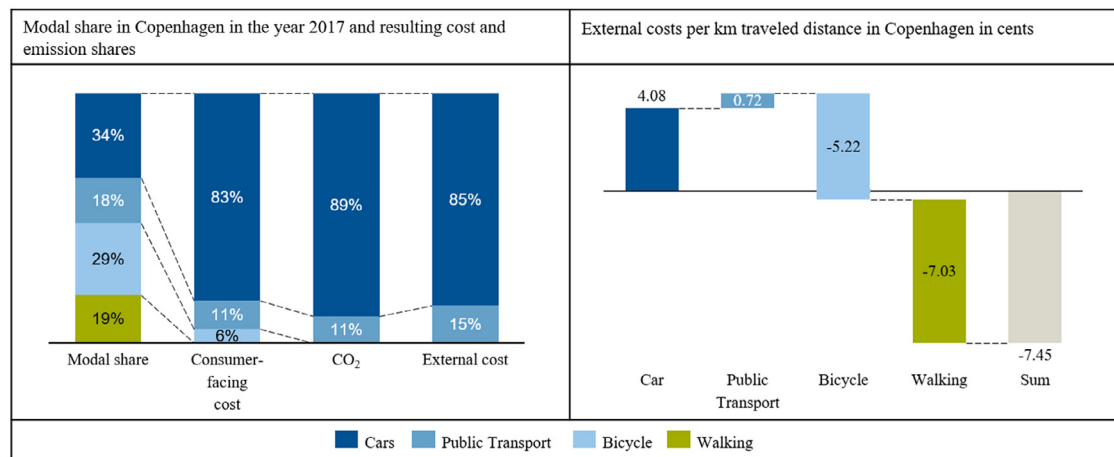
Fig. 12. Modal share and external costs per km in Copenhagen.

of using OD matrices for real trips that were made by citizens in that area. This can reflect the actual travel demand, making more accurate analyses possible. The necessary data can be extracted from popular German mobility surveys (BMVI 2021; infas Institut, DLR, IVT Research 2021) and will be investigated in future studies.

This method already offers several strengths and aspects that are not included in other studies. The exact OTP routing in this model gives the difference between distance traveled and linear trip distance, which is an important aspect for comparing different transport modes. It increases the accuracy of the calculations and offers high comparability for potential interpretations. In particular, the possibility of cost comparisons between the performance of public mobility services and private vehicles is the leading cause for the significance of this method. Another advantage is the inclusion of spatial aspects such as trip type, compass direction or regional zones which gives the opportunity to draw conclusions about the local infrastructure and transport network. Finally, the large amount of data offers a high level of accuracy for general statements about the transport system of a whole region such as the Munich metropolitan area. Therefore, despite yielding limitations, the presented method can offer the claimed comparison of travel costs for private and public transport modes and thus give valuable information for consumers to either stay with their private vehicle or shift to public services.

6. Conclusions

In this study, the unique approach of combining a spatial mobility model with a cost model was taken. The spatial model calculates distance and duration of random trips using the OTP routing algorithm and other APIs, whereas the cost model calculates total-costs-of-ownership for privately owned vehicles and service prices for public mobility options as well as emissions and external costs for all trips created in the spatial model. The combination of both models generates a multidimensional dataset that can be analyzed for the mobility stakeholder interests of society, industry, and political actors. The main results of the data show that sharing services are a viable solution for users with low annual mileages, and that society and industry could invest in electric propulsion systems to produce and use sustainable mobility products. In order to not only consider environment-friendly mobility but also reduce the external or social costs of mobility, municipalities could increase the share of active mobility such as cycling and walking within cities by investing in infrastructure improvements. In addition to the results described and interpreted in Section 4 and 5, this approach offers several other advantages and uses:

- The trade-off between occupation and availability of vehicles or stations of sharing services for outer regions can be optimized by using this tool with minor adaptions.
- By adapting input parameters for the cost model, forecasts and future scenarios can be analyzed and used for strategic decisions or investment made by industry or municipalities. At the same time, "What-if scenarios" can be investigated and prepared for future strategies.
- The same approach can be used for cities other than Munich to compare these cities and benchmark different mobility measures (in e.g. infrastructure and cost reduction).
- In general, a high utilization for measures in society, industry and politics is possible due to the high accuracy and comparability as well as comprehensive view of the results for all transport modes in urban mobility

Ultimately, this study is used to generate transparency towards citizens in cooperation with municipalities and transport associations in the Munich metropolitan area. Furthermore, the interdependencies in the model translate guidance principles and strategies into suggested incentives for specific transport modes. This relationship will be used for a new pricing concept for all transport modes within Munich that is implemented in a Mobility-as-a-Service (MaaS) platform. Future studies will concentrate on the conception of such pricing models and a principle guided MaaS platform. Additionally, a further analysis of external costs is recommended in order to identify the different influence factors on external costs and more reliable external cost parameters.

Author contributions

Lead author, D.S.; conceptualization, D.S.; methodology, D.S.; investigation, D.S. and F.G.; data curation, D.S. and F.G.; writing-original draft preparation, D.S. and F.G.; writing-review and editing, D.S.; visualization, D.S.; supervision, D.S. All authors have read and agreed to the published version of the manuscript.

Formula directory

$C_{\text{depreciation}}$: Annual depreciation costs in € for a newly acquired vehicle with a holding period of 5 years and a decline in value proportional to the annual mileage (König et al., 2021)

C_{energy}: Average energy costs in € per kilometer

C_{external}: External costs in € per trip

$C_{\text{ext,lit}}$: Literature values for external costs in € per kilometer summarized in (König et al., 2021)

C_{fuel}: Average fuel or electric energy costs in € per liter, kWh or kg (König et al., 2021)

$C_{\text{inspection}}$: Average annual costs in € for vehicle insurance (König et al., 2021)

C_{park}: Average annual costs in € for parking (König et al., 2021)

C_{repair}: Average annual costs in € for repair services (König et al., 2021)

C_{tax}: Annual taxation costs in € depending on vehicle segment and propulsion type (König et al., 2021)

C_{tires}: Average annual costs in € for tires (König et al., 2021)

$C_{\text{TCO}\_i\_j}$: TCO per trip in € with i = 5/10/15 thousand kilometers annual mileage for cars and j = 1/2/5 thousand kilometers annual mileage for other vehicles (scooter, bicycle, etc.)

$C_{\text{TÜV}}$: Average annual costs in € for TÜV (German regulatory authority for road vehicles) (König et al., 2021)

$CO2_{\text{prod}}$: CO_2 emissions for the production of fuel and electric energy in gram per liter, kWh or kg (König et al., 2021; Lienkamp et al., 2021)

$CO2_{\text{sum}}$: Total CO_2 emissions per trip in gram

$CO2_{\text{tw}}$: Tank-to-wheel CO_2 emissions per trip in gram

$CO2_{\text{veh}}$: CO_2 emissions for the combustion in the vehicle in gram per liter (König et al., 2021; Lienkamp et al., 2021)

$CO2_{\text{wt}}$: Well-to-tank CO_2 emissions per trip in gram

f_{cons}: Average fuel or electric energy consumption in liter, kWh or kg per 100 km (König et al., 2021)

P: Actual mean value of the population

Q: 1-P

D_{annual}: Annual mileage in kilometers

D_{linear}: Linear distance for each transport mode

D_{traveled}: Traveled distance for each transport mode

T_{traveled}: Travel time for each transport mode

Z: Safety probability in %

ε: Tolerated error in %

Declaration of Competing Interest

The authors declare no conflicts of interest, and the funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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References

Ababio-Donkor, A., Saleh, W. &., & Fonzone, A. (2020). The role of personal norms in the choice of mode for commuting. *Research in Transportation Economics, 83*, Article 100966. 10.1016/j.retrec.2020.100966.

Adenaw, L., Kreibich, J., Wittmann, M., Merkle, L., Waclaw, A. &., & Lienkamp, M. (2019). MAGIS – A geographic information system for mobility data analysis. In *2019 IEEE Intelligent Transportation Systems Conference (ITSC). 2019 IEEE Intelligent Transportation Systems Conference - ITSC, Auckland, New Zealand* (pp. 135–141). IEEE. 27–30 Oct2019 - 2019ISBN 978-1-5386-7024-8.

Ahmed, F., Catchpole, J. &., & Edirisinghe, T. (2020). Understanding young commuters' mode choice decision to use private car or public transport from an extended theory of planned behavior. *Transportation Research Record*, Article 036119812096793. 10.1177/0361198120967936.

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

Ajzen, I. (2020). The theory of planned behavior: Frequently asked questions. *Human Behav and Emerg Tech, 2*, 314–324. 10.1002/hbe2.195.

Anita Bugiel; Anne Vonderstein; Chrstina Denz. Klimabewusst unterwegs: Verkehrsmittel im Umwelt-, Zeit- und Kostenvergleich, Berlin, 2010. Available online: https://www.verbraucherzentrale-bayern.de/sites/default/files/migration_files/media221043A.pdf (accessed on 2 January 2010).

Büttner, B., Kinigadner, J., Ji, C., Wright, B. &., & Wulfhorst, G. (2018). The TUM accessibility atlas: Visualizing spatial and socioeconomic disparities in accessibility to support regional land-use and transport planning. *Netw Spat Econ, 18*, 385–414. 10.1007/s11067-017-9378-6.

Barbeau, Sean et al. (2020)OTP Routing Bibliography. Available online: https://docs.o-pentripplanner.org/en/latest/Bibliography/ (accessed on 4 July).

Binzen, Michael& ; Termer, Dr. Frank (2017).Open Data – Neue Konzepte erfolgreich umsetzen, Berlin, Available online: https://www.bitkom.de/sites/default/files/file/import/171103-Open-Data.pdf (accessed on 2 January 2021).

BMVI. Deutsches Mobilitätspanel (MOP). Available online: https://www.bmvi.de/SharedDocs/DE/Artikel/G/deutsches-mobilitaetspanel.html (accessed on 26 January 2021).

Buzási, A. &., & Csete, M. (2015). Sustainability indicators in assessing urban transport systems. *Period. Polytech. Transp. Eng., 43*, 138–145. 10.3311/PPtr.7825.

Chakraborty, D., Hardman, S. &., & Tal, G. (2020). Why do some consumers not charge their plug-in hybrid vehicles? Evidence from Californian plug-in hybrid owners. *Environmental Research Letters, 15*, 84031. 10.1088/1748-9326/ab8ca5.

City of Copenhagen. Copenhagen of cyclists - facts & ficures 2017. Available online: http://www.cycling-embassy.dk/wp-content/uploads/2017/07/Velo-city_handout.pdf (accessed on 13 January 2021).

Condon, Patrick M., & Dow, Kari (2020) A_Cost_Comparison_of_Transportation_Modes. Available online: https://www.researchgate.net/publication/237126920_A_Cost_Com-parison_of_Transportation_Modes (accessed on 23 June).

Cornelius Müller. WoBike - Documentation of Bike Sharing APIs. Available online: https://github.com/ubahnverleih/WoBike/blob/master/Emmy.md (accessed on 12 January 2020).

Dällenbach, N. (2020). Low-carbon travel mode choices: The role of time perceptions and familiarity. *Transportation Research Part D: Transport and Environment, 86*, Article 102378. 10.1016/j.trd.2020.102378.

DB Connect GmbH. Flinkster API NG - v1: Schnittstellenbeschreibung der Flinkster-API-NG. Available online: https://developer.deutschebahn.com/store/apis/info?name=Flinkster_API_NG&version=v1&provider=DBOpenData# (accessed on 12 January 2021).

Di, Z., Yang, L., Qi, J., & Gao, Z. (2018). Transportation network design for maximizing flow-based accessibility. *Transportation Research Part B: Methodological, 110*, 209–238. 10.1016/j.trb.2018.02.013.

European Environment Agency. CO2 emission intensity. Available online: https://www.eea.europa.eu/data-and-maps/daviz/co2-emission-intensity-5 (accessed on 13 January 2021).

Follmer, R.& ; Belz, J. (2017).Mobilität in Deutschland - MiD: Kurzreport Stadt München Available online: https://www.muenchen-transparent.de/dokumente/5499206/datei (accessed on 13 January 2021).

Fowri, H. R &., & Seyedabrishami, S. (2020). Assessment of urban transportation pricing policies with incorporation of unobserved heterogeneity. *Transport Policy, 99*, 12–19. 10.1016/j.tranpol.2020.08.008.

Georgakis, P., Almohammad, A., Bothos, E., Magoutas, B., Arnaoutaki, K., & Mentzas, G. (2019). MultiModal route planning in mobility as a service. *IEEE/WIC/ACM International Conference on Web Intelligence on - WI '19 Companion.* ACM Press ISBN 9781450369886.

Gidam, M., & Kalasek, R. (2020). GTFS in Public Transport Accessibility Analysis. Gidam, M.; Kalasek, R.; Pühringer, F., Eds.. *AGIT 2020 – Symposium und Fachmesse Angewandte Geoinformatik, 06.07 - 10.07.*

Google LLC. Google Directions API Documentation. Available online: https://developers.google.com/maps/documentation/directions/overview (accessed on 12 January 2021).

Ibrahim, A. N. H., Borhan, M. N &., & Rahmat, R. A. O. (2020). Understanding users' intention to use park-and-ride facilities in Malaysia: The role of trust as a novel construct in the theory of planned behaviour. *Sustainability, 12*, 2484. 10.3390/su12062484.

infas Institut, DLR, IVT Research. Mobilität in Deutschland. Available online: http://www.mobilitaet-in-deutschland.de/ (accessed on 26 January 2021).

Javeed, Faizi Ahmad, Jayeshn. R, Juremalani, Sanket, Bagadia, & Dharmesh, Juremalani (2019). A critical appraisal of mode choice model of work trips. *IJEAT, 9*, 1766–1770. 10.35940/ijeat.F9056.109119.

Jin, F., Yao, E. &., & An, K. (2020). Analysis of the potential demand for battery electric vehicle sharing: Mode share and spatiotemporal distribution. *Journal of Transport Geography, 82*, Article 102630. 10.1016/j.jtrangeo.2019.102630.

Juschten, M. &., & Hössinger, R. (2020). Out of the city – but how and where? A mode-destination choice model for urban–rural tourism trips in Austria. *Current Issues in Tourism, 46*, 1–17. 10.1080/13683500.2020.1783645.

König, A., Nicoletti, L., Schröder, D., Wolff, S., Waclaw, A., & Lienkamp, M. (2021). An overview of parameter and costs for battery electric vehicles. *World Electric Vehicle Journal.* 10.3390/wevj12010021.

König, Arnd (2005). *Entscheidungsmodelle in der Verkehrsplanung: Einführung und Herleitung.* ETH Zürich, Zürich: Materialien zur Vorlesung Verkehrsplanung, Mai.

Kamargianni, M., Li, W., Matyas, M. &., & Schäfer, A. (2016). A critical review of new mobility services for urban transport. *Transportation Research Procedia, 14*, 3294–3303. 10.1016/j.trpro.2016.05.277.

Kim, J., Rasouli, S. &., & Timmermans, H. J. (2017). The effects of activity-travel context and individual attitudes on car-sharing decisions under travel time uncertainty: A hybrid choice modeling approach. *Transportation Research Part D: Transport and Environment, 56*, 189–202. 10.1016/j.trd.2017.07.022.

Kizielewicz, B. &., & Dobryakova, L. (2020). How to choose the optimal single-track vehicle

to move in the city? Electric scooters study case. *Procedia Computer Science, 176*, 2243–2253. 10.1016/j.procs.2020.09.274.

Komanduri, A., Wafa, Z., Proussaloglou, K. &, & Jacobs, S. (2018). Assessing the impact of app-based ride share systems in an urban context: Findings from Austin. *Transportation Research Record, 2672*, 34–46. 10.1177/0361198118796025.

Lättman, K., Olsson, L. E. &, & Friman, M. (2018). A new approach to accessibility – Examining perceived accessibility in contrast to objectively measured accessibility in daily travel. *Research in Transportation Economics, 69*, 501–511. 10.1016/j.retrec.2018.06.002.

Löhrer, Dr. Rene; Riemann, Miriam; Satli, Andrea; Schlegel, Petra (2021) Open Data – Potenziale für die Wirtschaft: über den Nutzen von offenen (Geo-) Daten. Available online: https://www.bmwi.de/Redaktion/DE/Publikationen/Geobusiness/standpunkte-kongress-16.pdf?_blob=publicationFile&v=4 (accessed on 2 January).

Landeshauptstadt München. Umweltfreundliche Verkehrsstruktur. Available online: https://www.ris-muenchen.de/RII/RII/DOK/ANTRAG/2337762.pdf (accessed on 26 January 2021).

Li, X., Tang, J., Hu, X. &, & Wang, W. (2020). Assessing intercity multimodal choice behavior in a Touristy City: A factor analysis. *Journal of Transport Geography, 86*, Article 102776. 10.1016/j.jtrangeo.2020.102776.

Lienkamp, ; M.; Schmid, ; W.; Wolff, ; S.& ; Hessel, ; Homm F. (2021))Status Elektromobilität: Das Endspiel nach der Corona Krise. Available online: https://www.researchgate.net/publication/341670568_Status_Elektromobilitat_2020_Das_Endspiel_nach_der_Corona-Krise (accessed on 26 January).

Liyanage, S. &, & Dia, H. (2020). An agent-based simulation approach for evaluating the performance of on-demand bus services. *Sustainability, 12*, 4117. 10.3390/su12104117.

Müller-Görnert, Michael (2021))Verkehrsmittel im Vergleich - Intelligent mobil. Available online: https://www.vcd.org/themen/klimafreundliche-mobilitaet/verkehrsmittel-im-vergleich/ (accessed on 8 January).

Marcus Young. OpenTripPlanner - creating and querying your own multi-modal route planner. Available online: https://www.researchgate.net/publication/321110774_OpenTripPlanner_-_creating_and_querying_your_own_multi-modal_route_planner (accessed on 2 January 2021).

Martínez, L. M., Correia, G. H. d. A. &, & Moura, F. (2017). Mendes Lopes, M. Insights into carsharing demand dynamics: Outputs of an agent-based model application to Lisbon, Portugal. *International Journal of Sustainable Transportation, 11*, 148–159. 10.1080/15568318.2016.1226997.

Mitropoulos, L. K. &, & Prevedouros, P. D. (2015). Life cycle emissions and cost model for urban light duty vehicles. *Transportation Research Part D: Transport and Environment, 41*, 147–159. 10.1016/j.trd.2015.09.024.

Mitropoulos, L. K., Prevedouros, P. D. &, & Kopelias, P. (2017). Total cost of ownership and externalities of conventional, hybrid and electric vehicle. *Transportation Research Procedia, 24*, 267–274. 10.1016/j.trpro.2017.05.117.

Mossig, I. Stichproben (2021) Stichprobenauswahlverfahren und Berechnung des minimal erforderlichen Stichprobenumfangs. Available online: http://hdl.handle.net/10419/90425 (accessed on 25 January).

Nam, D. &, & Cho, J. (2020). Deep neural network design for modeling individual-level travel mode choice behavior. *Sustainability, 12*, 7481. 10.3390/su12187481.

Nieuwenhuijsen, M. J. &, & Khreis, H. (2016). Car free cities: Pathway to healthy urban living. *Environment International, 94*, 251–262. 10.1016/j.envint.2016.05.032.

(2013). *7th IEEE International Conference Humanoid, Nanotechnology, Information Technology, 3 Hotel Centro* (pp. 12–16). November.

OSM. *Open Street Maps. Available*online: https://www.openstreetmap.de/ (accessed on 21 January 2021).

Pajares, E. GOAT - Open Accessibility. Available online: https://www.open-accessibility.org/ (accessed on 7 January 2021).

Poelman, H., Dijkstra, L. &, & Ackermans, L. (2020). *How many people can you reach by public transport, bicycle or on foot in European cities?: Measuring urban accessibility for low-carbon modes*. Luxembourg: Publications Office of the European Union ISBN 978-92-76-10253-3.

Pomykala, A. (2018). Effectiveness of urban transport modes. In *MATEC Web of Conferences: 180* (p. 3003). 10.1051/matecconf/201818003003.

Qiao, Q., Zhao, F., Liu, Z., Hao, H., He, X., Przesmitzki, S. V. &, & Amer, A. A. (2020). Life cycle cost and GHG emission benefits of electric vehicles in China. *Transportation Research Part D: Transport and Environment, 86*, Article 102418. 10.1016/j.trd.2020.102418.

Runkler, T. A. (2015). *Data Mining: Modelle und Algorithmen intelligenter Datenanalyse, 2*. Wiesbaden: Aktualisierte Aufl. 2015; Springer Fachmedien Wiesbaden ISBN 978-3-8348-2171-3.

Saighani, A., Leonhäuser, D., Eds. (2017) Ökonomischer Vergleich städtischer Verkehrssysteme; Saighani, A.; Leonhäuser, D., Eds. HEUREKA '17 Optimierung in Verkehr und Transport, Stuttgart, 03/2017.

Sałabun, W., Palczewski, K. &, & Wątróbski, J. (2019). Multicriteria approach to sustainable transport evaluation under incomplete knowledge: Electric bikes case study. *Sustainability, 11*, 3314. 10.3390/su11123314.

Sallis, J. F., Bull, F., Burdett, R., Frank, L. D., Griffiths, P., Giles-Corti, B. &, & Stevenson, M. (2016). Use of science to guide city planning policy and practice: How to achieve healthy and sustainable future cities. *The Lancet, 388*, 2936–2947. 10.1016/S0140-6736(16)30068-X.

Schneider, Adrian (2021))MVG API 1.2.7: A library for fetching departures, routes and service interruptions from Munich Transport Authority MVG, using the newer JSON-api on mvg.de. Available online: https://pypi.org/project/mvg-api/ (accessed on 12 January).

Skrúcaný, T., Kendra, M., Kalina, T., Jurkovič, M., Vojtek, M. &, & Synák, F. (2018). Environmental comparison of different transport modes. *Naše more, 65*, 192–196. 10.17818/NM/2018/4SI.5.

SOMMER, C., Saighani, A., & Leonhäuser, D. (2021). *Ökonomische Bewertung städtischer Verkehrssysteme: Kosten des Stadtverkehrs - welche Kosten verursachen verschiedene Verkehrsmittel wirklich?* (1st Ed.). Springer ISBN 978-3-658-32068-3.

Statista GmbH. Mobility Market Outlook. Available online: https://www.statista.com/outlook/mobility-markets (accessed on 13 January 2021).

Statistisches Amt München und Landeshauptstadt München. Allgemeine geographische Angaben 2019. Available online: https://www.muenchen.de/rathaus/Stadtinfos/Statistik/Geografie.html (accessed on 25 January 2021).

Statistisches Bundesamt. Berufspendler - Erwerbstätige nach Stellung im Beruf, Entfernung, Zeitaufwand und benutztem Verkehrsmittel für den Hinweg zur Arbeitsstätte1 2016. Available online: https://www.destatis.de/DE/Themen/Arbeit/Arbeitsmarkt/Erwerbstaetigkeit/Tabellen/pendler1.html?nn=206552#fussnote-1-103722 (accessed on 25 January 2021).

Tenkanen, H. &, & Toivonen, T. (2020). Longitudinal spatial dataset on travel times and distances by different travel modes in Helsinki Region. *Science Data, 77*. 10.1038/s41597-020-0413-y.

TIER Mobility GmbH. TIER API Version 1. Available online: https://www.notion.so/TIER-API-Version-1-0a9bfc571e8f41859d994e736a51315b (accessed on 12 January 2021).

Tirkolaee, E., Hosseinabadi, A., Soltani, M., Sangaiah, A. &, & Wang, J. (2018). A hybrid genetic algorithm for multi-trip green capacitated arc routing problem in the scope of urban services. *Sustainability, 10*, 1366. 10.3390/su10051366.

Wachotsch, Ulrike, Kolodziej, Andrea, & Specht, Bernhard (2021))E-Rad macht mobil. Available online: https://www.umweltbundesamt.de/likationen/hgp_e-rad_macht_mobil_-_pelelecs_4.pdf (accessed on 26 January).

Wessel, N., Farber, S. (2019). The effect of route-choice strategy on transit travel time estimates, 10.31235/osf.io/3r4p6.

Wilde, M., Gather, M., Neiberger, C. &, & Scheiner, J. (2017). *Verkehr und Mobilität zwischen Alltagspraxis und Planungstheorie*. Wiesbaden: Springer Fachmedien Wiesbaden ISBN 978-3-658-13700-7.

Witchayaphong, P., Pravinvongvuth, S., Kanitpong, K., Sano, K. &, & Horpibulsuk, S. (2020). Influential factors affecting travelers' mode choice behavior on mass transit in Bangkok, Thailand. *Sustainability, 12*, 9522. 10.3390/su12229522.

Wittmann, M., Neuner, L. &, & Lienkamp, M. (2020). A predictive fleet management strategy for on-demand mobility services: A case study in Munich. *Electronics, 9*, 1021. 10.3390/electronics9061021.

Yu, X., Miao, H., Bayram, A., Yu, M. &, & Chen, X. (2021). Optimal routing of multimodal mobility systems with ride-sharing. *Intl. Trans. in Op. Res., 28*, 1164–1189. 10.1111/itor.12870.

Zapolskytė, S., Vabuolytė, V., Burinskienė, M. &, & Antuchevičienė, J. (2020). Assessment of Sustainable Mobility by MCDM Methods in the Science and Technology Parks of Vilnius, Lithuania. *Sustainability, 12*, 9947. 10.3390/su12239947.