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Urban transportation at an inflection point: An analysis of potential influencing factors

Julian Reul[a,*], Thomas Grube[a], Detlef Stolten[a,b]

[a] Institute of Energy and Climate Research - Techno-economic Systems Analysis (IEK-3), Forschungszentrum Jülich GmbH, Wilhelm-Johnen-Straße, 52428 Jülich, Germany

[b] RWTH Aachen University, c/o Institute of Energy and Climate Research - Techno-economic Systems Analysis (IEK-3), Forschungszentrum Jülich GmbH, Wilhelm-Johnen-Str., 52428 Jülich, Germany

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ABSTRACT

Urban transportation is in the midst of a two-fold transformation: On the one hand, cities are beginning to acknowledge their climate responsibilities and are seeking to establish environmentally-friendly, sustainable transport systems. On the other hand, new transportation trends, such as shared mobility and autonomous driving, carry the potential to disruptively change conventional practices. In this study, we develop an activity-based transport demand model to quantify the effects of potential influencing factors on urban transportation in a synthetic city. We develop 18 scenarios to investigate urban transportation against the backdrop of mode availability, the deployment of shared mobility services, urban structure and societal change, such as urbanization and an aging population, as well as behavioral shifts in mode choice preferences. With respect to the results, we highlight the derived modal split for a city without private cars but with access to shared autonomous vehicles for all agents: We find a distribution of mode choices of 55% for walking and biking, 40% for public transportation and 5% for shared modes. Given this modal split, the total driven distance, as well as the total number of vehicles in the city, decreases by over 90% against current levels. Thus, an efficient future urban transport system should build upon public transportation for meeting the major share of transport demand, with slow modes for convenient travel across short distances and shared mobility for the inter-modal connection of both.

1. Introduction

The transport industry is in the midst of a comprehensive transformation towards more sustainable, efficient and connected transportation technologies and systems. The impending climate crisis is putting pressure on manufacturers and public authorities to acknowledge their ecological responsibility and shift their focus to zero-emission vehicles and sustainable transportation systems. At the same time, the advent of new transportation trends, such as electrification, autonomous and connected driving and shared mobility, bears the potential to disruptively change the industry and conventional transportation. The question left open is, how will individuals react to these changes?

Thus, this paper aims to evaluate individual mobility behavior and transport demand against the backdrop of altered conditions of

* Corresponding author at: 52425 Jülich, Germany.
E-mail address: j.reul@fz-juelich.de (J. Reul).

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Table 1
Overview of the key findings of selected studies on shared mobility in urban areas. VKT: Vehicle Kilometers Travelled, ITF: International Transport Forum, MIT: Motorized Individual Transport, PT: Public Transport, Slow: Slow modes, such as walking and cycling.* The values for the ITF study refer to the respective car- and ridesharing scenarios with a penetration of 100% shared self-driving vehicles and high-capacity public transport being available.

Publication	Fleet Size Reduction	Annual VKT	Modal Share
Fagnant et al., 2014	−92%	+10%	Not modeled
ITF, 2015*	−83%	+44%	PT: 22% Shared Vehicles: 70% Slow: 8%
ITF, 2015*	−90%	+6%	PT: 22%, Shared Vehicles: 70% Slow: 8%
Boesch et al. 2016	−90%	/	Not modeled
Bischoff et al, 2016	−90%	+17%	Not modeled
(Heilig et al., 2017)	−85%	−20%	PT: 17% Shared Vehicles: 39% Slow: 44%

the transport system, urban environment and society with a particular emphasis on shared mobility. Therefore, we analyze the impact of mode availability, the structure of the urban space, societal change and behavioral shifts on the transportation system within an activity-based, bottom-up transport demand model for a synthetic metropolis.

Section 2 reviews current research on the influence of shared autonomous vehicles (SAVs) on urban transportation, as shared mobility is a focus of this study, and positions our research within the context of the reviewed literature. Section 3 presents the methodology of the activity-based transport simulation as well as the replication of shared mobility with car- and ridesharing fleets. The application of the model within a scenario analysis follows in Section 4. A discussion of the results is delivered in Section 5, while Section 6 expands on possible future research directions.

2. Literature review

Over the past decade, significant research has been conducted on the effects of shared autonomous vehicles on urban transportation systems. Qualitative and empirical studies analyze the implications of autonomous and shared vehicles on individual behavior, as well as on transportation flows and society as a whole (Milakis et al., 2017; Fagnant and Kockelman, 2015). Quantitative simulation studies investigate the effects on the required fleet size, vehicle-kilometers travelled (VKT) by the fleet, the reduction potential of parking lots and the operational costs of SAV fleets.

Hörl et al. and Hao et al. summarize key research results of both qualitative analyses and quantitative simulations (Hörl et al., 2016; Hao and Yamamoto, 2018). The major outcomes reveal that SAV fleets have enormous potential to decrease the number of cars in a city while sufficiently meeting the transport demand of the urban population. Nevertheless, traffic is not necessarily reduced by the incorporation of SAVs due to the empty relocation rides of those vehicles.

In the following, we concentrate on presenting relevant quantitative publications in this study field. Fagnant et al. simulate ride-pooling services for a synthetic city that resembles Austin, Texas, for a time period of 100 days (Fagnant and Kockelman, 2014). Martinez et al. model car- and ridesharing in the city of Lisbon in a report for the International Transport Forum (ITF) (Martinez and Viegas, 2015). Boesch et al., as well as Bischoff et al., build carsharing models for Zurich and Berlin based on the MATSim software for simulating transport demands (Bischoff and Maciejewski, 2016; Boesch et al., 2016). Finally, Heilig et al. incorporate the travel demand model mobiTopp to simulate ride-pooling in the city of Stuttgart (Heilig et al., 2017). All of these models have distinct approaches to modeling transport demand in urban regions and employ different algorithms to replicate shared mobility.[1] Table 1 provides an overview of the key findings of the presented studies.

The studies presented above reveal two key observations related to SAV fleets. First, the substitution of private passenger cars by autonomous vehicles has the potential to reduce the required fleet size by 83–92%, while sufficiently meeting transport demand in urban regions. Second, relocation trips and empty rides by autonomous vehicles add additional mileage, which can be substantial, as is shown by the ITF study (+VKT 6–91%). If the model considers ridesharing, this effect is challenged by the substitution of trips, leading to lower additional annual VKT of the total car fleet (Fagnant and Kockelman, 2014; Martinez and Viegas, 2015) or even to a possible reduction in the total annual VKT (Heilig et al., 2017), compared to an exclusive analysis of carsharing. Furthermore, the total VKT of the SAV fleet depend on the consideration of a shift in the modal shares. The studies by the ITF and Heilig et al. consider public transportation and slow modes (walking and cycling) in addition to shared mobility. Both studies identify an increase in public transportation, the ITF-study by +7% and Heilig et al. by +4%, respectively. The increase in the modal share of public transportation translates into reduced annual VKT of the autonomous fleet, as the demand for SAVs is decreased.

Several substantial changes can be identified with the advent of autonomous cars: Urban transportation will be more shared and efficient, all modes will profit from a substitution of conventional passenger cars and the car design itself might be revised and adapted

[1] Refer to section A in the appendix for a detailed description of the model characteristics.

to the needs of shared mobility.

Research on the impact of autonomous and shared vehicles on urban transport already covers a broad range of aspects. Nevertheless, some research questions remain unaddressed.

First, a dynamic response of travel demand to the introduction of SAVs is not replicated in any of the above-mentioned studies. Either transport demand is assumed to be static (Bischoff and Maciejewski, 2016; Boesch et al., 2016; Fagnant and Kockelman, 2014) or the distribution of demand across modes of transport is replicated in a simplified manner (Heilig et al., 2017; Martinez and Viegas, 2015). Only Martinez et al., as well as Heilig et al., have simulated other modes of transport than passenger vehicles. Martinez et al. develop a simplified heuristic for mode choice. Meanwhile, Heilig et al. developed a nested logit model for mode choice, but assume the coefficients of the shared autonomous modes to be equal to those of private passenger vehicles. We address the problem of replicating dynamic transport demand by utilizing a nested logit model to simulate mode choice across different modes of transport, explicitly estimating coefficients for a shared mode.

Second, only a few studies have presented efficient algorithms for dispatching SAVs on the requested trips of agents, as well as for the relocation of vehicles to more advantageous locations within the transport system. Fagnant et al. develop a dispatching heuristic to attribute SAVs to agents, as well as four relocation strategies for idle SAVs. The authors state that the modeling of "driverless dynamic ridesharing (…) will facilitate additional VMT reductions" (Fagnant and Kockelman, 2014). Other studies also rely on heuristics (Bischoff and Maciejewski, 2016; Boesch et al., 2016; Fagnant and Kockelman, 2014; Heilig et al., 2017; Martinez and Viegas, 2015; Heilig et al., 2017; Bischoff et al., 2016), developed by the authors, to manage the dispatch and relocation of SAVs. We approach this task of efficiently matching the demand side of open trip requests with the supply side of idle SAVs by applying the concept of time–space prisms to the movement of SAVs (Hägerstrand, 1970).

Finally, most of the cited studies limit their research scope to the assessment of the influence of shared mobility on the transport system. We go beyond and additionally investigate the influence of divergent urban structures as well as societal and behavioral changes on urban transport demand.

This study builds upon a newly developed activity-based transport demand model that utilizes a nested logit model to replicate activity- and mode-choice of the simulated agents, as well as a gravity model to represent the destination choice. The model parameters are estimated based on two German national travel surveys, "Mobility in Germany 2017" (MiD17) (infas, DLR, IVT, infas 360, 2018) and "German Mobility Panel" (MOP) (Karlsruhe Institute of Technology, 2020). We conduct an analysis of mobility behavior in a synthetic city with one million inhabitants, resembling the city of Cologne in Germany, for a simulated timeframe of 28 days or 4 weeks. Furthermore, we manipulate several exogenous parameters within a scenario analysis to observe the model behavior, replicating potential future impacts on the transportation system: We assume a city without private cars and introduce a mode for SAVs. We analyze the utilization of SAVs in a carsharing and a ridesharing scenario to evaluate a potential reduction in the required fleet size to meet the transport demand of the city, as well as to quantify the total driven distance. The simulation of the SAV fleet is embedded within the simulation of the entire urban transport system, allowing the model to capture systemic interactions on a regional scale and between modes. The model sequentially dispatches SAVs, incorporating time–space prisms, to optimally meet transport demand while considering the autonomous relocation of the vehicles to the closest open request at any time during the simulation. Furthermore, we scale the distribution of simulated SAV trips in time and space to fit an approximated realistic distribution. This procedure yields a more realistic occupation of the SAV fleet compared to other dispatching algorithms. Additionally, we alter the characteristics of the urban space and structure, such as the distribution of the attractiveness of TAZs for certain activities, as well as the distribution of the population throughout the city. We expect the manipulation of the spatial distribution of these entities to influence the average distance covered to participate in certain activities. Finally, we incorporate societal changes, such as an aging population and urbanization, as well as behavioral shifts, such as an increased adoption of working from home and possible outcomes of the COVID-19 health crisis, in the study.

3. Methodology

We propose an urban transport demand model, which can be applied to an arbitrary city of the researcher's choice, as population size, distribution of population density and the availability, attractiveness and location of activities are exogenous parameters. In this study, we simulate the mobility behavior of 1,000 agents over a time period of 28 days within a synthetic city, based on the structural characteristics of Cologne, a major city in Germany with over one million inhabitants. The choice of 1,000 simulated agents is a compromise between computing time and result accuracy, while preserving the statistical representativeness of the results. We segment the population into six different socio-economic groups, differentiated by age and occupation type in order to classify the individuals and their urban mobility behavior. Consequently, we attribute the agents to socio-economic groups in such a way that the actual demographic distribution of the population in Cologne is matched. The urban space under analysis, hereafter referred to as the study area, has a size of 30 km × 30 km, partitioned into a grid of 500 m × 500 m TAZs, following the regional resolution of the underlying MiD17 dataset.

3.1. Model framework

We model transport demand within the synthetic city with an activity-based approach, simulating the long- and short-term mobility-related decisions of each agent. Long-term decisions include choices on mobility preferences, such as car-ownership and carsharing-membership and location choices, such as home and work location, as well as behavioral routines, such as typical working hours and the probability to work from home. These decisions are incorporated before the simulation of short-term decisions takes

Table 2
Activity-, mode- and nest-choices within the decision process.

Activities	Modes	Nests
Work Onsite	Walk	Slow
Work Offsite	Bike	Slow
Education	Car (self)	Individual
Shopping	Car (co)	Individual
Private Obligations	Bus (local)	Public
Service	Train (local)	Public
Home	Train (city)	Public
Leisure	Bus (long-distance)	Public
	Train (long-distance)	Public
	Carsharing	Individual

place and are probabilistically modelled by drawing from distributions of the German travel survey, “Mobility in Germany 2017” (MiD17) (infas, DLR, IVT, infas 360, 2019).

The simulation of short-term decisions incorporates a combined choice of activity, destination and mode for each agent. Table 2 depicts the choice options for activities and modes, as well as the mode-nests that are attributed to the modes.

The activity type “Work Onsite” refers to working at one’s usual workplace, which is predefined during the long-term decision process, while the activity type “Work Offsite” refers to work-related activity at other locations, such as business trips. “Private Obligations” comprise duties that are not work-related, such as going to a public authority. The activity “Service” refers to accompanying another person during an activity.

Within the mode “Car (self)”, the car is driven by the agent, while the mode “Car (co)” refers to an agent being a co-driver. We categorize the modes “Bus” and “Train” further into short-range or local modes and long-distance modes, as the transportation characteristics of these modes differ with the distances covered.

The decision process for the joint choice of activity (a), destination (d), nest (n) and mode (m) is modelled with the respective marginal and conditional probabilities as follows (Ben-Akiva and Lerman, 1985):

$$P(adnm) = P(a)^*P(d|a)^*P(n|a)^*P(m|na) \tag{3.1}$$

The marginal choice probability for an activity, as well as the conditional choice probabilities for the mode-nest and the mode itself, are independent of the destination choice. This is why the combined choice of an activity and mode is separately calculated from the choice of destination, utilizing a nested logit approach (Ben-Akiva and Lerman, 1985; Train, 2009). The destination choice is modelled independently with a conventional gravity model for each possible activity type (McNally, 2008; Bouchard and Pyers, 1965).

3.2. Activity and mode choice with nested logit

The marginal probability of an activity choice, P(a), primarily depends on a factor, the *ActRatio*, that indicates the total time already spent on a certain type of activity in relation to the amount of time that an agent of a certain socio-economic group usually spends on that activity type, up until the simulated time. This means that if an agent does not pursue a certain activity for a longer period of time, the urge for the agent to pursue that activity within the next time-step increases. This characteristic of the choice process ensures that the activity choice is interwoven with past activity choices and thus creates an interdependency between activity choices over time. As the aggregate choice-process, P(adnm), combines activity, destination and mode choice, the chosen activity is also dependent on the transportation impedance (travel time, travel cost) associated with the activity. Furthermore, the model constrains the set of possible activities by rules and heuristics for the pursuit of activities. The entirety of available activities constitutes the choice set, which we describe in Section 3.4. The systematic component of the utility function, V_{act}, for an activity option a and an individual i belonging to a certain socio-economic group, is defined by the linear equation (3.2):

$$V_{act_{a,i}} = ASC_{act\,a,i} - ActRatio^* x_{act\,a,i} \tag{3.2}$$

The alternative-specific constants (ASC_{act}), as well as the coefficients x_{act} are estimated based on the MOP dataset, which captures the mobility behavior of 3,100 persons over the period of one week (Karlsruhe Institute of Technology, 2020). The longitudinal study design enables the analysis of the interdependency of activity choices over time.

The model replicates the mode choice by calculating conditional probabilities for the nest and mode. The partition of modes into nests corresponds to the superordinate decision of a real decision-maker for a general transportation type (slow, individual, public) before deciding on the specific mode.

The systematic component of the utility function of the nest layer, V_{nest}, for a nest option n and an individual i of a certain socio-economic group only consists of the alternative-specific constants.

$$V_{nest_{n,i}} = ASC_{nest\,n,i} \tag{3.3}$$

Within the simulation, the attribution of modes to nests improves the ability of the model to capture the influence of varying unobserved factors, which are described by the error term within the utility function of the nested logit model. The conditional probability of the mode choice, P(m|na), primarily depends on the transportation impedances, such as the time and cost of travel. We derive the travel time as the sum of out-of-vehicle and in-vehicle time from the MiD17 dataset, dependent on the transport mode and travel distance. Equation (3.4) depicts the systematic component of the utility function, V_{mode}, for transportation mode option m and an individual i:

$$V_{mode_{m,i}} = ASC_{mode\,m,i} - TravelTime^{*}x_{time\,m,i} - TravelCost^{*}x_{cost_{m,i}} \tag{3.4}$$

An estimation of the model parameters (ASC_{mode} and x_{mode}) is conducted using the MiD17 dataset, which contains approximately one million trips by 316,000 persons. In contrast to the MOP, the MiD17 tracks the mobility behavior of persons over the course of only one day.[2]

We estimate the coefficients of the nested logit model using a maximum likelihood approach.[3]

3.3. Destination choice with gravity model

We model the destination choice, P(d|a), with a conventional gravity model approach, estimated and validated on data for the Cologne region from the MiD17 survey (infas, DLR, IVT, infas 360, 2018). Therefore, we segment the area of Cologne into a grid, consisting of 500 m × 500 m TAZs. The gravity model calculates the probabilities for each of these 1600 TAZs within the city, which are chosen by the agent as sites to conduct a certain type of activity. The probability is dependent on the current TAZ of the agent, the distance between the TAZ and a relative measure of the attractiveness of the target zone for a certain type of activity (McNally, 2008).

Each zone has a relative measure of attractiveness for each defined activity type attributed in order to capture the dependency of the destination choice on the choice of the activity. We subsequently reference this activity-specific measure of attractiveness as the attraction factor. The distribution of these attraction factors is an exogenous model parameter and is determined by two variables. First, we evenly define distributed centroids, which specify the origin from which the distributions are calculated. Secondly, we define the type of distribution, which is either a quadratically-increasing function or a normal distribution, both centered at the origin. This procedure of distributing the attraction factors across the TAZs of the city is also adapted to distribute the population. Thus, it is possible to construct synthetic cities with different characteristics of how activity-opportunities and the population are distributed. The alteration of this inherent urban structure additionally influences the simulation of mobility behavior within the urban space.

Before the model calculates the probabilities for each TAZ to be a target zone, the superordinate choice is made, whether the target zone lies within the urban space under analysis or not. This step is required, as we only calibrate the gravity model for trips that start and end within the study area. This probability is drawn from a density derived from the travel survey MiD17 and is therefore not part of the actual gravity model. In case the target zone lies outside the city area, the gravity model is not utilized to define the target zone and the location of the agent is simplified to "Outside_City". For the time outside of the city, the model approximates the agent's mobility by drawing covered distances for the chosen activities from densities derived again from MiD17.

We estimate the gravity model for destination choice with the local dataset of the MiD17 study (infas, DLR, IVT, infas 360, 2019).[4]

3.4. Choice set

In order to replicate realistic mobility and activity profiles of the agents, the availability of activities, destinations and modes in the model is temporally- and spatially-constrained. The choice set includes all available choice options of the agents for each step in the decision process with consideration of these constraints. The definition of this choice set is primarily dependent on the current location of the agent and the time of the day. Additionally, the model considers general mobility preferences and working routines, as well as age and occupation type, in its definition of the choice set.

3.5. Shared mobility

Central to the analysis of shared mobility in this study are the questions of how many SAVs are required to fully meet the transport demand and what total distance is covered by the SAV fleet. The simulation of agents provides mobility profiles, containing information about the distances covered per person and mode. From these mobility profiles, the model derives temporal requests of shared vehicles per TAZ. In order to determine the required number of SAVs and the total mileage of the SAV fleet, we employ different dispatching algorithms for the carsharing and the ridesharing scenarios. The carsharing scenario allows for only one agent per SAV and ride while the ridesharing scenario allows for multiple agents per SAV, as well as detours for single rides. The detours within the ridesharing scenario must not add up to>10% of the expected travel time for each agent. In both scenarios, the SAVs pick up and drop off the agents in their desired TAZ. Thus, we simulate a free-floating SAV fleet, contrary to station-based approaches to shared mobility. The relocation of SAVs to locations that are more beneficial to meet the demand is considered in both scenarios.

The simulation of the shared mobility supply, i.e., the attribution of SAVs to open requests of agents, is executed following the simulation of the agents' mobility profiles. Thus, the demand simulation of open requests, captured by the mobility profiles, is independent of the subsequent supply simulation. This prevents the model from considering variations in the waiting time of the agents due to supply fluctuations over the day.

[2] The descriptive statistics of the mobility surveys MiD17 and MOP are attached in appendix B.

[3] The estimation results and summary statistics are listed in appendix C.

[4] The estimation results are shown in the appendix, part D.

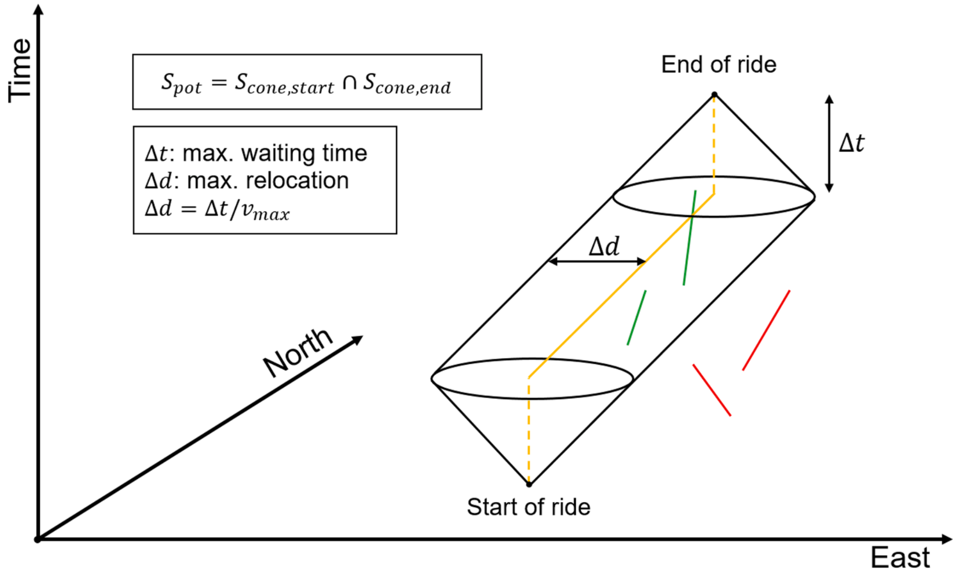

Fig. 1. The concept of time–space prisms applied to ridesharing. S_{pot}: Potential locations of shared vehicles under relaxed travel conditions.$S_{cone,start}$: Potential locations that can be reached from the start location.$S_{cone,end}$: Potential locations from which the end location can be reached.

In the carsharing scenario, the algorithm sequentially dispatches single SAVs to open requests in the TAZ, until the demand is fully met. The algorithm begins by attributing a SAV to the first open request. After the ride is completed, the next open drive within a defined timeframe in the current TAZ is identified. This timeframe is set to five minutes, which refers to the average travel time of an SAV between two TAZs. If no open request in the current TAZ and timeframe can be found, the service area of the SAV is expanded to all of the neighboring TAZs that can be reached within the defined five minutes. The algorithm continues this repetitive procedure of searching and expanding the possible service area until an open request is found. The SAV is attributed to open requests until the end of the simulation is reached. After completing to simulate the mobility of a SAV, the dispatching algorithm proceeds by creating a new SAV and attributing it to open requests until the demand is fully met. This procedure entails that the SAVs, which are dispatched towards the end of the algorithm, have lower occupancy rates and higher relocation costs.

3.6. From carsharing to ridesharing

In the ridesharing scenario, multiple agents can be transported together in a single autonomous ridesharing vehicle. In order to pool rides together, the individual travel conditions, such as travel duration, boarding and exit area, must be relaxed. Only if the traveler allows such relaxations of the expected travel conditions will single rides overlap in time and space so that they can be pooled together. We model this pooling process with the concept of time–space prisms, which is visualized in Fig. 1 (Hägerstrand, 1970; Miller, 2005; Wang et al., 2016).

The original movement of a vehicle is represented by the solid yellow line through a three-dimensional system, describing a two-dimensional relocation in space with the corresponding progression over time. The cone at the starting point of the ride represents all potentially accessible locations for a vehicle travelling at a maximum speed, v_{max}. The inclination of the cone within the three-dimensional system describes the maximum travel speed. The inverted cone at the end point of the ride represents all potential locations from which the end point can be reached by a vehicle travelling with a maximum speed, v_{max}. If the travel conditions of the original ride are relaxed, as the vehicle is allowed to depart early and arrive late by Δt, the cones are shifted along the time axis, following the intersected yellow line. This lets the start and end cone intersect in space, forming a time–space prism. This prism is constituted of two small cones and a tilted cylinder, describing all potential locations of the vehicle, S_{pot}, which are possible in the realm of the relaxed travel conditions. The relaxation of the travel conditions allows for detours within the time–space prism, spanned by the intersection of the two cones. Therefore, each further ride that fits completely into the time–space prism can be pooled together with the original ride.

For the pooling of rides and the dispatch of ridesharing vehicles to these, the maximum relaxation of the departure and arrival time, Δt, must be set. Δt is directly linked to the maximum relocation range Δd via the maximum speed of the vehicle v_{max}. These definitions of the time–space prism lead to maximum deviations from the original drive that must be accepted by persons travelling with ridesharing vehicles. A traveler must be ready for departure Δt ahead of the desired departure time, accept a delay of Δt and must be willing to travel a maximum distance of Δd to the departure location or from the locations of arrival to the desired, actual target location.

The model executes the ridesharing algorithm in three key steps, following the theoretical concept of time–space prisms for the description of vehicle movement:

Table 3
Distribution of socio-economic groups in German metropolises according to the mobility survey "Mobility in Germany 2017" (MiD17) compared to the distribution within the Base Simulation. Keys for the socio-economic groups: 1st digit – 1: <18 years, 2: 18–65 years, 3: >65 years; 2nd digit – 1: Full-time job, 2: Part-time job, 3: Education, 4: No Occupation.

Socio-Economic Group	Distribution of Persons in German Metropolises, According to MiD17 [Absolute (Relative)]	Distribution of Persons in Base Scenario [Absolute (Relative)]
13	2,135,525 (15%)	170 (13%)
21	5,147,643 (36%)	447 (35%)
22	1,619,323 (11%)	151 (12%)
23	1,004,410 (7%)	100 (8%)
24	1,857,013 (13%)	162 (13%)
34	2,687,877 (19%)	251 (20%)
Total	14,451,791 (100%)	1,281 (100%)

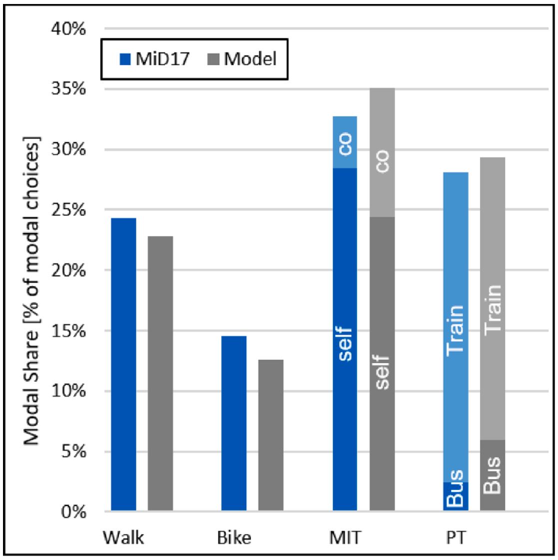

Fig. 2. Modal split of the base simulation and MiD17 data for metropolises in Germany (Berlin, Hamburg, Munich, Cologne). MIT: Motorized Individual Transport. PT: Public Transport. MIT-self: Person drives the vehicle. MIT-co: Person is co-driver of the vehicle.

1) Definition of time–space prisms for every shared ride by relaxation of the travel conditions (early departure, late arrival).
2) Pooling of rides that fully lie in the same overarching time–space prism.
3) Attribution of ridesharing vehicles to the pooled rides, similar to the dispatching algorithm applied to carsharing.

3.7. Scaling of shared trips

The sample of shared rides is only simulated by a fraction of agents, ca. 1,000, compared to the population size, which we assume to be one million. This discrepancy in scale results in a less frequent occurrence and non-representative distribution of trips. The attribution of car- and ridesharing vehicles to shared trips not only depends on the ratio of population size to simulated agents but also on the distribution of shared trips over time and space (Parry and Evans, 2008; Parry and Bithell, 2012; Llorca and Moeckel, 2019). Thus, we scale up the individual shared trips with a scale factor, depending on the location and time of its occurrence, before the attribution of car- and ridesharing is simulated. This varying scale-factor is determined by comparison to a large reference simulation.[5]

4. Scenario analysis: Model application to a synthetic metropolis

We apply the activity-based model for simulating individual mobility behavior in urban environments to a synthetic city, resembling the German city of Cologne in population and area size. Therefore, we develop 18 different scenarios to analyze the influence of alternated mode availability, urban structure, societal change and behavioral shifts on individual mobility behavior. In these scenarios, the mode availability is alternated between the two cases that, on one hand, all conventional modes are available and on the other hand motorized individual mobility, such as private cars, become unavailable and new, shared autonomous services are

[5] The scaling procedure is described in section E of the appendix.

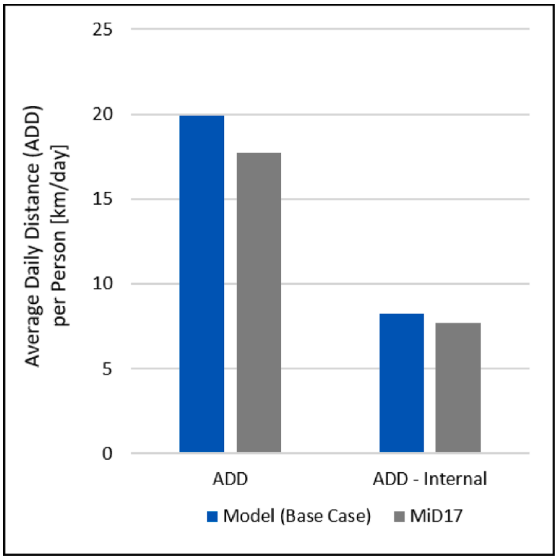

Fig. 3. Average daily distance (ADD) covered per person for all trips originating from the study area, as well as for trips that start and end within it (internal).

introduced. The research question that correlates to this scenario parameter aims at analyzing the potential of shared mobility to reduce traffic and the necessary number of vehicles while still meeting the transport demand of the city. Furthermore, we apply different distributions of the population and activity-specific attraction factors across the urban area under study to observe the impact of the urban structure on mobility behavior. The research question, which is connected to these scenario parameter questions, whether divergent and spread distributions of the population and their activities induce more traffic. In turn, we consider the effects of societal and behavioral change such as a growing urban population, the demographic shift towards an aging society, the increasing trend to conduct work from home and an alternated attractiveness of transportation modes in further scenarios.

4.1. Validation of model runs

The base scenario is designed to reflect the current transportation situation in German metropolises. We validate this base simulation against an evaluation of the mobility survey MiD17 for German urban centers, by a comparison of typical mobility characteristics, such as modal split and average daily distance (ADD) per person. Additionally, we evaluate the capability of our model for capturing the influence of shared mobility and the restricted use of private vehicles against real world data from a car-free district in Cologne, Germany.

A total number of 1,281 agents (target: >1,000) is simulated for a timeframe of 28 days. We simulate>1000 agents to allow for a sufficient representation of the mobility behavior of all socio-economic groups. Table 3 depicts the distributions of persons over socio-economic groups within the MiD17 compared to the distribution of agents in the base simulation.

We evaluate the transport characteristics, modal split and ADD per person, for the base scenario and compare these against a subset from the survey MiD17. This subset describes the transport characteristics in the four metropolises in Germany: Berlin, Hamburg, Munich, and Cologne. Fig. 2 depicts the modal split for the base scenario compared to the MiD17 data for the aggregated modes Walk, Bike, Motorized Individual Transport (MIT), and Public Transportation (PT). The aggregated mode MIT is further separated into MIT-self and MIT-co, referring to whether the person completed the respective trip as the driver or as a co-driver. The PT mode is further distinguished into Bus and Train.

The slow modes Walk and Bike are slightly overrepresented in the base scenario compared to the MiD17 data. Walk shows a divergence to the reference data of +1.5%, with a modal split of 24.3%, while Bike diverges by +2.0% for a total share of 14.6%. The slight overrepresentation of slow modes could also be connected to an underrepresentation of these modes in the MiD17 data. The utilized data only displays the main mode of transport. As slow modes are generally of minor importance in multimodal ways, this could be one reason for potential underrepresentation. The underrepresentation of slow modes, such as walking and biking, is a typical phenomenon in transport surveys (ITF, 2012).

The modal share of MIT reveals an underrepresentation compared to the MiD17 data. Nevertheless, the base scenario shows an acceptable divergence of −2.2% from the MiD17 data, with a total share of 33.1%.

The modal share of PT for the base scenario features a value of 28.1%, below the modal share of PT, found for the MiD17 reference data. The base simulation reveals a divergence of −1.3% from the MiD17 data.

The maximum divergence of the modal split values of the base simulation to the MiD17 data is below the target value of 5%, with 2.2% for the MIT-share. Thus, the evaluation of the modal split for the base scenario against the MiD17 reference data reveals that divergences are within an acceptable range.

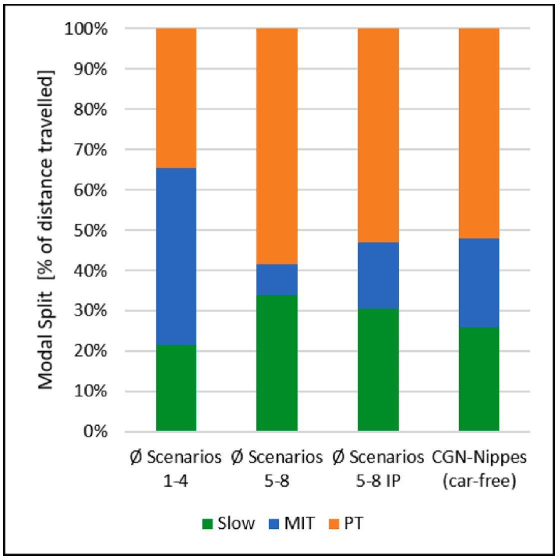

Fig. 4. Modal split measured with respect to distance, on average, for scenarios 1–4 and 5–8, compared to a car-free district in Cologne (car-free area in Cologne-Nippes) (Field, 2010). The column also labeled with "IP" uses the interpolated values for scenarios 5–8 to reflect the car ownership rate of 29%, which still prevails within the designated car-free district of Cologne (Nippes). MIT: Motorized Individual Transport. PT: Public Transport. Slow: Slow modes, such as walking and biking.

Table 4
Parameters of the scenario analysis. All scenarios simulate mobility behavior across 28 days in a synthetic urban area, resembling the city of Cologne. ACT: Distribution type of attraction factors for activities. POP: Distribution type for population. ND: Normal distribution, centered at the defined centroids and decreasing with increasing distance from centroids. QD: Quadratic distribution, centered at the defined centroids and increasing with increasing distance from the centroids.

Scenario (Scenario Names)	Mode AV	#Centroids	Distribution Type from centroids	#Agents
1 (All_1_Centre)	All Modes available	1	ACT: Normal POP: Normal	1281
2 (All_1_Outer)	All Modes available	1	ACT: Normal POP: Quadratic	1428
3 (All_4_Centre)	All Modes available	4	ACT: Normal POP: Normal	1396
4 (All_4_Outer)	All Modes available	4	ACT: Normal POP: Quadratic	1437
5 (NoMIT_1_Center)	No Private Cars	1	ACT: Normal POP: Normal	1281
6 (NoMIT_1_Outer)	No Private Cars	1	ACT: Normal POP: Quadratic	1428
7 (NoMIT_4_Center)	No Private Cars	4	ACT: Normal POP: Normal	1396
8 (NoMIT_4_Outer)	No Private Cars	4	ACT: Normal POP: Quadratic	1437

Fig. 3 displays the ADD covered per person for all trips originating from the study area, as well as for trips that start and end within it.

The ADD for the base scenario, evaluated for all trips, originating from within the study area lies +12.5% (+2.2 km) higher than the ADD for the MiD17 case with an average distance of 19.9 km/day*person. The ADD for the base scenario decreases to 8.3 km/day*person, if only trips are considered that start and end within the study area. The deviation to the reference data also decreases to +0.6 km or +7.5%. This study models trips that lie exclusively within the study area. Trips outside the study area are not attributed to a specific TAZ and the travelled distance is derived by drawing from a statistical distribution, based on an evaluation of the MiD17 data. This is why there is a larger deviation in the ADD for external trips compared to exclusively internal ones.

Fig. 4 displays the average modal split, measured with respect to the ADD, across scenarios 1–4 (all modes available; see Table 4) and 5–8 (no private cars available; see Table 4) as well as an interpolated modal split of both.

We interpolated the modal split to achieve a comparability to data from a car-free district in Cologne-Nippes (Field, 2010). Within this district of Cologne, no cars are allowed and car ownership is limited. A total of 29% of the people living in the district own a car, compared to 0% for scenarios 5–8. Therefore, the average ADD of scenarios 5–8 is interpolated with the values from scenarios 1–4, in

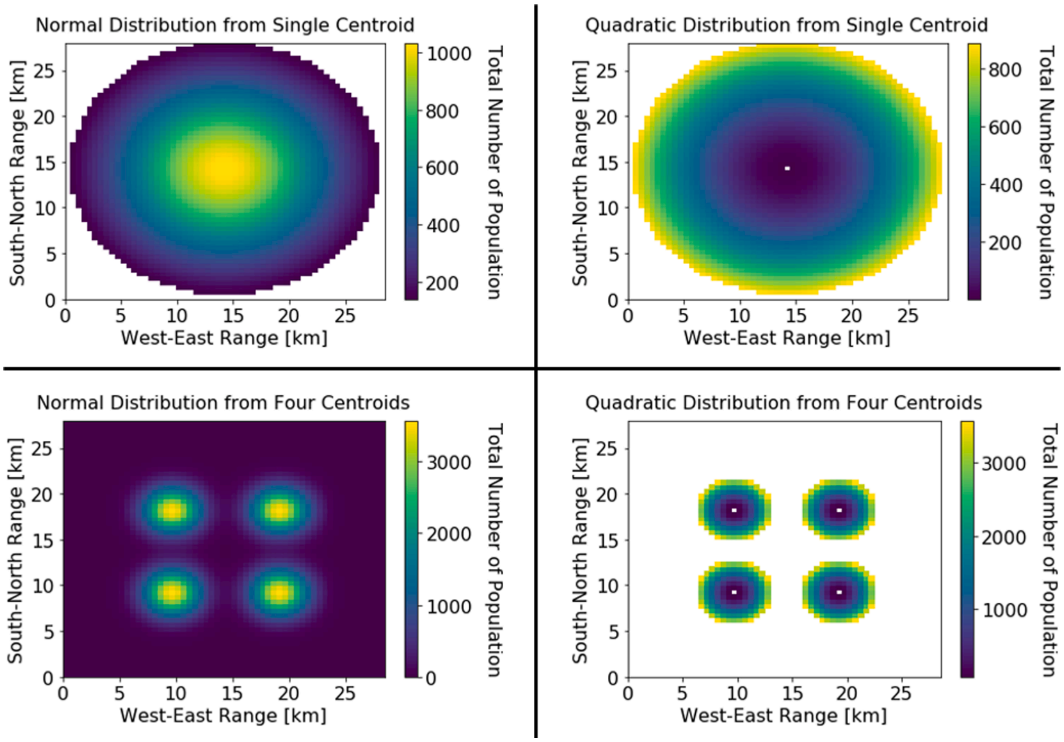

Fig. 5. Different configurations for the distribution of the population.

which MIT is allowed. The comparison of the interpolated data shows good similarity with data from the district in Cologne-Nippes: The modal share of PT diverges by +1% with 53% in the simulation and 52% for Cologne-Nippes. The MIT modes account for 16% in the interpolated simulation and for 22% in Cologne-Nippes, resulting in a divergence of −6%. The slow modes show a divergence in the other direction by +4%, with 30% for the interpolated scenarios 5–8 and 26% for Cologne-Nippes. Following these results, it can be stated that all modes are replicated within a satisfactory range (<5% divergence), whereas slow modes are slightly overrepresented (+4%) and MIT modes slightly underrepresented (+6%). This could also be explained by the potential underrepresentation of slow modes within the survey data for Cologne, as short routes by foot and bicycle are more likely to not be mentioned in a questionnaire (ITF, 2012).

The analysis of the modal split and average daily distance covered per person for the base scenario compared to the MiD17 reference data confirms the plausibility of the base scenario and its validity to displaying the current transportation situation in German urban metropolises. Additionally, we proved the capability of our model to dynamically respond to an alternated mode availability by comparing its results for a scenario with the limited use of private cars to real-world data from a car-free district in Cologne.

4.2. Impact of shared mobility and urban structure: Definition of scenarios 1–8

The first eight scenarios focus on the impact of the urban structure on mobility behavior and the resulting traffic. Furthermore, we evaluate these scenarios in terms of their potential for a deployment of shared mobility services. Table 4 gives an overview of the scenario parameters. The scenario names indicate crucial scenario parameters, which are mode-availability (All or NoMIT), the number of centroids (1 or 4) and the type of distribution of the population (Center or Outer). The term “Center” refers to an increased population density in the city center, whereas “Outer” refers to a spread of the population density towards the outskirts of the respective centroid.

Fig. 5 displays the four different configurations for the distribution of the population dependent on the number of centroids and distribution type, which is either normal or quadratic. The distributions of the attraction factors of the activities are always defined by a normal distribution, anchored in the center of the reference centroid and decreasing with increasing distance from the centroid. The number of centroids for the distribution of the population and the attraction factors is equal in each scenario and either one or four. Thus, four different scenarios (1–4) are defined that can only be distinguished by varying urban characteristics. The total of eight simulations is achieved by an alteration of the mode availability, defining four additional scenarios (5–8). The latter scenarios do not allow a choice of MIT modes, such as private cars, and assume that shared mobility is available to the entire population. Within these scenarios, we evaluate the potential impact and limitations of shared mobility in urban spaces.

The top-left of Fig. 5 represents a distribution that drops from a maximum at a central centroid towards the outskirts of the study

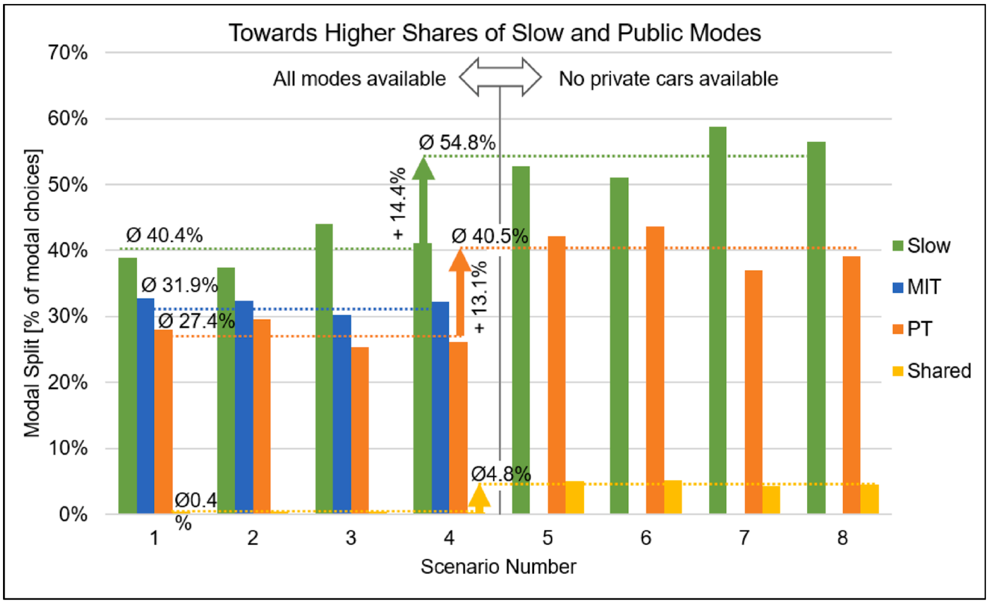

Fig. 6. Modal split for scenarios 1–8.

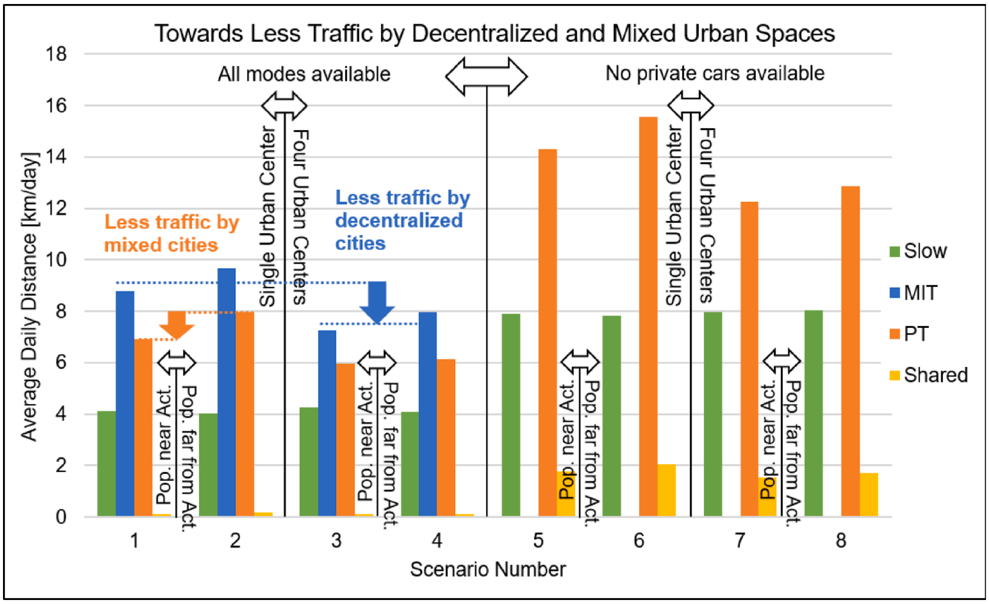

Fig. 7. Average Daily Distance (ADD) for scenarios 1–8. Pop.: Population. Act.: Activities.

area, following a normal distribution. We choose the variance of the distribution, that 68% (standard deviation) of the population lives within a radius of ca. 7.5 km (ca. 1/4th of the total observation range of 30 km × 30 km). This configuration also applies to the reference case, as a simplified approximation of the actual distribution of inhabitants in the city of Cologne. The distribution of the attraction factors is likewise defined in this scenario.

The top-right of Fig. 5 depicts an inverse distribution of the population, compared to the base scenario. Here, the population is defined by a quadratic distribution, increasing with an increasing distance from the central centroid and reaching the maximum population density at the maximum distance. As the attraction factors are still normally distributed from the center, this scenario describes a maximum segregation of urban areas designated for living and to pursuing activities away from home. The analysis of this scenario yields quantitative insight into how much impact a segregation of exclusively-designated urban space has on the occurrence of traffic.

The scenario on the bottom-left defines four centroids and allocates the population and activities densely around these. The

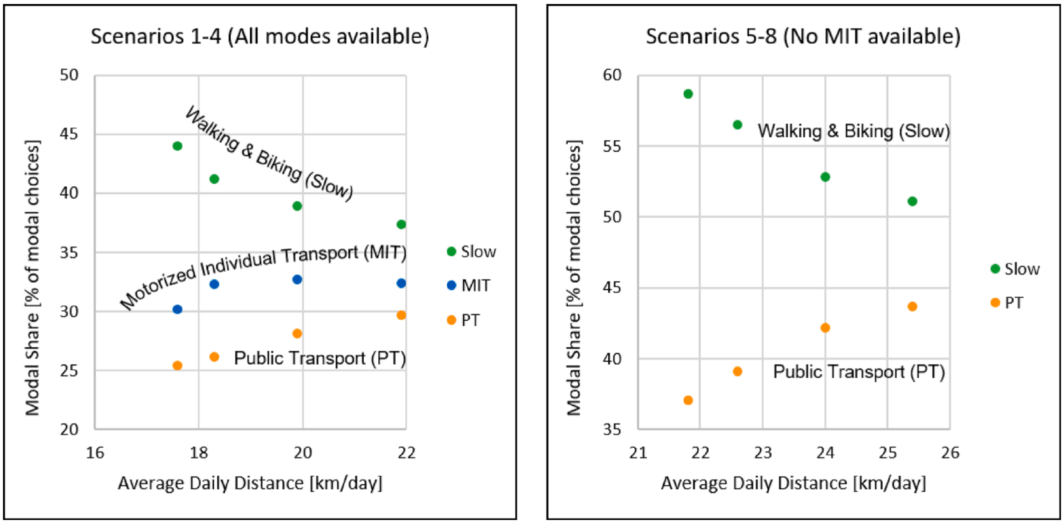

Fig. 8. Modal share of selected modes dependent on of the average daily distance per person, depicted for scenarios 1–8. MIT: Motorized Individual Transport. PT: Public Transport. Slow: Slow modes, such as walking and biking.

standard deviation of the normal distribution is defined such that 68% of the population lives within a radius of two kilometers from each of the four centroids. In contrast to the scenario on the top-right, the evaluation of this scenario delivers insight into whether highly condensed urban spaces lead to less traffic.

The scenario on the bottom-right follows the former scenario in defining four centroids, but allocates the population more towards the outskirts of the nuclei.

4.3. Impact of shared mobility and urban structure: Modal split and average daily distance per person

Fig. 6 displays the modal split while Fig. 7 shows the ADD travelled per person across the eight scenarios, which we present in section 4.2.

Initially, the influence of the urban structure on modal split and ADD is discussed, before the effects of an alternated mode availability are laid out.

The right-hand side of Fig. 6 illustrates the ADD for the scenarios. An overview of the simulation results of scenarios 1–8 can be found in section E of the appendix.

The total ADD ranges from 17.6 km in scenario 3 (All_4_Centre) to 25.4 km in scenario 5 (NoMIT_1_Centre), depending on urban structure and mode availability. The lowest values for the ADD correspond to the urban structures of scenarios 3 (All_4_Centre: 17.6 km) and 7 (NoMIT_4_Centre: 21.8 km), which is defined with four centroids and a similar, center-oriented distribution of home locations and the attraction-factors of the activities.

A more centralized urban structure, with only one central centroid, as depicted in scenarios 1 (All_1_Centre), 2 (All_1_Outer), 5 (NoMIT_1_Centre) and 6 (NoMIT_1_Outer) leads to an increase in the ADD: Scenario 1 (All_1_Centre) has an equal distribution of home locations and activities, but only one centroid compared to scenario 3 (All_4_Centre). This results in an increase of +13.0% of the ADD, with 17.6 km for scenario 3 (All_4_Centre) and 19.9 km for scenario 1 (All_1_Centre). Similar relations are observed for the comparison of scenarios 4–2, 7–5 and 8–6, with increases in the ADD between +10.1% and +19.7%. Thus, a centralized urban structure leads to more traffic, while a more scattered urban structure, with several city centroids across the urban area, leads to a significant decrease in the traffic volume. Furthermore, an urban structure that interweaves spaces for living and pursuing activities also decreases the traffic volume. Scenarios 1 (All_1_Centre), 3 (All_4_Centre), 5 (NoMIT_1_Centre) and 7 (NoMIT_4_Centre) follow this scheme, evenly distributing home locations and activities. This causes a reduced ADD of −8.8%, comparing scenario 2 (All_1_Outer: 28.5 km) to scenario 1 (All_1_Centre: 26.0 km). Similar proportions of the ADD-reduction in the range of −3.4% to −5.1% show the comparisons of scenarios 3–4, 5–6 and 7–8.

The evaluation of the modal split against the backdrop of the urban structure and ADD shows, that a decreased ADD corresponds to an increased share of slow modes, such as walking and biking. The comparison of scenarios 1 to 3 (ADD −11.6%) reveals an increase in the modal share of slow modes from 38.9% to 44.0%. The other modes of transport such as MIT and PT show a decrease of −2.5% (MIT) and −2.7% (PT) for the same scenario comparison. These trends, correlating the modal share of the modes Slow, MIT and PT, are depicted in Fig. 8 for scenarios 1–8.

The analysis of the correlation of the modal share to the ADD reveals that a decrease in the average daily distance results in an increase of slow modes, such as walking and biking and in a decrease of motorized modes, whether individual or public.

Scenarios 5–8 (No MIT) consider an alternated mode availability compared to scenarios 1–4 (All), as private cars are not available and shared modes of transport are available to all agents. These assumptions cause a significant increase in the modal shares of all other

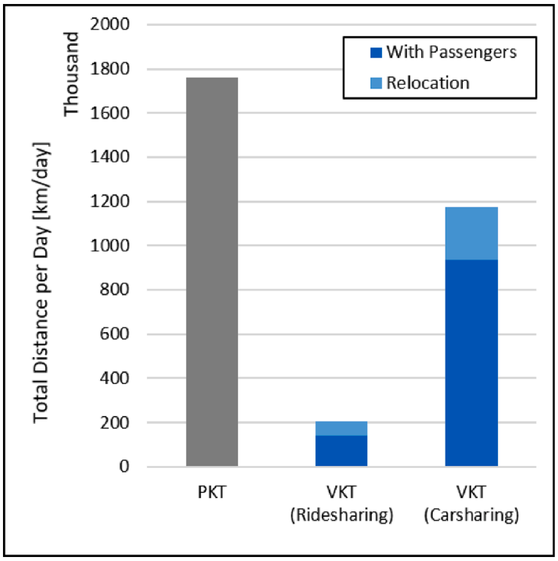

Fig. 9. Total covered distance of shared modes per day in passenger-kilometers travelled (PKT) and vehicle-kilometers travelled (VKT) for car- and ridesharing services, segregated into distance with passengers on board and distance for relocating the shared autonomous vehicle (SAV).

modes. Slow modes increase on average by 14.4%, from 40.4% to 54.8%, PT by 13.1%, from 27.1% to 40.5%, and shared modes by 4.4%, from 0.4% to 4.8%. Thus, public transportation and slow modes (walking and biking) are crucial keys on the path towards an efficient urban transportation system.

The ADD, evaluated for the scenarios with no MIT, increases on average by 21.1%, from 19.4 km (1–4) to 23.5 km (5–8). The public transportation modes account for the majority of the distance travelled within these scenarios, with an average of 13.8 km (58.7%). The slow modes, such as biking and walking, are chosen for 7.9 km (33.6%) in scenarios 5–8, compared to 3.5 km (18.5%) in scenarios 1–4. This translates into an increase of +15.1% in the modal share, measured by distance, for these modes. The shared modes make up a minor share of the ADD, with 1.8 km (7.7%). This evaluation shows that, although shared modes are widely available, they remain a niche choice for the traveler within an urban transportation system.

4.4. A closer look at shared mobility

We assume a city without MIT modes for the scenarios 5–8, while making shared mobility services available to every simulated agent. Most of the simulated transport demand is met by increasing shares of slow modes (Ø 54.8%) and public transportation (Ø 40.5%). Shared mobility services account for the remaining 4.8% of trips in the city and for 7.7% of the total distance covered. Nevertheless, shared vehicles constitute an important component of future urban transportation systems, as they bridge the gap between highly individual slow modes (walking and biking) and effective but static public modes of transportation.

This section analyzes the potential deployment of car- and ridesharing in scenario 5 (Shared_1_Centre), which is derived from the base scenario. The general findings of this analysis also apply in scenarios 6–8, which is why only scenario 5 is depicted in detail. Fig. 9 displays total vehicle-kilometers travelled (VKT) and passenger-kilometers travelled (PKT) of shared modes in the study area of the city during one day for car- and ridesharing services.

The 1.76 million PKT/day are the same for car- and ridesharing, as it refers to the transport demand of shared mobility of each individual in the study area. The vehicle kilometers describe how this transport demand is met by shared vehicles and how many kilometers these cover in the course of the day.

The total daily distance of the entire carsharing fleet amounts to ca. 1.17 million VKT/day, which is nearly six times as much as the ridesharing fleet covers per day, with ca. 0.2 million VKT/day. The total distance traveled by the carsharing fleet does not match the total passenger kilometers traveled, although carsharing vehicles do not allow more than one person per trip, because trips that lead outside the study area are neglected within the analysis of shared mobility services. This follows the example of current shared mobility service providers, working with limited service areas (Share Now GmbH, 2020). The discrepancy in the total daily distance between ridesharing and carsharing stresses the advantage of ridesharing in terms of transport efficiency.

Furthermore, the share of the total daily distance that is designated to relocating vehicles to locations that are more beneficial in order to meet transport demand is depicted in Fig. 9. Relocation accounts for 20% of the daily VKT of the carsharing fleet, while this makes up 32% of the ridesharing fleet's daily VKT. The relocation share is higher for ridesharing than for carsharing, as ridesharing routes are more flexible and complex, given that ridesharing vehicles combine the routes of several people being pooled together. Thus, the amount of additional transportation to relocate the vehicle, which takes place without any person in the vehicle in the case of carsharing, is substantial compared to the total transport demand of shared mobility. Nevertheless, assuming no MIT modes within the city results in a high decrease in car transportation and traffic. In the case of carsharing, the VKT decreases by 87% from 8.78 million

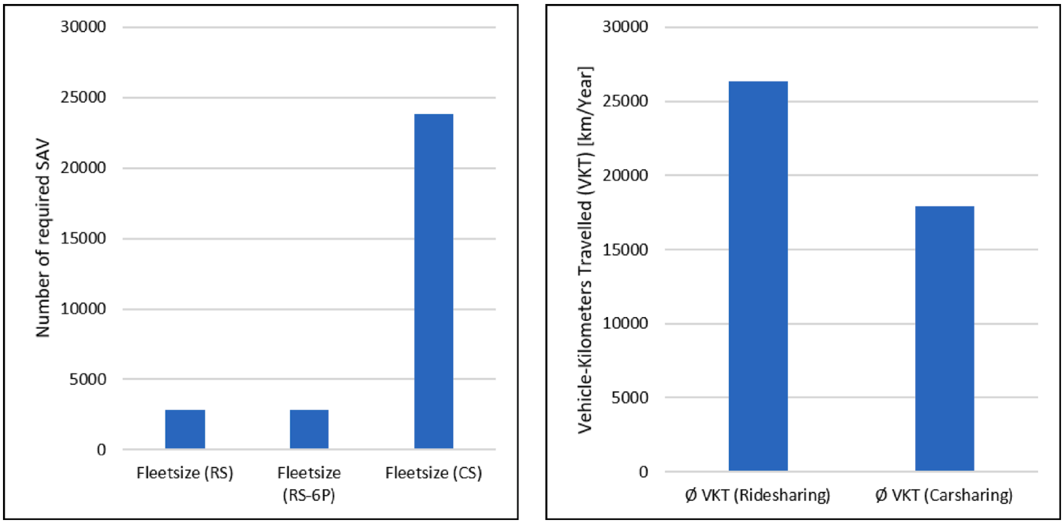

Fig. 10. Left: Fleet size of required shared autonomous vehicles (SAVs) for ridesharing and carsharing services of different sizes. Right: Yearly covered mileage per SAV for ridesharing and carsharing.

VKT (derived from the base scenario) currently to 1.17 million VKT, and by 98% for ridesharing, to 0.2 million VKT. This enormous reduction of MIT transportation is mainly substituted by a ramp-up of PT transportation, as is shown in the analysis above. In the case of ridesharing, car traffic can additionally be reduced by 83% compared to carsharing, as rides and people are pooled together.

Fig. 10 displays the required fleet sizes for different assumptions on the capacity of ridesharing vehicles and for the carsharing fleet on the left-hand side and the average yearly mileage per SAV on the right-hand side.[6]

The required fleet size for the ridesharing scenario is depicted for two different assumptions regarding vehicle capacity: No limitation and a maximum of six persons per vehicle. The case for six persons is derived from the German shared mobility provider MOIA and is equal to the case of no limitation if the vehicle capacity is assumed for this specific simulation (MOIA, 2020). Thus, the vehicle capacity of six persons is never exceeded in this simulation, which is not true for the other calculated scenarios, 6–8. The limitation to a maximum of six persons per vehicle leads to an increase in the required number of vehicles by 30% in scenarios 7 and 8.

Nevertheless, the total number of required SAVs is substantially lower for ridesharing than for carsharing in all scenarios for two reasons. First, the total daily distance is multiple times lower for ridesharing than carsharing, as is shown above. Second, the ridesharing fleet is more efficiently utilized, as the average yearly mileage per vehicle is ca. 47% higher. Furthermore, we conclude that a city without motorized individual transport and a simultaneous introduction of shared mobility decreases the total number of cars, similar to the reduction of the total VKT. The fleet size decreases by −95.1% for the carsharing scenario, from ca. 483,000 vehicles (reference) to ca. 24,000, and by −99.4% to ca. 3,000 vehicles for the ridesharing scenario, respectively. The reference values for the total number of vehicles in the city for the current situation are drawn from the KBA statistic for the city of Cologne (KBA, 2019). Besides positively affecting traffic in the city, a reduction in the total number of vehicles also leads to an increase in the available urban space. Required parking space is reduced by at least the same amount, as the number of cars in the city is reduced. We expect that even more former parking space can be re-designated for other purposes, as the efficiency of use of shared vehicles is higher compared to privately used ones.

The analysis of shared mobility within the simulated synthetic city reveals a possible pathway to an urban environment with substantially decreased motorized transportation. A city without MIT modes significantly increases the utilization of all other modes, with public transportation (ca. 60% of the total distance) and slow modes (ca. 33% of the total distance) taking over the major share of transport demand. Shared mobility plays a crucial role in this transformation, as it interlinks public transportation and slow modes with the necessary degree of individualized transportation.

In addition to that, we find that ridesharing services have significant advantages in transportation efficiency over carsharing (nearly six times reduced total distance).

4.5. Impact of societal Change, working from home and shifted mobility Preferences: Scenarios 9–18

Scenarios 9–18 focus on the impact of different societal changes and behavioral shifts within the upcoming 20 years on individual mobility behavior and the resulting traffic. Demographic change is considered across all scenarios, as the urban population is anticipated to grow and age (Cologne Statistical News, 2016; Munich Office for Urban Planning, 2019; Destatis, 2019). As long-term effects

[6] Section G in the appendix expands on the required fleet sizes for public transportation by analyzing the distribution of rides across transport modes throughout the day.

Table 5
Demographic change in German metropolises (Berlin, Cologne, Hamburg and Munich) between 2020 and 2040. Depiction of age structure and total population.

Age Group	Population Share 2020 BER, CGN, HH, MUN [%] (MiD17 (infas, DLR, IVT, infas 360, 2018)	Population Share 2040 BER, CGN, HH, MUN [%] (Demographic Forecasts (Cologne Statistical News, 2016; Munich Office for Urban Planning, 2019; Destatis, 2019)	Change [%]
< 18	14.8%	15.2%	+0.4%
18–65	66.6%	63.2%	−3.4%
> 65	18.6%	21.5%	+2.9%
	Total Population 2020 BER, CGN, HH, MUN	Total Population 2040 BER, CGN, HH, MUN	
Total	8.248.032	8.818.905	+6.9%

Table 6
Parameters of scenarios 9–18, focusing on the impact of societal change through 2040 on mobility behavior. All scenarios are simulated with 1281 agents and a projection of socio-economic characteristics of the study area, such as age and population, through the year 2040.

Scenario (Scenario Names)	Mode AV	Working from Home	Attractiveness of Shared and Public Modes Relative to Individual Modes (Utility Level)
9 (All_HO_0)	All modes available	0%	Reference
10 (All_HO_50)	All modes available	50%	Reference
11 (All_HO_80)	All modes available	80%	Reference
12 (NoMIT_HO_0)	No Private cars	0%	Reference
13 (NoMIT_HO_50)	No Private cars	50%	Reference
14 (NoMIT_HO_80)	No Private cars	80%	Reference
15 (All_More_Shared)	All modes available	80%	+50%
16 (NoMIT_More_Shared)	No Private cars	80%	+50%
17 (All_Less_Shared)	All modes available	80%	−50%
18 (NoMIT_Less_Shared)	No Private cars	80%	−50%

of the COVID-19 pandemic in 2020, we assume two potential developments: First, the emerging trend of working from home becomes more established (Boland et al., 2020). Second, the attractiveness of public and shared transportation might decrease due to an increased awareness of infection risks while traveling together with strangers, as revealed by recent surveys (Furcher et al., 2020; Follmer, 2020). Contrary to these developments, we develop scenarios in which shared and public transportation become more attractive, as they profit from beneficial urban transport regulation.

4.5.1. *Parameters of scenarios 9–18*

Table 5 depicts the average demographic change in the German cities of Berlin, Cologne, Hamburg and Munich from 2020 to 2040. The population in these urban centers will grow by an average of ca. 7% over this time period according to an evaluation of demographic projections for each city (Cologne Statistical News, 2016; Munich Office for Urban Planning, 2019; Destatis, 2019). This is mainly due to the increasing trend of urbanization over the next few years, as the total population of Germany stagnates within the same timeframe (Destatis, 2019). Furthermore, it can be elicited that the average age of the urban population will increase, as the middle age group from 18 to 65 years is expected to decline by ca. 3.4%, while the older age group over 65 years is expected to grow by ca. 2.9%.

We implement these demographic projections in scenarios 9–18, together with different assumptions regarding how widely working from home will be adopted and how the perception of transportation modes might change. Table 6 indicates the parameters of scenarios 9–18. In scenarios 9 and 12, working from home is not possible, and so they constitute a reference case for the subsequent scenarios, which allow working from home. Surveys conducted during the first COVID-19 lockdown phase in spring 2020 showed that the percentage of employees working from home increased to 35% in Germany (Follmer, 2020) and 62% in the US (Boland et al., 2020; Brenan, 2020). Following these surveys, we set the probability for conducting work from home to an average of 50% in scenarios 10 and 13. In order to reflect the influence of a more progressive shift in work practices, we simulate scenarios 11 and 14 with an 80% probability of being able to work from home. The four scenarios looking into different degrees of attractiveness of transport modes are also simulated, with 80% of agents working from home.

4.5.2. *Societal change until 2040*

Fig. 11 displays the average daily distance per person and the total daily distance of all inhabitants for scenarios 1 (All_1_Centre), 5 (NoMIT_1_Centre), 9 (All_HO_0) and 12 (NoMIT_HO_0). All of these scenarios are based on the same urban structure (single centroid, normal distribution of population and activities). Furthermore, scenarios 1 (All_1_Centre) and 9 (All_HO_0) incorporate the same assumptions regarding mode availability, which also holds for scenarios 5 (Shared_1_Centre) and 12 (NoMIT_HO_0). Thus, comparing scenarios 1 and 5 as well as 9 and 12 reveals the impact of societal change during the next 20 years on urban transportation.

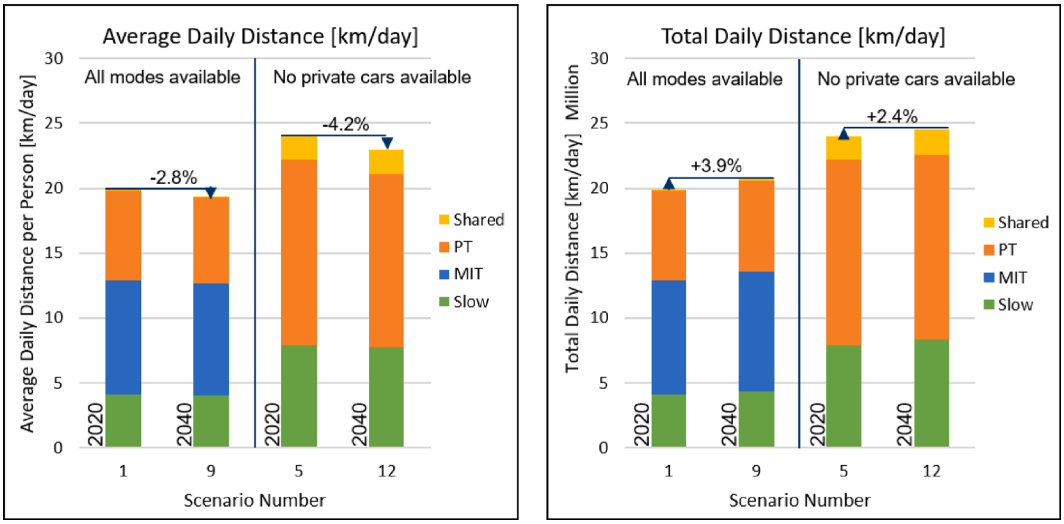

Fig. 11. Average daily distance per person and total distance of all inhabitants per day for scenarios 1, 5, 9 and 12. MIT: Motorized Individual Transport. PT: Public Transport. Slow: Slow modes, such as walking and biking.

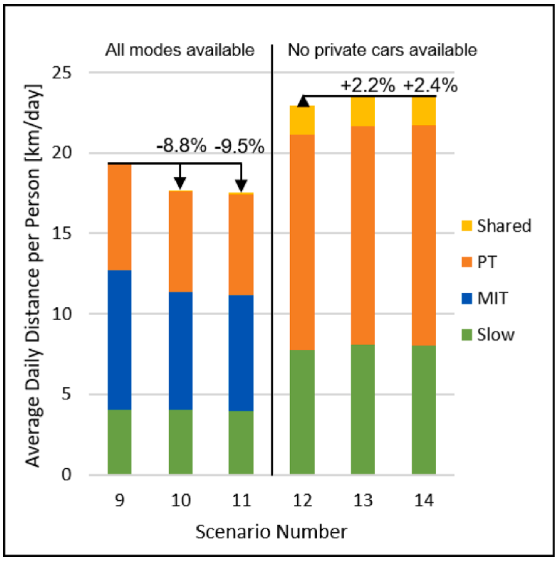

Fig. 12. Average daily distance per person (ADD) for the scenarios 9–14, depicting mobility in 2040 and the impact of working from home. MIT: Motorized Individual Transport. PT: Public Transport. Slow: Slow modes, such as walking and biking.

The left-hand side of Fig. 11 shows the average daily distance (ADD), which decreases in scenario 9 (2040, all modes) compared to scenario 1 (2020, all modes) by 2.8%, from 19.9 km/day to 19.4 km/day. The comparison of scenario 5 (2020, no MIT) to 12 (2040, no MIT) shows a decrease by 4.2% from 24.0 km/day to 23.0 km/day. The slight decrease in the ADD from 2020 to 2040 is explained by the demographic shift towards an aging society, which is reflected in the scenarios of 2040. A higher percentage of agents in the > 65 years age group results in a decreased average distance travelled, as decreased mobility is attributed to older people.

The total daily distance of all inhabitants is illustrated on the right-hand side of Fig. 11. In contrast to the evaluation of the ADD, this shows in the comparison of scenarios 1 to 9 and 5 to 12 an increase in the total daily distance. This total daily distance increases by 3.9%, comparing scenario 9 to 1 and by 2.4% for the comparison of scenario 12 to 5, respectively. Thus, the decrease in the ADD from 2020 to 2040, due to the demographic shift in the urban population, is compensated by the population growth of 6.9%, resulting in an overall increase in transportation demand in 2040.

4.5.3. Adoption of working from home until 2040

Fig. 12 depicts the evaluation of the ADD for scenarios 9–14, which describe transportation in the year 2040 for different assumptions for mode availability and working from home. Scenarios 9–11 represent transportation for the availability of all modes,

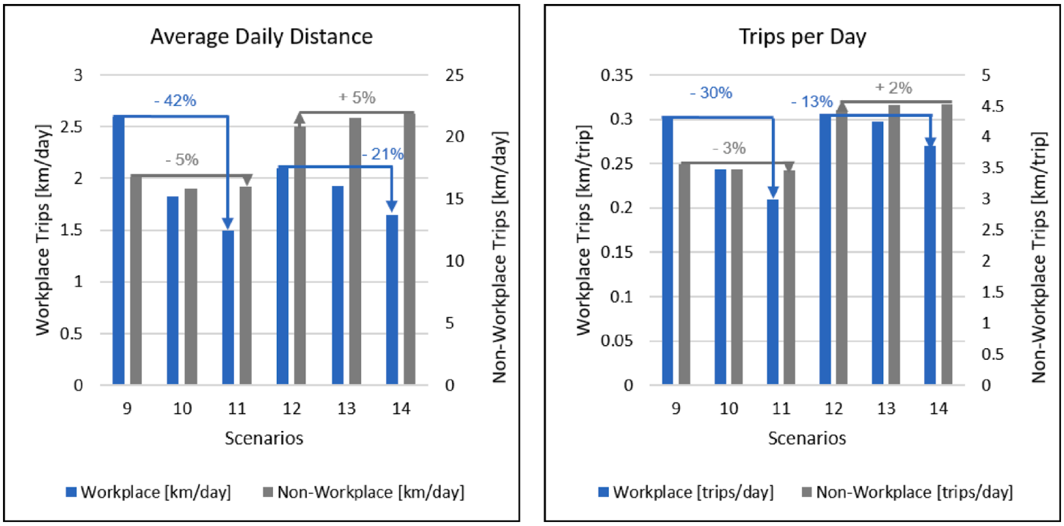

Fig. 13. Average daily distance per person for scenarios 9–14, depicting transportation in 2040 and the impact of working from home. MIT: Motorized Individual Transport. PT: Public Transport. Slow: Slow modes, such as walking and biking.

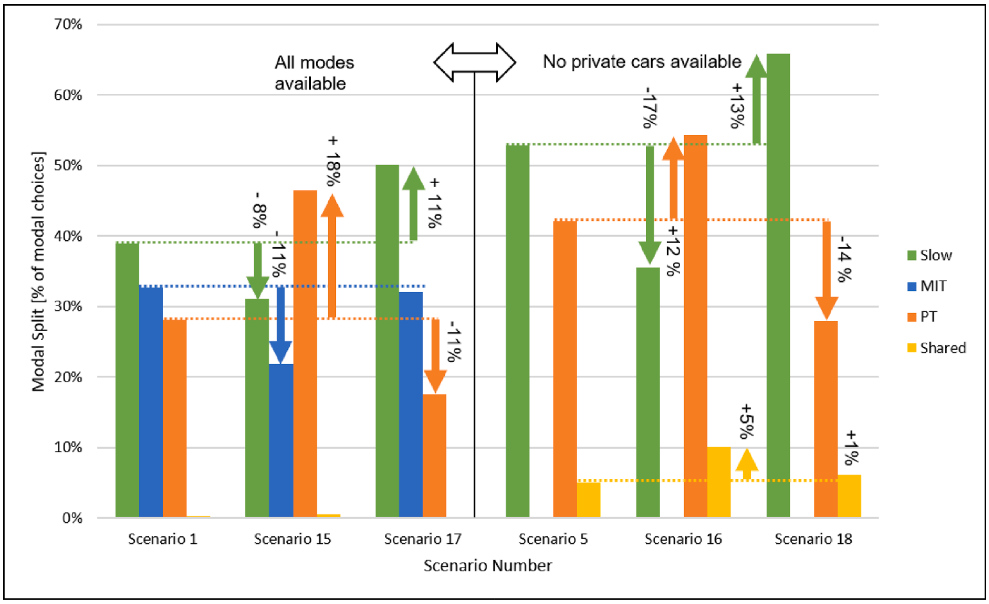

Fig. 14. Modal split of scenarios 15–18 compared to base scenarios 1 and 5. Scenarios 15–18 depict a shifted attractiveness of shared and public modes relative to individual modes, such as private cars, walking and biking.

while scenarios 12–14 reflect mobility behavior in a city without motorized individual transportation. Working from home is thus incorporated, with either 0% (scenarios 9 and 12), 50% (scenarios 10 and 13) or 80% (scenarios 11 and 14) of work-activities being conducted at home.

The ADD for scenarios 9–11 (all modes) decreases from 19.4 km/day in scenario 9 (0% work from home) by −9.4%, to 17.7 km/day in scenario 11 (80% work from home), as is shown on the left-hand side of Fig. 12. In contrast to that increases the ADD within the scenarios 12–14 with no MIT modes slightly by 2.4%, as the rate of working from home increases to 80% in scenario 14. Fig. 13 displays the ADD and the number of trips per day, segmented into trips to workplaces and into trips with other destinations, to discuss the displayed trends of the overall ADD from Fig. 12.

The daily distance travelled to workplaces correlates as expected with the increase of working from home from 0% to 80% across the scenarios 9–11 and 12–14. The ADD decreases by −42% from 2.6 km/day in scenario 9 (0% work from home) to 1.5 km/day in scenario 11 (80% work from home) and by −21% from 2.1 km/day in scenario 12 (0% work from home) to 1.6 km/day in scenario 14 (80% work from home). Trips to other destinations than the designated workplace are only slightly affected by the increase of working from home. The ADD of those trips varies in the range of 5% with a decrease in the scenarios 9–11 and an increase in the scenarios 12–14. These trends translate into an overall decrease of the daily distance travelled for the scenarios 9–11 and into an overall increase for the scenarios 12–14, as the probability to work from home increases in these scenarios from 0 to 80%. We find the cause of these trends in the correlation of the number of trips per day with the probability to work from home in the respective scenarios, as displayed on the right hand side of Fig. 13. The number of trips to workplaces decreases by −30% with an increase of the probability to work from home to 80% for the scenarios 9–11 and by −13% for the scenarios 12–14, respectively. Trips to other destinations than workplaces vary only slightly by −3% for the scenarios 9–11 and by +2% for the scenarios 12–14.

These findings show that a broader acceptance and implementation of working from home does not necessarily result in a decrease in transport demand, but is additionally dependent on mode availability and non-work-related activity.

4.5.4. Behavioral change until 2040: Between efficient transportation and the outcomes of COVID-19

The scenarios 15–18 depict diverging developments of the attractiveness of public and shared modes relative to individual transportation. Assuming a continued political support of public transportation and a further liberalization of the market for shared mobility, the scenarios 15 and 16 represent a positive development of these modes. Therefore, we increase the alternative specific constants of the respective modes within the discrete choice model by 50% in relation to the alternative specific constants of the individual modes. Scenarios 17 and 18 display a negative development of public and shared modes as an outcome of the COVID-19 crisis, assuming that people prefer traveling alone to avoid infections. Thus, we decreased the alternative specific constants of shared and public modes in relation to individual modes by 50%. Fig. 14 shows the modal split for the scenarios 15–18.

Although the ASC can be interpreted as a general level of attractiveness of a mode, we must be cautious with quantitative deductions from the model results to reality. Nevertheless, the depicted scenarios reveal the directions of the modal shifts, assuming potential positive or negative developments for public transport and shared mobility.

An increase of the attractiveness of public transportation and shared modes results in a significant shift to public transportation in the scenarios 15 and 16. Shared modes do only profit from that development in scenario 16, assuming no private cars in the city. The individual modes, such as walking, biking and private cars see an even decrease in their modal shares. Thus, attractive public and shared modes allure travelers from all individual modes of transportation.

The decrease of the attractiveness of public transportation and shared modes results in a significant reduction in the modal share for public transportation. The transport demand of public modes is substituted by an increase of slow and shared modes, while motorized individual transportation stays rather constant. Thus, travelers which tend to choose public transport switch to slow modes or even to shared mobility, but not to motorized individual mobility. This development of the modal shift towards higher shares of primarily slow modes, if public modes become temporarily less attractive, was also observed within a mobility survey by Follmer et al. during the COVID-19 lockdown phase in early 2020 (Follmer, 2020).

5. Discussion of key findings

This section discusses the key findings of transport demand analysis against the backdrop of an alternated urban environment and mode availability, as well as shared mobility and societal change.

5.1. Towards decentralized, heterogeneous urban structures

The conducted simulations reveal a correlation between the structure of the urban environment and the amount of traffic. A centralized urban structure displays an average surplus of +14.3% in ADD travelled by the simulated agents compared to scenarios with four evenly-distributed urban nuclei. Additionally, a similar distribution of activities and population density across the study area benefits traffic reduction, as it reduces the ADD of the agents in the respective scenarios by −5.5%.

Thus, with respect to the simulated scenarios, a decentralized urban structure with several nuclei, as well as similar spatial distributions of housing and activity opportunities in the urban structure are desirable in order to decrease urban transport demand. Both conditions for urban structure favor the spatial proximity of activity opportunities and people who seek to conduct activities, resulting in a heterogeneous urban space. According to our simulations, the combined potential for the reduction of the ADD lies at −19.4%.

5.2. Towards efficient urban transportation with more public and slow transport modes, linked by shared autonomous vehicles

The substitution of private cars with a fleet of SAVs bears the potential to decrease the total number of cars in the city and to redesignate valuable urban space for purposes other than parking. Thus, we investigate scenarios of urban transportation without private cars and a citywide introduction of SAVs to quantify the potentials and limits of shared mobility.

The results indicate a substantial shift in the distribution of modal shares: The share of slow modes (walk and bike) increases by +14.4% to 54.8% and the share of public transport increases by +13.1% to 40.5%, while shared modes account for a total of 4.8%. An expected extensive use of shared modes of transportation, such as car- or ridesharing, fails to materialize, as the total modal share remains low. Moreover, slow modes and public transportation take over to substitute large parts of the transport demand, which had been met by private cars beforehand.

These findings contrast with other studies, analyzed above. Heilig et al. simulate shared vehicles with the same model parameters as derived for MIT modes of transportation and find a modal share of 39% for SAVs (Heilig et al., 2017). The authors of the ITF study heuristically choose the mode of transportation, which results in a 70% modal share for shared vehicles in the scenarios, where public transportation is also considered.

In order to analyze the divergence of the presented findings, we investigate the sensitivity of our model results to the assumed transportation costs and the estimated parameters of the applied discrete choice model. Reducing the cost of public transportation (PT) by 50% results in an increase of the respective modal share by 0.9%, while an increase of 100% in costs for public transportation yields a decrease of 5.0% for PT in the modal share compared to the reference scenario. Furthermore, we observe an increase of 4.4% of the modal share for SAVs if transportation costs for these vehicles are cut by 50%. Therefore, we conclude that the sensitivity of the model results on the input parameter of transportation costs is fairly low, as no substantial changes in the modal shift are observed. Furthermore, we simulate a scenario in which we define the calibrated model parameters of the discrete choice model for shared modes to equal those of the MIT modes, analogously to Heilig et al. The results for this scenario deliver a modal share 35.4% for shared modes of transportation, which is comparable to the results of Heilig et al., with a share of 39%. This significant change in the modal share for shared modes in this scenario indicates that the model is highly sensitive to the calibrated parameters of the discrete choice model. Thus, simplified assumptions regarding those parameters must be made with caution. In terms of our model, we find a large gap between the estimated parameters for shared modes and MIT modes, resulting in divergent shares in the modal split. We identify several reasons for this difference: Travelers often neglect the true cost of transportation if travelling in private cars (Gardner and Abraham, 2007). As our model is calibrated on the true cost of transportation for every mode, the respective model parameter attributed to transportation costs for MIT modes must be low to replicate the market shares that we currently observe (infas, DLR, IVT, infas 360, 2018). In contrast, the traveler is always confronted with the true cost of transportation when choosing shared modes. Additionally, the service area of shared mobility services is often restricted to city boundaries. Thus, shared modes are rarely chosen for transportation outside of urban areas. These characteristics of shared modes currently lead to low modal shares in the surveys and thus to detrimental model parameters, compared to MIT modes.

For the future attractiveness of shared modes, we can observe two contrary trends: On the one hand, shared vehicles could become more attractive due to beneficial policies and a regulation of private cars. On the other, the current health crisis indicates a trend towards even more individual transportation and slow modes (Follmer, 2020). Depending on the development of these trends, we expect a future modal share of SAVs in the city between 5% (current attractiveness) and 35% (attractiveness equal to private cars).

Based on our simulations, we highlight two central findings: First, slow modes and public transportation see a significant increase in their modal shares if private cars are substituted by SAVs. Second, we expect shared modes to remain a secondary transportation concept. Nevertheless, carsharing and ridesharing will be integral elements in future transportation systems, as they bridge the gap between highly individual, slow modes and efficient but rigid public transportation.

5.3. Towards less traffic via shared mobility

The scenarios that do not allow for private cars in the simulated city show a strong decrease in the total daily driven mileage of shared vehicles: A decrease of 87% to 1.17 million km/day from 8.78 million km/day (base scenario) is simulated for the carsharing scenario. The consideration of ridesharing further decreases the total daily driven mileage of all cars in the city to 0.2 million km/day. Thus, the ridesharing fleet is nearly six times as efficient as the carsharing fleet in meeting the transport demand, as it pools rides and people together. Therefore, current regulations that limit the implementation of ridesharing fleets, especially in Germany, should be reconsidered (German Federal Ministry of Justice and Consumer Protection, 2020).

The strong reduction in car traffic that we find in the results of the respective scenario calculations contrasts to other studies, as referenced above (Bischoff and Maciejewski, 2016; Boesch et al., 2016; Fagnant and Kockelman, 2014; Heilig et al., 2017; Martinez and Viegas, 2015). These studies calculate a change in the total mileage driven by cars, from −20% to +44% for car- and ridesharing scenarios. The strong decrease in car traffic noted in this study is explained by the extensive substitution of travel demand by slow modes and public transportation that was met by private cars beforehand. Other studies concentrate on the representation of shared mobility (Bischoff and Maciejewski, 2016; Fagnant and Kockelman, 2014) or do not assume a dynamic transportation system (Boesch et al., 2016). The substantial changes in the modal share, such as for slow modes and public transportation, indicate that a holistic and dynamic representation of all components of the transportation system, as conducted in this study, is indispensable.

The required fleet size of shared vehicles is reduced by −95% from ca. 483,000 in the base scenario to ca. 24,000 in the carsharing scenario. The fleet size is reduced even more in the ridesharing scenario, to ca. 3,000 vehicles. The studies discussed above show a decrease in the required fleet size of vehicles between 85% and 92%. The overall decrease in the required fleet size of shared vehicles corresponds to the decrease in required parking spaces in the city, which is at least as large as the decrease in the fleet sizes. Former parking spaces could be re-designated to extend the available space public life or to increase the attractiveness of slow modes.

The average yearly mileage of shared vehicles amounts to 18,000 km/year in the carsharing scenario and to 26,400 km/year in the ridesharing scenario. Thus, the yearly mileage for ridesharing is 47% higher than for carsharing, which underlines the more efficient utilization of vehicles in the ridesharing scenarios.

5.4. Impact of societal change

The scenarios that are simulated to depict urban transportation in 2040 incorporate a growing urban population, as well as a demographic shift towards an aging society. The former trend outweighs the latter in the simulations, as the ADD increases by 3.2% on average in the year 2040, compared to 2020.

5.5. Impact of working from home

Working from home is expected to become more established across industries as digitalization proceeds and new approaches to work are implemented (Brenke, 2016). The trend of working remotely is further fostered by the current health crisis, which is expected to have a lasting effect on how people work (Boland et al., 2020).

The simulated scenarios assume probabilities for working from home of 0%, 50% and 80%. The average distance of work-related trips decreases by −17.8% for the 80% scenario compared to the 0% scenario if all modes are available, and by −12.3% if no private cars are considered. Non-work-related trips show a slight decrease in the average distance of trips (up to −3.3%) in those scenarios with all modes, while a slight increase (up to +2.4%) is observed if MIT modes are excluded from the mode choice. These trends result in an overall decrease in the average trip length by −9.5% from the 0% scenario to the 80% scenario, considering all modes. The evaluation of the scenarios, without the utilization of private cars, shows a slight increase of 2.4%.

Thus, an increased probability for working from home decreases work-related trip lengths but does not necessarily decrease the overall transport demand.

5.6. Impact of behavioral Change: Attractiveness of shared and public modes

Short- and long-term trends, such as emerging new transportation concepts and technologies but also the current COVID-19 health crisis are altering the preferences of travelers regarding mode choice. In order to investigate the influence of a shifted perception of transportation modes, we vary the attractiveness of shared and public modes in relation to individual modes, such as walking, biking and private cars.

On the one hand, we simulate a positive development of the attractiveness of shared and public modes compared to individual modes, assuming a continued political support for public transportation and an extended liberalization of shared mobility markets. We observe an increase in the modal share for public transportation, as expected. Shared modes only profit, if a significant modal share already exists.

On the other hand, as a possible outcome of the COVID-19 health crisis people might prefer individual transportation to minimize infection risks. Thus, we investigate a decreased attractiveness of shared and public modes. The scenario results indicate that especially slow modes profit from that assumption. Motorized individual transportation, such as private cars, remains at a relatively constant modal share, while public transportation decreases. These depicted tendencies of the modal shift go in line with a mobility survey conducted in Germany during the COVID-19 lockdown phase in May 2020 (Follmer, 2020).

6. Outlook

The transportation industry is at an inflection point, with new trends emerging, such as automated and connected driving, electrification and shared mobility. Urban transportation planners must react and adapt to these changes while simultaneously delivering answers to the challenges of increasing congestion and pollution. In order to account for the complexity of these trends, new holistic and dynamic transport demand models must be developed that integrate all elements of the transport system and also consider the links to other sectors.

This model constitutes an activity-based, bottom-up approach to modeling transport demand intended to capture the dynamic mobility behavior under the alternated external conditions of the transport system (urban structure, mode availability, societal change). Further research, which builds upon this model, will incorporate a link to the energy system to depict energy provision pathways and the required energy infrastructure. Furthermore, the study region must be expanded to enable a nationwide evaluation, including intercity transport and to allow for a holistic analysis of potential transformation pathways to a zero-emission transport sector.

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CRediT authorship contribution statement

Julian Reul: Methodology, Software, Validation, Formal analysis, Data curation, Writing - original draft. **Thomas Grube:** Conceptualization, Writing - review & editing, Supervision, Project administration, Funding acquisition. **Detlef Stolten:** Conceptualization, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declared that there is no conflict of interest.

Appendix

Appendix A: Literature review of selected studies

Fagnant et al. developed an agent-based model to analyze the implications of shared-autonomous vehicles (SAVs) on traffic, transport and environmental matters within a synthetic, grid-based urban space (Fagnant and Kockelman, 2014). Their model operates with distinct modules, replicating the functionalities of creating personal trips, the movement of SAVs and fleet management in terms of relocating SAVs to more beneficial positions. The generation of trips is modeled with distributions from the U.S. National Household Travel Survey (DOT, 2009) and is dependent on the start-location of the trip being generated within the urban space. The frequency of trip generation increases towards the city center to reflect the higher population density in this area. The destination choice for the trips is represented by a heuristic search algorithm, calculating feasible destinations within the synthetic urban grid. Trip origins and destinations are not bound to stations in the city, and so the model represents a free-floating carsharing operation. A virtual fleet manager sends relocation requests to free SAVs in order to relocate to areas that are more beneficial. Several relocation strategies are employed to best compromise the trade-off between waiting-times for passengers and the total driven distance per year. Furthermore, the model procedure is segregated into two model runs. In the first run, the SAV fleet size is estimated to service all issued trips. In the second run, the model calculates 100 consecutive days in 5-minute time steps. In contrast to other models, Fagnant et al. only substitute 3.5% of the total conventional car fleet to analyze the impact of SAVs.

The results of this model approach show that one SAV could potentially substitute eleven conventional cars (-92% cars), while the vehicle-kilometers travelled (VKT) per SAV would increase by up to 10%. An improvement in the model approach could incorporate a more detailed representation of the trips via an activity-based model approach or the integration of choice models at several levels. Furthermore, a realistic representation of the underlying road network is not incorporated in this study, in contrast to comparable analyses.

The International Transport Forum (ITF) published a study in 2015 assessing the effects of car- and ridesharing with autonomous vehicles in the city of Lisbon with an agent-based model (Martinez and Viegas, 2015). Similar to Fagnant et al., Lisbon is segregated into traffic analysis zones (TAZs) with a size of 200×200 m. Additionally, the authors of the study incorporated a representation of the actual infrastructure system of the city in order to improve the depiction of traffic flows. The congestion in the infrastructure system is statically-dependent on the time of the day and does not allow for dynamic interaction of the modeled vehicles. The trip generation is modeled with a fuzzy theory approach, according to Viegas et al., thus replicating the transportation demand found in a travel survey for Lisbon (Viegas, 2010). The mode choice for each trip is implemented as a rule-based approach, in contrast to various activity-based choice models in other studies (Alazzawi et al., 2018; Bischoff and Maciejewski, 2016; Boesch et al., 2016; Heilig et al., 2017; Scheltes and Correia, 2017; Llorca et al., 2017). The ITF study assumes a station-based sharing system where customers must walk to the stations in order to board a vehicle. Other studies choose a different approach to replicate the free-floating operation of the shared vehicle fleet (Bischoff and Maciejewski, 2016; Boesch et al., 2016). However, as long as transport models segregate the city into TAZs, the modeled systems resemble an operation with a station in every TAZ, but not a true free-floating operation. The authors of the study describe several different scenarios. The parameters, which are varied across these, are the mode choice between car- and ridesharing, the availability of high-capacity transport, the penetration rate of autonomous vehicles and the time period under analysis (one day or only peak hours). Unlike Fagnant et al., not only are 3.5% of conventional vehicles replaced in the fleet, but 50% or 100%, depending on the scenario. Due to these larger penetration rates of autonomous vehicles, the effects and limits of SAVs are captured to a larger extend.

The results show that within the ridesharing scenario, up to 90% of the vehicles can be removed from the city, albeit the annual VKT of the fleet increases in all scenarios with surpluses from 6.4% (Ridesharing and high-capacity public transport) to 90.9% (carsharing, 50% private car use, no high-capacity public transport). In the course of a reduction in the fleet size, 40,000 parking lots in the city can potentially be re-dedicated to other uses than transportation.

Boesch et al. developed an application of the MATSim transport model environment for the city of Zurich in order to analyze the impact of different sizes of autonomous vehicle fleets on the transportation system (Boesch et al., 2016). MATSim is a widespread activity- and agent-based model environment to simulate macroscopic transport demand, as well as microscopic traffic flow. The travel demand is assumed to be provoked by the modeled activities of the agents (activity-based approach), which contrasts to the approaches of Fagnant et al. and the ITF study. The daily activities of the agents are derived from a travel survey and evaluated against their total utility for the day. Within a co-evolutionary process, the day plans are updated until the activities of the day match the mobility constraints. The derived transport demand is static, such that it does not vary with the arrival of new transport modes such as autonomous vehicles. Within the outlook of the publication, the authors describe further advantages of an integration of dynamic transport demand. The model runs for a time-period of one week in the simulated environment with a resolution in time of one second. Boesch et al. mention the sensitivity of the model for the initial distribution of vehicles at the start of the simulated week. They initialize the model with the vehicles being located at the home locations of the agents. Contrasting to the ITF study, Boesch et al. only consider passenger vehicles within the model, despite the ability of MATSim to replicate other transport modes. The congestion levels are derived from pre-calculations, incorporating all other modes in the city. Further improvements of the model could be achieved by the simultaneous simulation of all modes to more realistically display the impact of autonomous vehicles on urban congestion. The model does not segregate the city into TAZs, but incorporates meter-fine coordinates of the agents. Thus, the spatial resolution of the model is more fine than in comparable studies (Fagnant and Kockelman, 2014; Martinez and Viegas, 2015; Heilig et al., 2017; Spieser et al., 2014; Zachariah et al., 2014; Burghout et al., 2015). Boesch et al. do not incorporate a relocation algorithm for the SAVs to move them to more beneficial locations for serving travel demand.

The results of the study by Boesch et al. show, that 90% of the current fleet size could be replaced by autonomous and shared vehicles. These findings are in line with other studies, and have been discussed (Bischoff and Maciejewski, 2016; Boesch et al., 2016; Burghout et al., 2015; Fagnant and Kockelman, 2014; Heilig et al., 2017; Martinez and Viegas, 2015).

Bischoff et al. base their analysis of an autonomous taxi fleet in Berlin on the MATSim framework, similar to Boesch et al. (Bischoff and Maciejewski, 2016). Thus, the publication covers an analysis of carsharing scenarios, where no ridesharing is considered. Comparable to Boesch et al. and other discussed studies (Martinez and Viegas, 2015; Spieser et al., 2014; Burghout et al., 2015), the model assigns the simulated routes to the underlying road-network of Berlin. The simulated time-period is limited to one weekday. Other modes, apart from car transport, are not depicted in the simulation and congestion levels, and vehicle speeds are derived from previous model runs that incorporate all modes of transport. Furthermore, the authors developed a dispatching strategy for the assignment of trip requests to vehicles. The model's state is evaluated against the number of idle cars and open requests in the system. In the case of an undersupply with open requests but no idle cars, the next idle car is dispatched to the closest request. In the case of oversupply with idle cars but no open requests, the closest car is dispatched to the next open request. The authors underpin the advantages of this strategy over the first-come-first-served procedure of conventional taxi fleet operators. The model is run for varying fixed fleet sizes of between 50,000 and 250,000 vehicles to find an optimal compromise of service quality in terms of passenger waiting times and fleet utilization with the goal of substituting all private car trips on one typical day in Berlin. The transport demand is derived from previous model runs, while only those trips are considered that can potentially be substituted by SAVs, which start and end within Berlin.

The results of the study by Bischoff et al. show that minimum fleet sizes between 90,000 and 110,000 vehicles achieve a sufficient level of service quality for customers. This equals a potential substitution of 10 to 12 vehicles per autonomous taxi. Due to empty vehicle trips, the total vehicle drive time increases by 17%. Both findings are in line with comparable studies, which are discussed above.

Heilig et al. evaluate the impact of ride-pooling with a fleet of autonomous vehicles in the Stuttgart region (Heilig et al., 2017). The travel demand was simulated with the agent-based transport model mobiTopp (Mallig et al., 2013). In that model, the process of demand modelling is divided into long-term and short-term mobility-related decisions by the agents. Long-term decisions include the localization of work and education, as well as decisions on car or transit pass ownership. Short-term decisions comprise the daily activities of the agent, such as activity, destination and mode choice, that are modeled with a nested logit approach. Furthermore, the authors assume the parameters of the future mode, 'autonomous vehicle', which the nested logit model requires, to be equivalent to the estimated parameters for the mode, 'car as passenger'. The costs of the autonomous mode are reduced by 70% compared to conventional cars due to ridesharing and fleet operation. The modeled time-period is one week with a resolution time of 15 min. The spatial resolution assumes a segregation of the Stuttgart region into distinct TAZs, but does not conduct an assignment of traffic to the actual infrastructure network. The model also allows deductions in the future modal split in a scenario where all passenger cars are substituted by autonomous vehicles, as all available modes in the Stuttgart region are considered. The substitution of private car trips leads to an increase of every mode. Short trips are allocated to the walk and bike modes, while longer trips are conducted with autonomous car mode. Additionally, the average distance travelled with autonomous cars increases compared to the trip length of conventional cars due to reduced travel costs and thus different outcomes of the destination choice model. The model pools car trips together if they start in the same 15-min time-slot and the same TAZ. The relocation of the autonomous cars to places with higher demand is only undertaken at night.

From the model runs, it can be concluded that 45% of all vehicle movements and 20% of all vehicle kilometers could be reduced if autonomous ride-pooling substituted the conventional car fleet in the Stuttgart region. In addition to that, 85% of all vehicles are potentially dispensable.

Appendix B: Descriptive statistics for transportation surveys MiD17 and MOP

The German Federal Ministry of Transport and Digital Infrastructure (BMVI) commissions a range of complementary transport surveys to capture the divergent aspects of the German transportation system, from passenger to freight transport. The "German Mobility Panel" (MOP) is conducted each year and aims to track short-term changes in individual mobility behavior. In contrast, the study "Mobility in Germany" (MiD) is conducted roughly every ten years, but draws upon a much larger and deeper set of surveyed information on mobility and transportation.

Mobility in Germany 2017 (MiD17)

The BMVI commissioned the last MiD in 2017, collecting information on nearly one million trips of 316,000 persons from 156,000 households in Germany (infas, DLR, IVT, infas 360, 2018). The survey data is segregated into six datasets: Persons, households, cars, trips, trip-legs, and travels. These datasets are available in different configurations, each being a trade-off between regional and socio-demographic resolution in order to ensure the data privacy of the survey participants.[7] We incorporate the dataset MiD17-B3 with the finest regional resolution of 500 m*500 m traffic zones in order to estimate the gravity model for urban destination choice. Furthermore, we use the data configuration MiD17-B1, with a higher socio-demographic resolution, to estimate the nested logit model for activity and mode choice. Table 7 provides an overview of the attributes of the dataset-configurations used for the model estimation.

[7] We do not combine information on two dataset configurations (B1 & B3) at any point, in compliance with the respective data privacy regulations.

Table 7
Attributes of utilized data in the dataset configurations "B1" and "B3" of the Mobility in Germany 2017 (MiD17) data.

Attribute from MiD17 Data (Configuration)	Interpretation	Used for Estimation of Choice:	Derived Attribute or Information
Wegkm (B1, B3)	Trip-distance	Mode, destination	*Distance*
hvm_diff_2 (B1, B3)	Mode of transportation	Mode, destination	*Mode*
HP_ALTER (B1, B3)	Age of the person	Mode, destination	*Age group*
HP_TAET (B1, B3)	Occupation of the person	Mode, destination	*Occupation*
Zweck (B1, B3)	Trip-Purpose	Mode, destination	*Activity*, conducted at destination
RegioStaR7 (B1, B3)	Region-classification of home location	Mode, destination	*Region type*
W_SZS, W_SZM (B1, B3)	Start time of trip ("-S": Hour, "-M": Minute)	Mode	*Speed matrix,* which contains average travel speeds, dependent on *region type* and *mode*
W_AZS, W_AZM (B1, B3)	Destination time of trip ("-S": Hour, "-M": Minute)	Mode	
GITTER_SO_500m (B3)	Identifier of start-zone in EPSG:3035-coordinates (LAEA)		Start_zone_east, start_zone_north
GITTER_ZO_500m (B3)	Identifier of targer-zone in EPSG:3035-coordinates (LAEA)		Destination_zone_east, destination_zone_north

Table 8
Attributes of utilized data of the Germany Mobility Panel (MOP) dataset.

Attribute from MiD17 Data	Interpretation	Derived Attribute or Information
IDP	Identifier of person	*ID*
ALTER	Age of the person	*Age group*
BERUF	Occupation of the person	*Occupation*
IDREGIOSTAR7	Region-classification of home location	*Region type of home-location*
ABZEIT	Start time of trip	*Start-time, end-time, activity_duration* of activity at the destination, *ActRatio* (Parameter of utility function)
ANZEIT	Destination time of trip	
ZWECK	Trip-purpose	*Activity*
WOTAG	Weekday	*AV_Act (availability of an activity)*

Additionally, we use the MiD17 to derive probabilities for mode preferences, typical workday characteristics (duration and start time), vehicle ownership and the average speeds of different modes of transport.

German mobility Panel (MOP)

The German Mobility Panel is a longitudinal study that captures the mobility behavior of single individuals over the course of a whole week. We incorporated the data of the MOP 18/19, accessible since late 2019, which includes ca. 71,000 trips by 3100 persons (Karlsruhe Institute of Technology, 2020). Table 8 lists the attributes that we utilized for the estimation of the activity choice within the nested logit model.

Appendix C: Estimation results for the nested logit model: Activity and mode choice

The discrete choice model for the combined calculation of the choice probability for an activity and a mode follows a nested logit structure, as described in sections 3.1 and 3.2. The model calculates the choice probabilities for each combination of activities, mode nests and modes. The nested logit structure is generalized for the mode "Shared Mobility," as it combines the characteristics of individual and public transportation, i.e., "Shared Mobility" is attributed to both nests, Motorized Individual Transport (MIT), and Public Transport (PT), with an estimated ratio. We separately estimate the model coefficients with a maximum likelihood approach for each of the six socio-economic groups. Tables 9 and 10 display the estimation results for the activity and mode choice level of the nested logit model.

Table 11 lists the estimation results for the nest choice layer, the scale factor for the activity and nest choice layers (the scale factor for the mode choice layer is normalized to one) as well as the portion, with which the mode "Shared Mobility" belongs to a nest.

Table 12 displays the likelihood ratio index for the estimation of the complete nested logit structure, as well as the sizes of the utilized datasets of the mobility surveys "Mobility in Germany 2017" (MiD17) and the "German Mobility Panel" (MOP). Data wrangling and the regional focus on metropolises reduces the size of the datasets.

Appendix D: Estimation results for the gravity model - Destination choice

The probability P_a that a TAZ is chosen as the target TAZ is given by equation (A.1), with activity type *a*, start TAZ *i*, target TAZ *j*, attractiveness *A*, impedance *imp* and the travel *distance* (Juan de Dios Ortúzar and Willumsen, 2011):

Table 9
Estimation results for the activity choice layer of the nested logit model. Entries indicated with - (-) are not estimated, as the respective choice option is either not available or not relevant for the socio-economic group. Keys for the socio-economic groups: 1st digit – 1: <18 years, 2: 18–65 years, 3: >65 years; 2nd digit – 1: Full-time job, 2: Part-time job, 3: Education, 4: No Occupation.

Activity	Socio-Economic Group	Alternative Specific Constant (t-Statistic)	Coefficient of Parameter *ActRatio* (t-Statistic)
Work Onsite	13 (Student, <18 years)	- (-)	- (-)
	21 (Full-time job, 18–65 years)	2.110 (3.09)	4.288 (3.65)
	22 (Part-time job, 18–65 years)	0.869 (1.50)	2.668 (2.27)
	23 (Students, 18–65 years)	0.450 (0.22)	4.668 (1.94)
	24 (No occupation, 18–65 years)	- (-)	- (-)
	34 (No occupation, >65 years)	- (-)	- (-)
Work Offsite	13	- (-)	- (-)
	21	5.160 (3.04)	7.716 (3.64)
	22	2.279 (0.97)	5.819 (2.97)
	23	−1.608 (2.54)	4.277 (2.80)
	24	- (-)	- (-)
	34	- (-)	- (-)
Education	13	25.458 (5.06)	37.793 (6.11)
	21	- (-)	- (-)
	22	- (-)	- (-)
	23	1.456 (1.66)	4.682 (3.64)
	24	- (-)	- (-)
	34	- (-)	- (-)
Shopping	13	−8.599 (0.94)	15.998 (3.22)
	21	−1.833 (3.09)	3.049 (5.35)
	22	−1.060 (2.85)	1.195 (3.71)
	23	−0.326 (1.54)	3.340 (2.28)
	24	−0.038 (0.70)	1.882 (2.62)
	34	−0.251 (0.33)	3.080 (5.82)
Private Obligation	13	−4.808 (3.85)	25.423 (4.40)
	21	−0.638 (1.17)	4.584 (4.24)
	22	−0.361 (0.68)	2.777 (2.73)
	23	−0.153 (0.75)	3.444 (1.98)
	24	0.903 (1.22)	3.089 (1.48)
	34	−0.221 (0.19)	3.162 (5.67)
Service	13	−15.274 (0.72)	23.620 (2.41)
	21	0.236 (1.89)	6.618 (3.44)
	22	0.943 (1.52)	3.780 (2.35)
	23	−1.958 (2.08)	3.739 (2.10)
	24	0.292 (0.22)	3.984 (2.60)
	34	1.448 (1.00)	7.470 (5.35)
Home	13	Normalized to Zero	5.485 (3.35)
	21		1.230 (4.16)
	22		0.839 (3.02)
	23		2.055 (4.03)
	24		0.696 (2.29)
	34		1.119 (6.01)
Leisure	13	−0.347 (1.40)	15.519 (6.32)
	21	−0.045 (0.44)	3.509 (5.51)
	22	−0.245 (0.89)	2.186 (3.36)
	23	−1.552 (0.20)	1.429 (2.55)
	24	0.569 (2.25)	2.600 (2.85)
	34	0.293 (1.59)	3.312 (5.29)

$$P_{a,ij} = \frac{A_{a,j} * e^{-imp_a * distance_{i,j}}}{\sum_j A_{a,j} * e^{-imp_a * distance_{i,j}}} \tag{A.1}$$

We estimate the impedances for each activity type by minimizing the error of the travelled distance per trip between the model forecast and the survey data over the entire dataset. Table 13 displays the impedances as the estimation results.

Appendix E: Approach to correctly scale up the distribution of trips

As the number of simulated agents (1281 in the base simulation) is only a fraction of the actual population size (assumed to be one million), the simulated trips are less frequent and not equally distributed compared to the real world. General transport system characteristics such as the total mileage per mode can be scaled up by the constant ratio of the population size to the simulated number of agents, which we will consequently refer to as the scale factor *PopAgentRatio*. In contrast, the analysis of shared mobility requires a

Table 10
Estimation results for the mode-choice layer of the nested logit model. Entries indicated with - (-) are not estimated, as the respective choice option is either not available or not relevant for the socio-economic group. Keys for the socio-economic groups: 1st digit – 1: <18 years, 2: 18–65 years, 3: >65 years; 2nd digit – 1: Full-time job, 2: Part-time job, 3: Education, 4: No Occupation.

Mode	Socio-Economic Group	Alternative Specific Constant (t-Statistic)	Coefficient of Parameter *Trip-Duration* (t-Statistic)	Coefficient of Parameter *Trip-Cost*(t-Statistic)
Walk	13	1.116 (1.04)	0.1178 (2.23)	- (-)
	21	0.389 (16.15)	0.0830 (19.16)	- (-)
	22	0.392 (11.81)	0.065 (18.53)	- (-)
	23	0.661 (8.61	0.0647 (9.84)	- (-)
	24	0.517 (13.21	0.0598 (14.39)	- (-)
	34	0.703 (12.79)	0.0686 (13.81)	- (-)
Bike	13	0.420 (1.40)	0.0833 (2.58)	- (-)
	21	−0.0019 (3.63)	0.100 (6.84)	- (-)
	22	−0.210 (1.29)	0.0602 (11.39)	- (-)
	23	−0.226 (0.82)	0.0557 (11.06)	- (-)
	24	−0.707 (4.89)	0.0560 (10.64)	- (-)
	34	−0.447 (5.40)	0.0787 (7.50)	- (-)
Car-Self	13	- (-)	- (-)	- (-)
	21	0.161 (2.54)	0.0254 (2.29)	0 (3.20)
	22	0.0969 (3.20)	0 (2.34)	0.111 (2.74)
	23	0.0671 (0.97)	0 (3.05)	0.0844 (3.20)
	24	−0.187 (0.67)	0 (1.73)	0.179 (8.53)
	34	0.402 (0.85)	0.00198 (1.68)	0.316 (4.75)
Car-Co	13	Normalized to Zero	0.0179 (2.52)	0 (1.52)
	21		0.136 (2.20)	0.0650 (2.00)
	22		0.00146 (1.20)	0 (1.47)
	23		0.00960 (3.23)	0.0870 (3.28)
	24		0 (1.34)	0.114 (5.46)
	34		0 (1.56)	0.0540 (2.72)
Bus Near	13	−0.778 (0.45)	0 (1.47)	1.395 (2.38)
	21	−0.135 (5.37)	0.321 (3.36)	0.00974 (2.78)
	22	−0.718 (4.83)	0.0589 (2.99)	0 (1.94)
	23	−1.343 (2.74)	0.0458 (3.52)	0.852 (2.13)
	24	−0.671 (2.01)	0.0470 (6.27)	0.404 (3.56)
	34	−0.355 (3.23)	0.122 (2.87)	0.104 (3.20)
Train Near	13	−2.357 (1.88)	0 (1.42)	0.088 (1.32)
	21	−0.211 (6.52)	0.156 (1.86)	4.94E-08 (1.05)
	22	−1.493 (8.08)	0 (1.39)	0 (1.22)
	23	−2.256 (5.86)	0 (1.94)	0 (1.89)
	24	−2.075 (8.25)	0 (2.15)	0 (1.51)
	34	−1.112 (5.45)	0.0799 (2.02)	0 (1.10)
Train City	13	−1.009 (0.03)	0 (1.58)	0.131 (1.80)
	21	−0.159 (2.20)	0.146 (1.48)	8.19E-06 (4.57)
	22	−0.214 (1.09)	0 (1.50)	0.156 (3.80)
	23	−0.961 (3.36)	0 (1.80)	0.197 (4.67)
	24	−0.258 (5.23)	0 (1.90)	0.217 (4.01)
	34	−0.575 (4.59)	0 (1.63)	0.446 (4.41)
Bus Far	13	- (-)	- (-)	- (-)
	21	0.001907 (3.03)	0.117 (1.68)	0.0104 (3.19)
	22	0.306 (1.30)	0 (1.46)	0.151 (1.46)
	23	3.717 (2.85)	0.0447 (1.00)	0.193 (1.00)
	24	0.381 (1.51)	0 (1.00)	0.203 (1.00)
	34	0.172 (2.39)	0.0280 (2.33)	0.118 (1.89)
Train Far	13	- (-)	- (-)	- (-)
	21	−0.000689 (2.05)	0.152 (2.62)	0.00586 (1.80)
	22	0.0703 (1.16)	0.0368 (1.04)	0.0143 (1.20)
	23	0.528 (1.33)	0.0232 (1.00)	0.0389 (1.00)
	24	−0.0061 (1.00)	0.480 (1.00)	0.0168 (1.00)
	34	0.00168 (0.97)	0.459 (2.05)	0.0185 (1.25)
Shared Mobility	13	- (-)	- (-)	- (-)
	21	−0.0511 (4.73)	0.565 (1.43)	0.429 (2.93)
	22	−0.616 (3.05)	0.0150 (3.64)	0.220 (5.28)
	23	−0.0367 (0.45)	0.0195 (6.10)	0.572 (6.14)
	24	−0.426 (2.91)	0 (3.39)	0.199 (4.51)
	34	−0.0311 (3.19)	0.110 (3.86)	0.100 (4.05)

more complex scaling procedure, as its characteristics depend on the distribution of trips in time and space (Parry and Evans, 2008; Parry and Bithell, 2012; Llorca and Moeckel, 2019). Fig. 15 displays the distribution of shared trips in the base simulation (red) with 1281 agents over 28 days (1281*28 = 35.868 days) compared to a large reference simulation (blue) over one million days (=one

Table 11
Estimation results for the nest-choice layer of the nested logit model. Keys for the socio-economic groups: 1st digit – 1: <18 years, 2: 18–65 years, 3: >65 years; 2nd digit – 1: Full-time job, 2: Part-time job, 3: Education, 4: No Occupation.

Explanatory Variable of Nest-Layer	Socio-Economic Group	Coefficient (t-Statistic)
Scale-Factor Nest-Level	13	1
	21	0.914
	22	1
	23	1
	24	1
	34	0.559
Scale-Factor Activity-Level	13	0.1
	21	0.561
	22	0.882
	23	0.788
	24	0.896
	34	0.612
Portion, with which Mode "Shared Mobility" belongs to Nest MIV	13	0.5
	21	0.541
	22	0
	23	0.477
	24	0
	34	1
Alternative-Specific Constant (ASC) Nest Public Transport	13	1.016 (0.95)
	21	0.459 (3.68)
	22	−1.265 (5.79)
	23	0.671 (0.31)
	24	−1.771 (7.32)
	34	−0.901 (2.66)
Alternative Specific Constant (ASC) Nest Slow	13	2.535 (4.42)
	21	1.387 (15.31)
	22	1.181 (14.52)
	23	1.435 (11.99)
	24	0.811 (8.13)
	34	1.256 (7.66)

Table 12
Likelihood ratio index and size of the utilized input datasets for the estimation procedure.

Socio-Economic Group	Combined Likelihood Ratio Index for the Estimation of the Complete Nested Structure	Size Dataset Activity Estimation (MOP Data)	Size Dataset Nest & Mode Estimation (MiD17 Data)
13	0.325	912	16,016
21	0.251	5479	61,543
22	0.282	1885	22,500
23	0.179	383	8363
24	0.320	1288	11,883
34	0.312	2895	31,732
Dataset Utilized [#trips]		12,842	152,037
Dataset Original [#trips]		71,189	960,619

Table 13
Estimation results for the gravity model, depicting the impedances for each activity type.

Activity	Impedance
Work	0.25627
Education	0.38344
Shopping	0.57065
Private Obligation	0.42161
Service	0.45395
Leisure	0.30635

million inhabitants). The visualization shows that the scale factor by which a respective trip must be multiplied is dependent upon the location of the trip within the study area. This notion is equivalent to a spatially-dependent scale factor $PopAgentRatio = f(TAZ)$.

As the characteristics of shared mobility also depend on the distribution of trips over time, the scale factor for a trip also becomes

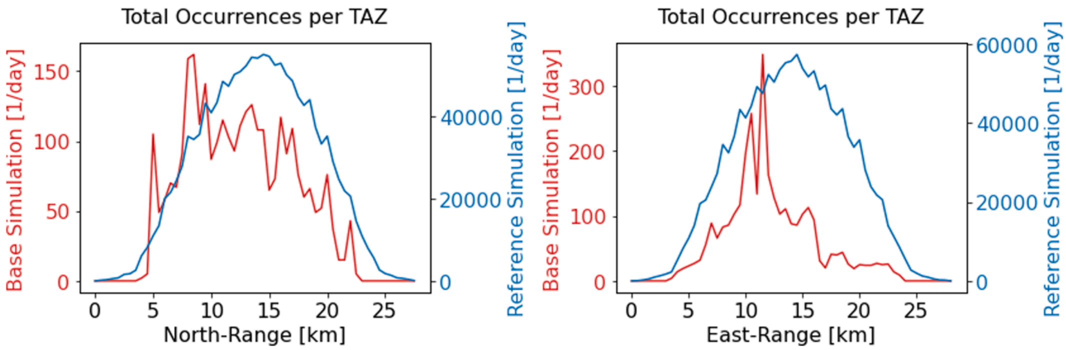

Fig. 15. Spatial distribution of trip occurrences, aggregated over the North- and East-range of the study region, for the base (red, ca. 36,000 days) and the reference simulation (blue, one million days). TAZ: Traffic Analysis Zone. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 14
Modal split and average daily distance covered per person for scenarios 1–8 (Urban Structure and Mode Availability). MIT: Motorized Individual Transport. PT: Public Transport. Slow: Walking and Biking. MiD17: German mobility survey ("Mobilität in Deutschland 2017").

Scenario	Average Daily Distance [km]	Average Daily Distance - Weekday [km]	Average Daily Distance - Weekend [km]	Modal Split – Slow [%]	Modal Split – MIT [%]	Modal Split – PT [%]	Modal Split – Shared [%]
1	19.9	26.0	4.7	38.9	32.7	28.1	0.4
2	21.9	28.5	5.3	37.4	32.4	29.7	0.5
3	17.6	23.0	4.1	44.0	30.2	25.4	0.4
4	18.3	23.9	4.4	41.2	32.3	26.2	0.3
5	24.0	31.4	5.5	52.8	0	42.2	5.0
6	25.4	33.1	6.2	51.1	0	43.7	5.2
7	21.8	28.4	5.0	58.7	0	37.1	4.3
8	22.6	29.4	5.6	56.5	0	39.1	4.5
MiD17	17.7	–	–	35.3	35.0	29.4	0.2

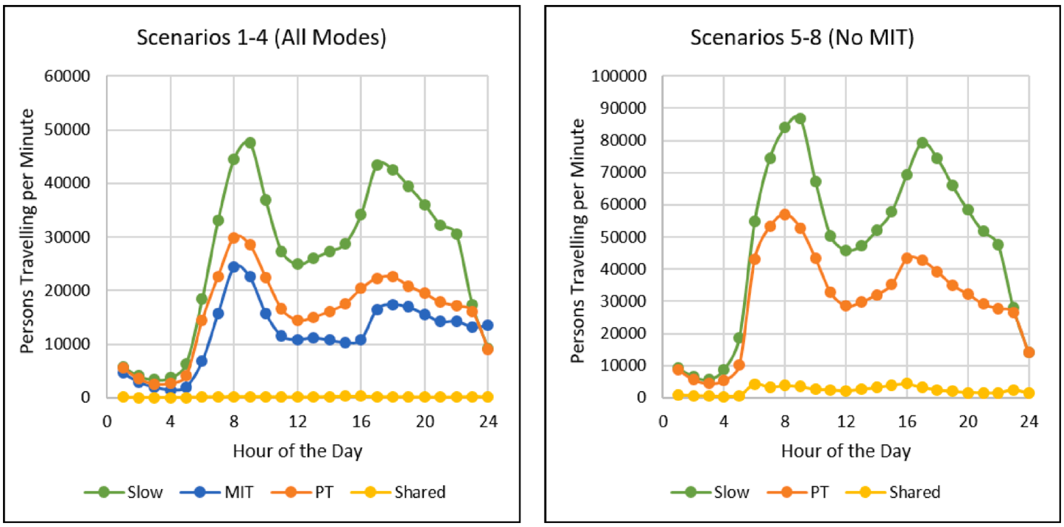

Fig. 16. Temporary number of persons travelling, averaged over one hour. Left-hand side: Average of scenarios 1–4, depicting mobility with all conventional modes available. Right-hand side: Average of scenarios 5–8, depicting mobility with no motorized individual transport. MIT: Motorized Individual Transport. PT: Public Transport. Slow: Slow modes, such as walking and biking.

dependent on its occurrence over time *PopAgentRatio* = *f(TAZ, Time)*. A single trip in the base simulation occurs at different points in time and space. Thus, we calculate the scale factor for a single trip as the average *PopAgentRatio* across all traffic zones and discrete time intervals in the course of the trip. The large reference simulation is parametrized similarly to the base simulation. If we analyze shared mobility in other scenarios than the base case, we adjust the scale factor to fit the respective frequency of shared mobility trips in the new scenario. A measure for this frequency is the modal split for shared mobility.

Appendix F: Results of the scenario analysis

Table 14 displays the results of the scenario analysis.

Appendix G: Distribution of rides throughout the day

The figure illustrates the average occurrences of the different mode choices Slow, MIT, PT, and Shared for scenarios 1–4 (all modes available) and 5–8 (no MIT available), aggregated over the course of the day. The mode occurrences are described by the temporary number of persons traveling, averaged over one hour.

The modal share of each mode of transport is reflected in the scale of the curves in Fig. 16, with slow modes having the highest share, followed by PT and MIT, as well as a minor importance in the case of the shared modes. Furthermore, in both sub-figures, the average curves for scenarios 1–4 on the left-hand side and the average curves for scenarios 5–8 on the right-hand side show a typical double-peak for the number of travelers over the course of the day. The first traffic peak is observed around 8–9 am, while the second takes place around 5–6 pm. The morning peak is sharper than the afternoon one for all modes of transportation. For the PT as well as for the MIT modes, the morning peak is higher than the afternoon peak by 32–40%. Thus, transport demand in the morning hours sets the requirements for the maximum fleet capacity. Comparing the PT demand of scenarios 1–4 to that of scenarios 5–8, which do not allow for MIT modes, the morning peak of the PT modes increases from ca. 30,000 persons traveling to ca. 60,000. This implies that the capacity of public transportation must be ramped up significantly in order to meet transport demand in an urban transportation system without motorized individual modes, such as private cars.

The required fleet size for shared modes depends on the chosen type of sharing, whether carsharing or ridesharing. Ridesharing services typically require fewer vehicles to meet transport demand, as rides and passengers are pooled together in a single vehicle.

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Glossary

Activity-based modeling: Modeling approach for disaggregate transport demand analysis. Follows the principle, that transport is induced by the human need to participate in activities.
Choice Set: The set of alternatives, which is available to a decision-maker within a specific choice situation. Accounts for individual limitations as well as constraints in time and space.
Discrete Choice: Econometric research field, which deals with the model-based analysis of discrete choices by individuals or aggregate groups.
German Mobility Panel (MOP): Longitudinal German mobility survey, conducted each year. Includes approximately 70,000 recorded trips. Individual mobility behavior is observed for a whole week.
Gravity Model: Mathematical model, that describes the destination choice by decision-maker, based upon Newton's gravity law.
Mobility in Germany 2017 (MiD17): German mobility survey, conducted in the year 2017. Includes approximately one Million recorded trips. Individual mobility behavior is observed for single days.
Modal Split: Characteristic of a transport system, that describes the distribution of choices or kilometers travelled per transport mode.
Shared Autonomous Vehicle (SAV): Self-driving vehicles that are employed in shared vehicle fleets.
Shared Mobility: Shared use or possession of means of transportation among individuals. Shared vehicle fleets are often owned and managed by a central organization. Individuals can get access to shared vehicles as a temporary service, provided by this organization.
Slow Modes: Slow modes of transportation, such as walking and biking.
Traffic Analysis Zone (TAZ): Smallest regional unit within a transport analysis.
Vehicle-kilometers travelled (VKT): The distance travelled by a vehicle or individual over a period of time (often a day or a year)