Transportation Effects of Connected and Automated Driving in Germany

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Abstract Connected and automated driving (CAD) is likely to affect the German transportation system. Three consecutive models assess the effects of private automated vehicles (PAV) and shared automated vehicles (SAV) on car ownership, car stock, and travel demand in 2050 based on different scenarios. Firstly, a car ownership model (COM) estimates car availability at household level including changes in accessibility through CAD. Based on the year of market entry and additional costs, a car stock model (CAST) quantifies the diffusion of CAD within the German car fleet in 2050. Finally, the effects of CAD on transportation volumes and key indicators for SAV services are determined using the national travel demand model of Germany (DEMO). The model results for PAV show an increase in ownership by up to 1% with a 44% diffusion of Level 4+ cars in 2050. They account for over 50% of kilometers driven and increase overall vehicle kilometers traveled by 3%. On the contrary, SAV will reduce car ownership in urban regions by up to 4%, but increase vehicle kilometers traveled by 5%. Automation improves the transportation system and makes traveling easier. But to cope with the environmental implications, it is necessary to provide a political framework which stresses the advantages of CAD.

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1 Introduction

The transportation system experiences disruptive changes through technological development, such as electrification and digitalization. One highly researched and current example is connected and automated driving (CAD), which will likely transform the transportation system. CAD consists of two aspects: the first part, "connected", means vehicles communicate with each other (vehicle-to-vehicle or V2V), or with infrastructure such as traffic lights (vehicle-to-infrastructure or V2I) [20]. This function is the basis for the second part, "automated", as it provides the technical requirements along with the onboard sensors. Therefore, both terms in combination lead to "connected and automated driving".

CAD refers to vehicles driving themselves without manual intervention, in specified or all situations. According to the definition of automated driving by the Society of Automotive Engineers SAE International [28], CAD refers to Level 4 and 5 (for levels of CAD see the Introduction), throughout the remainder of this chapter labeled as Level 4+. This includes private automated vehicles (PAV) and the emergence of new transportation modes with shared automated vehicles (SAV). The advantages of CAD are expected to be manifold, including:

- ensuring mobility for people with reduced mobility [41, 44, 48]
- maintaining accessibility in regions with low demand [25, 41]
- improving the efficiency of the transportation system [6, 48]
- increased comfort and the possibility to use the travel time alternatively [6, 25, 41]
- reduction of transportation-related emissions [41, 48].

Nevertheless, the expected effects only occur if the corresponding regulatory framework exists and society accepts the technology. The chapter "Governance, Policy and Regulation in the Field of Automated Driving: A Focus on Japan and Germany" of this book analyses the regulatory framework in Japan contrasted with Germany, while the chapter "Social Acceptance of CAD in Japan and Germany: Conceptual Issues and Empirical Insights" offers comprehensive insights on the social acceptance of CAD in Germany and Japan. As CAD is not yet part of the transportation systems, extensive research analyses and simulations are being conducted for different future scenarios to pave the way for transforming the transportation sector. With the technology and regulatory framework developing rapidly, the analyses at hand use a future scenario for the year 2050 in which automated vehicles such as PAV and SAV are available on the market. To quantify the impact of CAD on the transportation system, a framework consisting of three models is developed. The first is a car ownership model (COM) which forecasts the effect of CAD on private car ownership in households. The second is a car stock model (CAST) which simulates the diffusion of automated vehicles in the car stock until 2050. The third is a travel demand model (DEMO), which models changes in the transportation system. This combined model set provides a powerful framework for detailed quantification of the transformation effects of CAD in Germany.

The chapter begins with an overview of research regarding modeling the effects of automation. This is followed by a section about the modeled scenarios for CAD and the model framework. After providing the results of the model, a discussion of its limitations and a summary of the results concludes the chapter.

2 Literature Review

The transformation to a future sustainable transportation system requires suitable strategies and policies. A prerequisite for developing such guidance is understanding the relationships and dependencies in the mobility sector. In this context, models in the field of transportation research help to identify and quantify these mechanisms. Thus, the analysis of the effects of CAD on the private car market and new services needs an efficient modeling framework [61]. One crucial part of this framework models changes in car ownership, car stock, and travel demand. Although models of local or regional scope allow simulation of complex dependencies due to data availability and computational power, using models of a national scope has the advantage that the evaluation of transportation-related effects on a nation as well as differentiation for urban and rural regions are possible. Thus, policy recommendations can be derived at the highest level. It follows that the development of a dedicated model framework to assess the effects of automation on a national scale can be a crucial tool, which can also provide references and frameworks for simulations in specific regions.

Simulating the effects of CAD, beginning with car ownership, through car stock up to travel demand, is a dedicated and complex task. It covers long-term decisions about car ownership and type of automation, and short-term decisions such as mode choice [34]. Due to the wide range of decisions, it is worthwhile to analyze each model category alone, before evaluating comprehensive models.

Aspects affecting conventional car ownership are well researched [2, 3, 30, 31, 33]. The emergence of automation augments these factors through acceptance and adoption of new technologies (see chapter "Social Acceptance of CAD in Japan and Germany: Conceptual Issues and Empirical Insights", or e.g., Acheampong and Cugurullo [1]; Fraedrich and Lenz [16]; Hossain and Fatmi [26]; Lavieri et al. [40]), willingness to pay for automated cars and services (see chapter "Business Analysis and Prognosis Regarding the Shared Autonomous Vehicle Market in Germany", or e.g., Daziano et al. [10]; Gkartzonikas and Gkritza [21]), and changes in accessibility because of travel time savings, as the travel time can be used differently [35, 36, 52]. As automated vehicles are currently not available on a large scale, it is not yet possible to measure the impact of CAD on car ownership. Instead, research sheds light on the effects of automation by conducting surveys about (likely) behavior, or simulating automated systems.

This chapter focuses on modeling the implications of CAD on car ownership due to the additional accessibility caused by travel time savings. These savings occur because people can use the travel time otherwise, so the value of travel time reduces.

There are only a few models and studies that evaluate the impact of automation on car ownership [19]. Some of these models optimize vehicle usage by replacing private cars, either with PAV to share within households, or with SAV.

Schoettle and Sivak [47] use a National Household Travel Survey (NHTS) to identify idle times of household cars, in which other members of the household could use the car. By optimizing the time window for vehicle trips, they found that car ownership might reduce by up to 43%. As the sample does not include origin and destination locations, the model does not account for travel times between household members located at different places. Therefore, the estimation provides an upper boundary for car-ownership reduction. Zhang et al. [60] extend the previous methodology by adding travel patterns to a travel survey. They show that optimizing vehicle trips between household members can reduce car ownership by almost 10%. Further research simulates the effect of SAV fleets on car ownership, when people would be willing to give up their private cars. Results indicate that each SAV could replace between 10–12 private vehicles [7, 14, 29]. On the contrary, Stinson et al. [53] observe an increase of up to 6% in vehicle ownership. On the basis of a survey with over 600 participants, they perform a choice modeling of vehicle ownership in the context of a sharing economy. In the simulated scenarios, private vehicles generate income during idle times as they serve trip requests from strangers, such that owning a car becomes more affordable. As the previous studies show, vehicle ownership might increase or decline depending on the pathway of automation. Gruel and Stanford [22] describe these tendencies in their conceptual study. As private automation makes traveling by car more attractive it is likely to increase vehicle ownership. But as vehicle-sharing services make alternative modes more attractive, vehicle ownership might decline.

In addition to car ownership, the development of the car stock is crucial for simulating the effects of CAD. Therefore, car stock models forecast the diffusion of new and used cars as well as the existence of different levels of automation. Studies that model the dynamic diffusion of PAV in the passenger car stock are rare. Stock shares of PAV are mostly assumed rather than modeled. To assess the impact of CAD, some studies assume scenarios with a fixed PAV diffusion and compare different diffusion levels, for example Sonnleitner et al. [50]. However, full automation of the passenger car stock is unlikely in the foreseeable future for two reasons. First, additional costs of the technology compared to existing conventional vehicles and possible reservations of car purchasers are likely to make market shares of automated vehicles increase only gradually over time. Second, changes to the passenger car stock happen very slowly due to the long duration that passenger cars remain in the stock until they are scrapped or exported. Hence, even if PAV reach a significant market share within the next decade, the passenger car stock will likely remain a mix of PAV and conventional vehicles for another two decades after that.

The changes in car ownership and different levels of car automation in the car stock affect travel behavior. Car ownership determines the availability of a car and thus, the possibility to travel by car, whereas automated cars allow people to travel more safely and comfortably. Thus, in the context of CAD, changes in the destination choice, the mode choice and the route choice are likely. Travel demand models evaluate such changes in travel behavior. Soteropoulos et al. [51] provide an overview of current research findings regarding the impact of automated vehicles on travel behavior. The focus of past research has often been the implementation in travel demand models and traffic simulations, deriving effects on network capacity or performance of vehicle sharing systems. Many studies have been conducted using agent-based models and focused on the implementation of demand-responsive transportation with fixed demand (see Bischoff and Maciejewski [7]; Fagnant and Kockelman [15], or Richter et al. [46]). Regarding a national scale, microscopic simulations are not applicable with current computation limitations, and macroscopic travel demand models are preferred. A successful implementation on a macroscopic scale is Friedrich et al. [18], where a modeling framework to depict automated driving in macroscopic travel demand models is introduced, using findings from microscopic simulations and practice tests to model the effects on road capacity. They also describe methods to model demand and to implement ride-sharing services. These findings are applied in Sonnleitner et al. [50], where different diffusion scenarios with mixed traffic are analyzed for the city of Stuttgart and its surroundings. There is, however, no separate model step which includes the impact on car ownership and diffusion of PAV, as it is modeled in gradually increasing fixed diffusion rates. The analysis of effects is reflected in traffic performance, as there are different driving modes for driverless vehicles and demand calculation. This framework provides a straightforward approach for the inclusion of automated driving in macroscopic models. However, there are differences between a regional model and modeling on a national scale, which require alterations in methods.

Modeling the effects of CAD on car ownership, car stock, and travel demand separately provides good insight into future developments. By combining models, new relationships between variables occur, resulting in additional and detailed evaluation possibilities. Moreover, the accuracy of the model output increases as modeled predictions replace general assumptions, e.g., a constant share of automated vehicles changes to simulated variable rates. Despite the extra understanding of CAD implications, these model sets are rare because of the complex interaction between the models. Kröger et al. [38] provide an example where a vehicle technology diffusion model is combined with an aggregated travel demand model to assess diffusion rates of PAV and the impact on vehicle mileage and modal splits in Germany and the United States of America (USA). PAV diffusion is modeled based on observed market intake of automated cruise control systems in the different vehicle segments. The demand model is calibrated using NHTS, and PAV are introduced with a lower perceived travel time. This approach is further applied in Kröger et al. [39], who provide a nationwide assessment of the effects of automation, including both PAV and SAV for different scenarios in Germany. However, spatial effects can only be assumed as there is no network distribution. A classic macroscopic travel demand model with an upstream model for car ownership and PAV diffusion would provide a road network and cell structure, which opens up more possibilities regarding effects on road capacity, travel volumes and travel times. Llorca et al. [43] simulate the impact of PAV on household relocation in the Munich metropolitan area of Germany. They use a combination of an agent-based land-use and a transportation model. The land-use model contains a synthetic population including car ownership. Based on household or person attribute changes, car ownership diffuses over time. In addition to car diffusion, the households choose between conventional and automated vehicles as a function between household income and cost ratio between automated and conventional cars. As the study focuses on household relocation, there are currently no scenarios dealing with shared vehicle services. However, further attributes of the built environment such as available parking places are included. All information enters the travel demand model resulting in modal share for commute trips of approximately 90% by PAV and up to a tripling of vehicle distance traveled.

The study at hand contributes to the modeling of CAD implications for the transportation system by providing a dedicated nationwide combined simulation of car ownership, car stock, and travel demand.

3 Methodology

In order to assess the effects of CAD on the transportation system, different scenarios represent possible pathways for future automation. These scenarios are simulated within the model framework, providing insight into the distinct strategies and regulatory frameworks, such as possible services for integration of CAD into public transit, or definition of service areas required for sustainable transport systems.

3.1 Pathways for the Implementation of Automated Vehicles

As CAD is still under development, the future layout of automated vehicles within the transportation system is uncertain. Concerning technology readiness, it is widely debated when PAV or SAV will enter the market. As for fully automated vehicles, the predictions range from the end of the 2020s until the 2060s [42, 55]. Some experts are even skeptical about fully automated vehicles in general [45]. Besides technological hindrances, there might be further limitations due to cost efficiency, user acceptance, and policy regulations. The cost efficiency of ride-hailing services is discussed in the chapter "Business Analysis and Prognosis Regarding the Shared Autonomous Vehicle Market in Germany", user acceptance in the chapter "Social Acceptance of CAD in Japan and Germany: Conceptual Issues and Empirical Insights", and policy regulations in the chapter "Governance, Policy and Regulation in the Field of Automated Driving: A Focus on Japan and Germany".

This research focuses on the maximal effects of CAD as an upper boundary of implications on the transportation system, regardless of the previously-mentioned restrictions. Thus, the reference year for the models is the year 2050, as fully automated vehicles will likely exist in the mass market by then [42]. Furthermore, to deal with the uncertainties of CAD implementation and to draw conclusions about different pathways and regulations, the scenarios differ in two points:

- The availability of PAV and the design of SAV service varies from no automation (*scenario* (0)) up to full automation (*scenario* (3)). In order to distinguish the effects between PAV and SAV, one scenario only allows for PAV (*scenario* (1)). Moreover, SAV may operate either as door-to-door taxis (*scenario* (2*a*)) or as a feeder to public transit (*scenario* (2*b*)). To analyze the influence of the operation design, each service option is simulated separately. Finally, the scenario of full automation (*scenario* (3)) allows for PAV and both SAV services of door-to-door and feeder jointly.
- The spatial context divides Germany into urban and rural regions. For simplification and model runtime, municipalities with more than 100,000 inhabitants are classified as "urban" and all other regions as "rural". In addition, Germany is classified into four different region types [9] to increase the accuracy of the estimations (see Fig. 1). SAV are likely to operate in limited areas defined by the operator, as is the case with existing public transit. Therefore, one scenario reflects SAV operating in urban regions as a door-to-door service (*scenario* (2*a*)), as the high demand is likely to result in viable economic conditions. This assumption is further suggested by various field tests in urban regions in Germany [56, 57] and worldwide (e.g., Cruise, Waymo, Apollo Go). As SAV might reduce operational costs for public transit in areas with low demand due to reduced need for personnel, another scenario shows the application of such services as feeders in rural regions (*scenario* (2*b*)).

The combinations of the different variables result in a set of five scenarios (Table 1).

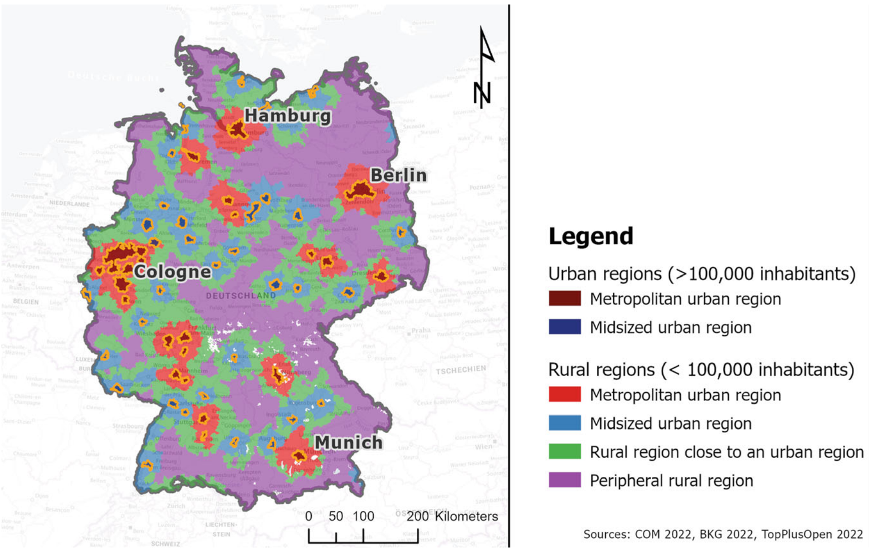

Fig. 1 Regional classification in urban and rural regions by a four-class typification [8, 9]

Table 1 Overview of CAD scenarios

	Scenario name	Private cars	Mobility as a service
(0)	Reference 2050	No automation	Not existent
(1)	Private car automation	Fully automated cars available	Not existent
(2a)	SAV in urban regions	Fully automated cars available	Door-to-door service in urban regions (more than 100,000 inhabitants)
(2b)	SAV in rural regions	Fully automated cars available	Feeder to railways in rural regions (less than 100,000 inhabitants)
(3)	Full automation	Fully automated cars available	Fully existent

(0) *Reference* 2050

The reference scenario (*scenario* (0)) represents the demographic situation of the year 2050, based on the population projections of the EU [12], Germany [11], and the Federal Institute for Research on Building, Urban Affairs and Spatial Development [5]. The projections assume that the German population will shrink by 0.6% to approx. 82.7 million in 2050. There will be approximately 22.5 million persons aged above 65 years, an increase of over 24%, showing an aging population. Concerning urban and rural population movement, the projection expects 37.49 million (+2.1%) persons living in metropolitan urban regions (red), 15.98 million (−2.5%) in midsized urban regions (blue), and 29.2 million (−2.8%) in rural regions (green & purple).

Further changes in the transportation system such as infrastructure construction and public transit schedules are difficult to project, such that the transportation network reflects the current status of about 2020. Moreover, using a transportation network without changes allows description of the pathway for CAD more directly, as external factors on the network have no influence. The direct effects of CAD on the transportation system can be derived by comparing the reference to the automated scenarios described in the following sections.

(1) *Private car automation*

The scenario of private car automation *scenario* (1) extends the reference scenario by making vehicle automation available to private households. The models assume that in 2050 all car types could be upgraded with automation. Thus, in the model every household has the possibility of choosing between a private conventional vehicle (PCV) or a private automated vehicle (PAV). In other words, as the automation of the private car does not seem reversible, future scenarios should always include PAV. In terms of space, the models assume that PAV can travel everywhere, like PCV. So, in the case of private car automation, there are no regional and/or infrastructural limitations.

(2) *SAV in urban and rural regions*

The scenario of SAV introduces an additional shared vehicle service as a transportation mode. First, users request a trip from A to B. Then, a dispatcher sends a vehicle to serve the request. The period between the request and the vehicle's arrival is defined as waiting time. The user can book SAV as car-sharing (SAVc) when the user wants to ride alone, and in this mode the vehicle travels on the fastest route between the origin and the requested destination. Or users can share their SAV as ride-sharing (SAVr), such that multiple users with different start and end locations might share a vehicle if the detour distance and additional travel time are within an acceptable tolerance. Thus, SAVr increases the travel time, but as a benefit, the users can share the costs to reduce travel expenses.

Regarding market entry, it seems realistic to assume that SAV will begin its operation in limited areas. Nevertheless, it is unclear if these areas will lie in an urban context with complex traffic situations but high demand, leading to higher revenue. Alternatively, rural regions provide less-complex traffic situations but might need new regulations in order to operate as a supplement to public transit. To evaluate the different implementation pathways of SAV, scenario (2) splits into two subsets. The first SAV scenario, "SAV in urban regions" *scenario* (2*a*), refers to all urban regions with more than 100,000 inhabitants. In these areas, the SAV serve requests door-to-door, fulfilling the users' specific requests. Thus, the service is in direct competition with public transit. In the second SAV scenario, "SAV in rural regions" *scenario* (2*b*), the vehicles only act as a so-called feeder to the railway. In other words, users must start or end their SAV trips at railway stations. Therefore, it is questionable if such a service is viable concerning user acceptance and cost-efficiency. Nevertheless, this scenario allows insights into the regulation of automated services and the effect of supplement services on public transit.

(3) *Full automation*

The third scenario allows for full implementation of PAV and SAV *scenario* (3). Thus, SAV operates door-to-door and as a feeder in all urban and rural regions in Germany. This scenario is presumably not very cost-efficient, but it provides an upper boundary of CAD affecting the transportation system.

3.2 Model Overview

The topic of CAD is complex as it affects mobility and transportation in various ways. Concerning the transportation system, the main drivers are the improvement of private car travel and the introduction of new transportation modes such as SAV. Both aspects fundamentally influence various long- and short-term decisions, making traveling easier. As models often either simulate long- or short-term decisions, missing information is concluded based on assumptions. By combining different models, it is possible to replace assumptions with more accurate simulation results. Such a modeling framework can simulate the various changes due to CAD.

The proposed framework consists of three models (see Fig. 2):

- a car ownership model (COM) estimating car densities

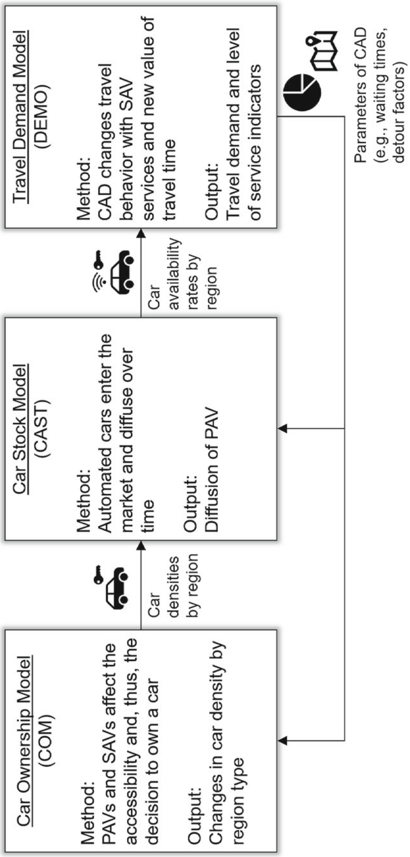

Fig. 2 Overview of model interaction

- a car stock model (CAST) adding diffusion of automation to the car densities
- a travel demand model (DEMO) using the level of automation of the fleet to simulate the interaction within the transportation system.

First, the car ownership model reflects a household's decision on whether to own a car or not. Besides socioeconomic attributes and the built environment, it includes accessibility attributes for various transportation modes. The implementation of PAV and SAV affects these accessibilities, resulting in changed car densities for every region type. Second, the new car densities enter the car stock model. As cars with different levels of automation enter the market over time, the households decide on whether to buy an automated car or not. Thus, automated cars diffuse in the vehicle stock over time, estimating the number of PCV and PAV for every region type and year. The car ownership model (COM) and the car stock model (CAST) simulate long-term household decisions affected by automation. Third, the travel demand model (DEMO) uses the vehicle stock of the reference year 2050 as a basis to model short-term decisions in travel behavior. It further simulates changes in travel behavior due to CAD. The model output shows various effects on the transportation system, such as changes in mode choice and travel distances. As the travel demand model simulates the SAV, it quantifies parameters such as the waiting time for SAV or detours because of ride-sharing. These parameters return to the previous models as they influence, for example, the accessibility and decision to buy a car.

3.2.1 Car Ownership Model (COM)

The car ownership model (COM) estimates car availability at the household level for Germany [49]. It is the first model within the proposed framework as it reflects on the long-term household decision of how many cars to own. This information is fundamental when forecasting car types or travel demand as it provides the limits within which car type choices or mobility choices take place.

The COM predicts car availability as the ratio of cars to the number of household members owning a driver's license. It has three levels: "no car available"—for households without cars or without household members owning driver's licenses; "shared car"—for households where the number of cars is less than the number of driver's licenses, and; "exclusive car"—for households where the number of cars is equal to or greater than the number of driver's licenses. To forecast car availability for the households, the model uses two successive binary logit models. The first model differentiates between households with and without a car. The second model separates the households with cars into the levels of "shared" and "exclusive" car availability. Furthermore, car availability can be transformed into car density by aggregating the households by region type.

The COM includes demographic, economic, built environment, and transportation supply attributes, as these categories influence car ownership and car availability (see Fig. 3 and Schrömbges and Kuhnimhof [49]). The basis for the model is the German NHTS "Mobility in Germany 2017" [27], in which households report on their socioeconomic circumstances and their mobility attributes, such as car ownership. After filtering for complete reporting households, the final sample consists of 264,270 persons living in 122,467 households. The NHTS survey includes individual demographic information (e.g., age or gender), household demographic attributes (e.g., household size or presence of children), and economic attributes (e.g., economic status or the number of workers). Further attributes append to the dataset based on the geo-location of the households' residences. The built environment covers variables such as population density or building density [13]. These serve as a proxy to describe the immediate surroundings of the households' locations. For example, high population and building densities indicate urban regions, whereas low values reflect rural regions. In addition to the immediate households' neighborhoods, accessibility to activity locations further away also affects car ownership. In the context of car availability in COM, accessibility means the number of inhabitants reachable by the available transportation supply. This method is known as the cumulative opportunities approach, as it sums up all accessible inhabitants who live within a set travel time budget of the start location [4]. In order to limit calculation time, a budget of 30 min is set for all transportation modes in the reference scenario to compare between walk & bike (non-motorized individual transportation—NMIT), car (motorized individual transportation—MIT), and public transit (PT).

The transportation supply is the key determinant for the CAD scenarios, as it is the only category that reacts to changes in the transportation system due to PAV and SAV. For example, the automation of private cars leads to a reduction in the value of travel time as driving becomes more effortless and in-vehicle time can be spent otherwise. In the COM context, this leads to an increased time budget for accessibility by car. Nevertheless, one could assume presumably realistic values, or conduct dedicated choice experiments in order to quantify this effect. Other research studies expect the impact of automation on travel time savings to lie between 25 to 50% [35]. Kolarova et al. [36] notice an effect of 40% for commuters, but measure no significant change

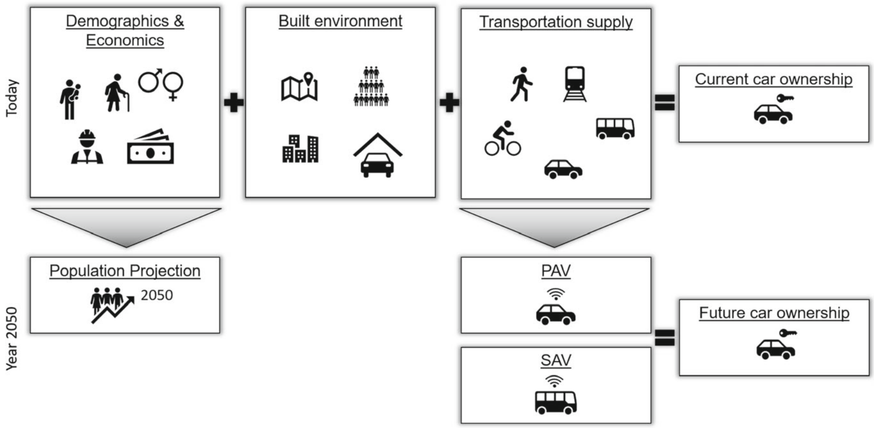

Fig. 3 Schematic methodology of modeling car ownership in the context of automation

for shopping or leisure trips. Therefore, the accessibility calculation of PAV uses a span of 20–25% for an increased travel time budget.

SAV, in the form of a door-to-door service, is expected to be a viable alternative to a private car as it offers high flexibility. SAV, in the form of a feeder to railway stations, is a supplement to public transit. Therefore, in the calculations the SAV accounts for public transit. SAV increases accessibility as it opens up new areas through direct connections. In other words, it is possible to reach more inhabitants within the same travel time budget.

Automated driving enters the COM by increasing the travel time budget for PAV and generating more direct connections via SAV. As a result, COM forecasts car availability, which enters the CAST by providing an upper boundary for car density by region type.

3.2.2 Car Stock Model (CAST)

The car stock model (CAST) provides data on the future development of the German passenger car fleet [32, 37]. CAST is used to map and evaluate the effects of transportation policy measures and changes in framework conditions on the passenger car fleet. One component of this is the diffusion of new technologies, e.g., automated vehicles and alternative powertrains. CAST output can be applied as an input for car availability by level of automation in different travel demand models.

CAST is a dynamic agent-based model that simulates the development of the German passenger car fleet in annual steps. The core of CAST is a decision model for car purchases by private households. The households are initially identified on the basis of the German NHTS “Mobility in Germany 2017” [27] and their composition is projected according to population forecasts of the Federal Statistical Office [11].

The decision model is composed of three discrete choice models that build on one other. Firstly, making use of a mixed logit model, households that buy a new or used vehicle in the respective year are identified. Secondly, used car buyers choose the quality of the vehicle according to preference of age and mileage of the vehicle, applying an ordered logit model. Thirdly, the car buyers choose the technology of the vehicle, which is a combination of the vehicle’s size, powertrain, and automation level (see Fig. 4).

As part of the model’s vehicle technology decision, households decide on the vehicle’s automation level. This decision is affected by three factors. First, additional costs of PAV compared to PCV affect investment costs and, thus, the utility of opting for an automated vehicle. Second, the year of market entry restricts availability of Level 4+ automation to the years after 2035. Before 2035, Level 4+ is not included in the choice set of households. These two factors are model inputs provided by industry experts. Third, due to the lack of empirical data, the vehicle technology decision is also based on model assumptions that refer to prevailing reservations of households about the automation technology. These reservations may relate to safety or data protection concerns, for example, or the enjoyment of independent driving. It is assumed that reservations decline steadily over time.

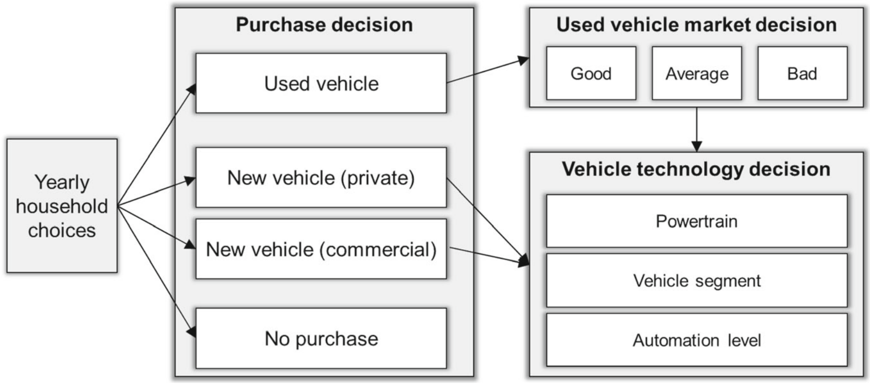

Fig. 4 Discrete choice modeling of passenger car purchases by households with CAST

CAST differs from other passenger car fleet models by integrating both the new and used car market. Since CAST does not model production volumes of vehicle manufacturers, the supply of PAV is not restricted on the new vehicle market. However, supply on the used vehicle market is restricted by the number of vehicles available each year. This number represents the sum of vehicles that enter the used vehicle market plus the unassigned vehicles every year (car dealer). If demand for a vehicle technology exceeds supply then the model applies an algorithm that alters the price of the specific vehicle technology incrementally and, in this way, changes the utility of this specific option. Consequently, some households will change their choice to another technology due to the higher price. This so-called shadow price methodology is used to achieve a fair distribution of vehicle technologies. This methodology is used twice, first for the size and powertrain combinations, and then for the automation levels, so that there are different shadow prices for each specification.

CAST models the vehicle purchases of private households. For the interface with the travel demand model DEMO, household information is disaggregated into person information referring to vehicle availability for every person in each household. Vehicle availability is modeled in such a way that all household members have access to a PCV or PAV, if such vehicles exist in the household. The CAST output (and DEMO input) is a dataset that contains information on how many persons in which region type of which age, gender, and employment have access to PCV and PAV per year until 2050.

3.2.3 Travel Demand Model (DEMO)

The German national travel demand model DEMO (DEutschland MOdell) is applied in order to forecast traffic flows and travel behavior depending on policy, socio-demographic, and technology developments [59]. There are modules for long-distance and short-distance passenger transportation. The effects of CAD are assessed for everyday trips, thus using the short-distance module. Travel demand in this module is determined using a four-step-approach, with trip generation, joint destination and mode choice, and a network assignment. The demand model was calibrated to represent mobility behavior observed in the German NHTS "Mobility in Germany 2017" [27]. It is expected that the introduction of CAD will influence travel behavior on different levels, as studies such as Kolarova et al. [36] suggest a shift in value of travel times with automation. Furthermore, SAV services provide new modes of transportation, which can influence accessibility and thus mode and destination choice preferences. Furthermore, diffusion rates of automated vehicles and general car ownership are important input values, which are influenced by the introduction of CAD. These changes are implemented in DEMO with an upstream car ownership model step, using COM and CAST.

In DEMO, car ownership is represented by a car availability rate for each transportation analysis zone, which is initially calibrated using the results of the NHTS "Mobility in Germany 2017". This variable describes the share of people with access to a private car in their household. With this method, regional differences in motorization can be represented in the model. The impact of CAD on car ownership determined in COM and CAST is included with an incremental adjustment of these availability rates, with different growth rates depending on regional types. These growth rates are derived by comparing car ownership in the different diffusion pathways to a baseline scenario without automation. This is however not the only adjustment regarding car availability, as the introduction of CAD also introduces a new car type with different choice parameters.

Since car ownership, and thus the decision for PAV, is a long-term household decision, this choice is not a logical part of a standard mode choice model. Therefore, the resulting diffusion of PAV among car owners is calculated in CAST and included as an input condition for a restructured demand model in DEMO, as shown in Fig. 5. These diffusion rates are used to distribute generated individual trips on two specialized mode choice models, where either PCV or PAV represent the car alternative. Mode and destination choice are calculated for both sub-models with the given total number of trips, as further described in Winkler and Mocanu [58]. Travel times and costs are important indicators for the formulation of utility. For automated driving, travel times are reduced using the findings of Steck et al. [52]. Empty trips from automated parking and relocation of vehicles are not regarded.

In order to include SAV into the demand model, new transportation modes are created. As stated in the description of scenario (2), the assumption is that a commercial service provider with a fleet of SAV offers taxi services with a ride-sharing option. In the demand model, this results in two options: either use SAV to travel alone (SAVc) or with other passengers (SAVr). The parameters and components for

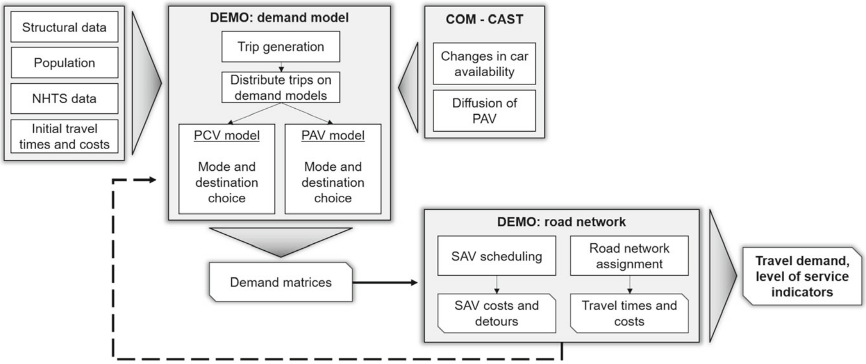

Fig. 5 Schematic overview of modeling CAD and SAV in the macroscopic travel demand model DEMO

the formulation of utility are determined as a mix between car and public transit. The main differences in the utility components are costs and detours, with SAVr trips having a lower cost due to their higher occupancy rates, and SAVc trips not having any detours. The costs and detours are calculated with a specialized SAV algorithm in the network model.

During the SAV algorithm, the first step is to match SAVr trips with similar directions using the approach of Friedrich et al. [17], where trip trajectories are compared by the zones they cross. This approach is adjusted for DEMO, as the granularity does not allow for a detailed depiction of trajectories with the base approach. Instead of the zones themselves, population centroids for each zone are used as pick-up locations, further allowing for the inclusion of inner-cell trips and calculation of detours [54]. As a result, vehicle trips for the calculated SAVr demand are determined. Afterwards, a scheduling algorithm is applied for the sum of SAVc and SAVr vehicle trips to determine fleet size and relocation trips [23, 46]. For cost calculation, further input by industry experts is used concerning fixed and running costs (see chapter "Business Analysis and Prognosis Regarding the Shared Autonomous Vehicle Market in Germany").

To assess the effects of CAD on transportation volumes and travel times, a network assignment is performed using all private car trips (conventional and automated), SAV trips and fixed road volumes for long-distance car trips and freight transportation. In an iterative process, mode and destination choice steps are repeated until there are no significant changes in travel times to the previous iteration. As a result, DEMO produces several indicators to evaluate the effects of CAD in road-based passenger transportation, including modal splits, vehicle mileage and travel times on a national and regional level.

4 Effects of Automation on the Transportation System

When applying the CAD scenarios in the model framework, diverse changes in the transportation system occur. Thereby, each model results in different outputs. Whereas COM primarily assesses changes in car density at household level and CAST concerns the fleet composition, DEMO is able to analyze the most effects as it is a full macroscopic model.

4.1 Effects of CAD on Car Ownership Due to Changes in Accessibility (COM)

The car ownership model simulates the emergence of CAD by adapting the accessibilities at the home location of the surveyed households. Therefore, a detailed analysis of the accessibility changes due to CAD is necessary to evaluate the model outcome of car densities. In total, the analyses include approximately 43,000 different households' home locations, with approximately 13,000 located in urban regions and 30,000 in rural regions (see Fig. 1).

For traveling by car, automation increases the accessibility by PAV due to the increase in travel time budget compared to PCV in the reference 2050 (see Methodology Sect. 3). For the scenario of private automation, that means all households have the accessibility potential provided by PAV, irrespective of their likelihood of adopting or owning a PAV. The theoretical background for this assumption is that households consider the additional accessibility benefits of PAV when purchasing a new vehicle. The travel accessibilities by public transit are linked to the accessibilities by SAV, leading to more direct connections (see Methodology Sect. 3). Again, the assumption is that SAV are fully accessible and available, resulting in a layout in which all households can afford to use SAV, and the fleet is large enough to fulfill all requests at any time. Nevertheless, the accessibilities include region-based waiting times and detour factors to make the calculations more realistic.

Figure 6 provides an overview of the relative changes in accessibility by urban and rural regions (columns) and scenarios of automation (rows). Each graph splits further into the four region types and a total value for all locations (see Fig. 1 for spatial regions). For every location, the improvement through automation leads to a higher number of accessible inhabitants. This improved accessibility is compared to the accessible inhabitants of the reference 2050. In other words, a value of one indicates no improvement, whereas a value of two refers to a doubling of accessible inhabitants.

The scenario (1) Private car automation (row 1) has only an improvement of 1.5 on average, whereas central rural regions profit most with 1.8 on average. The slight improvement in accessibility comes from the fact that the car already reaches a large number of residents within the assumed travel time budget of 30 min. Therefore, automation only contributes a little to the number of accessible inhabitants. The

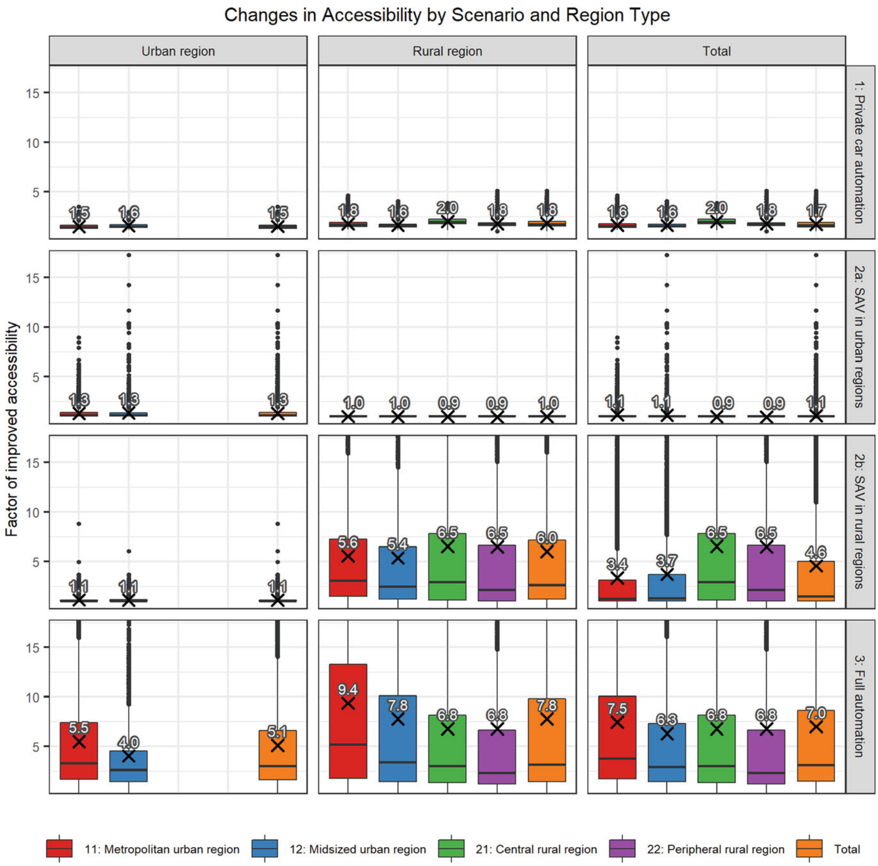

Fig. 6 Relative improvement of accessibility by region type and scenario (for readability upper boundary set at factor 17)

scenario (2a) SAV in urban regions (row 2) shows the improvement in accessibility due to the door-to-door service. As the left column shows the urban regions, it includes all locations where the service operates. However, it provides only a minor benefit as public transit is already of a good quality concerning accessible inhabitants in urban regions. The deviation from one for rural regions is due to errors in locating households limited by data privacy. The scenario (2b) SAV in rural regions (row 3) introduces a SAV as a feeder service to railway stations in rural regions. The direct access to the railway leads to a factor of about six times more accessible inhabitants via public transit. Urban regions inherit a slight improvement as traveling from urban to rural regions allows using the feeder service for egress from the railway stations. Scenario (3) Full automation (row 4) implements PAV and SAV as a door-to-door service and a feeder service in all regions. This scenario shows the upper boundary in accessibility gained through automation. Interestingly, urban regions benefit by a factor of approximately five less than rural regions, which differ between seven to ten. In detail, rural regions located close to metropolitan or midsized regions benefit more than central or peripheral rural regions as the population density decreases, such that fewer inhabitants are accessible within the given travel time budget.

These changes in accessibility enter the COM resulting in new probabilities of car availability and car densities. By comparing the densities of the reference scenario to the new densities, the impact of CAD is visible (see Fig. 7). The automation of the private car leads to an average increase of about 1% in car ownership. Providing a door-to-door service in urban regions results in a reduction of −3.6% on average. Adding a feeder system in rural regions reduces car ownership by −2.8%. The combination of PAV with full SAV reduces car densities on average by approx. −3.9%.

Despite the considerable improvement in accessibility, the effect on car densities due to CAD is only slight. By interpreting the COM model in detail, the conclusion is that socioeconomic factors such as changes in life circumstances or availability of income dominate the decision to own a car. Accessibility only contributes to minor changes in car densities. Nevertheless, small changes in car ownership due to CAD might affect the outcome of the car stock model (CAST) and travel demand model (DEMO).

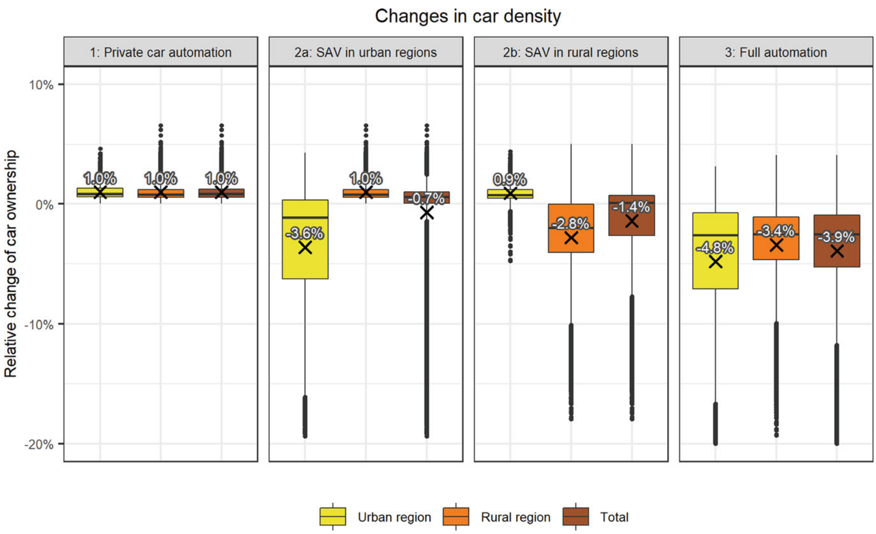

Fig. 7 Relative changes in car densities

4.2 Nationwide Assessment of Diffusion of Automated Vehicles (CAST)

In reference to the model descriptions above, the results of the effect of CAD on car densities in the respective scenarios by the COM enter into the model CAST that projects the share of PAV in the passenger car fleet. Fleet modeling results by CAST are based on three major inputs:

- the year of market entry of PAV and the additional costs of PAV compared to PCV vehicles, which comes from industry experts,
- car densities for the year 2050 for every scenario, which is the COM output,
- model assumptions on dynamic parameter changes that affect the utility of PAV. Those parameters pool all additional factors that hamper the purchase of PAV by households or companies. Such factors may relate to safety or data protection concerns, for example, or the enjoyment of independent driving.

Based on these inputs, CAST shows an uptake of PAV market shares (Level 4+) starting from 2035. Because of additional costs of and reservations about the technology, initial market shares of PAV are low. Mostly due to fading reservations caused by technology acceptance, market shares increase steadily and reach 70% in 2050.

Because of the small number of new registrations compared to total vehicle stock, the ramp-up of PAV in the German passenger car fleet progresses rather slowly. The duration that passenger cars stay in the fleet is modeled endogenously by CAST. On average, this modeled duration is 15 years for both PCV and PAV. As PAV market shares increase steadily over time, stock shares grow faster every year. However, the passenger car stock for the scenario year 2050 is still characterized by a mix of PCV and PAV, which then make up 44% of the stock. Figure 8 illustrates the yearly shares of PAV in the new registrations and the stock of passenger cars as modeled by CAST for scenario (1) Private car automation.

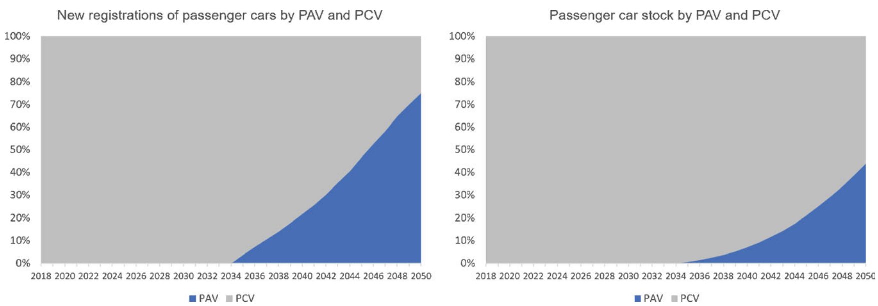

Fig. 8 New registrations and stock of passenger cars in Germany by PCV and PAV (CAST modeling, scenario (1) Private car automation)

While the year of market entry and the additional costs of PAV as well as the assumptions on fading reservations caused by technology acceptance are the same for all scenarios, the car densities modeled by COM differ slightly between the scenarios. Consequently, diffusion rates of PAV in the passenger car stock of 2050 differ only marginally between the scenarios. The diffusion rates for all scenarios are:

- 44.0% for scenario (1) private car automation,
- 43.5% for scenario (2a) SAV in urban regions,
- 43.3% for scenario (2b) SAV in rural regions,
- 42.8% for scenario (3) full automation.

The PAV and PCV in the 2050 fleet are transformed into car availability of individual persons disaggregated by region type, age, sex, and employment and, in this form, represent the input data for the travel demand model DEMO.

4.3 *Effects of CAD on Travel Demand (DEMO)*

The travel demand model DEMO was applied for three diffusion pathway scenarios:

- (0) Reference 2050
- (1) Private car automation
- (2a) SAV in urban regions.

In order to optimize computational effort while still modeling SAV, the scenarios SAV in rural regions (2b) and full automation (3) were omitted in DEMO. Additionally, scenario (2a) already covers large amounts of everyday travel, as trips within cities with SAV services make up 42% of all model trips, as shown in Fig. 9. The spatial distribution of model trips among the regional classification from Fig. 1 is also shown in Fig. 9.

Figure 10 shows key model results of DEMO for Germany, including modal splits, mileages and travel time changes. Looking at modal splits, there is a small increase in car trips with the introduction of PAV. Private conventional and automated cars are roughly used for the same number of trips. Adding SAV in urban regions however,

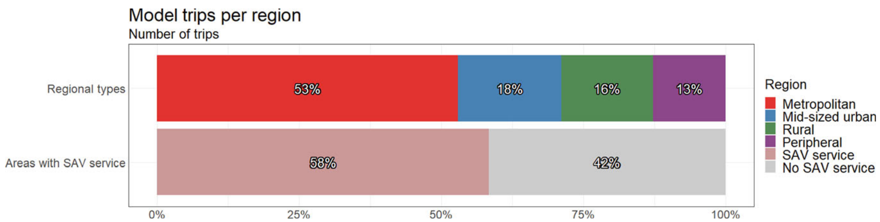

Fig. 9 Share of trips per region in DEMO

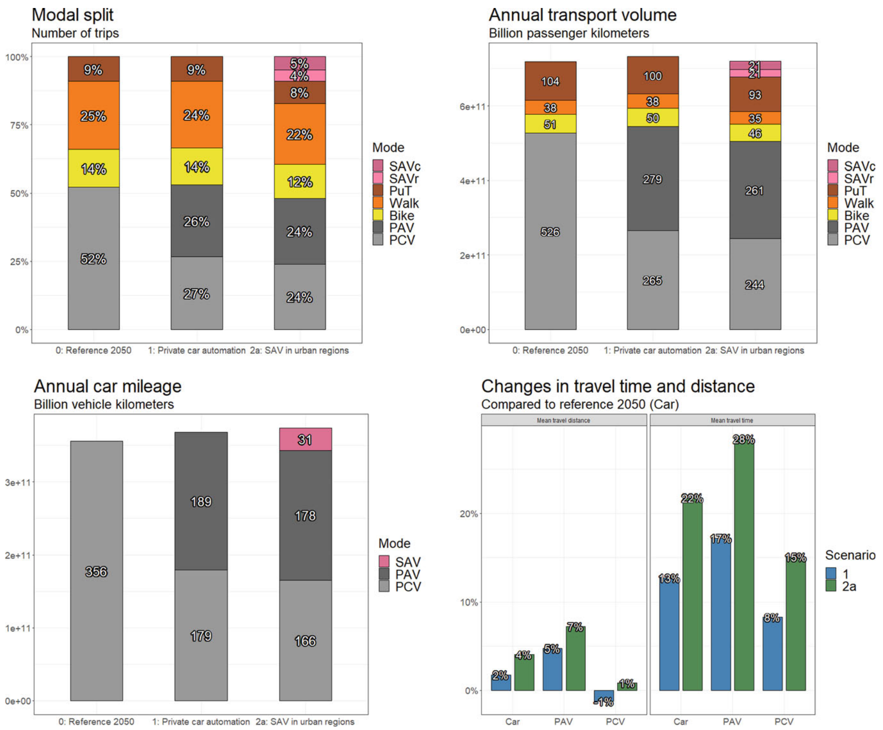

Fig. 10 DEMO results for Germany

leads to a decrease in car trips, as trips are replaced with new mobility options. In general, all modes suffer decreases in trips by 8–10%.

Comparing passenger transportation volume, the total volume faces a small increase with PAV and is similar to the reference with SAV in urban regions. The mean distances traveled by car are slightly higher in the automated scenarios, with the mean distance however staying similar over all trips. The combination of small increases in trip distance and number of trips for cars leads to a 3% increase in passenger kilometers traveled using cars in scenario (1). As the modeling approach using perceived travel times suggests, longer distances are more attractive with a PAV, thus PAV trips in the automated scenarios are around 5–7% longer than car trips in the reference scenario. In scenario (2a), the passenger transportation volume for cars decreases by 4%, as SAV takes up more of the travel volume.

Using occupancy rates based on the destination activity, which were calibrated using the German NHTS "Mobility in Germany 2017", the kilometers driven by cars are determined. Figure 10, bottom left plot, illustrates that the annual mileages of everyday car trips increase with automation. In scenario (1), with only PAV, the total car mileage is around 3% higher than in the reference scenario. The kilometers driven by PAV make up 51% of the total mileage. Similar to the passenger kilometers, vehicle mileage of PAV for the scenario with SAV in urban regions is roughly 4%

lower than the reference scenario. The total annual mileage is however highest for this scenario when SAV are included, with an increase of 5% to the reference and 2% to private automation only.

The mean travel time per car trip, as shown in the bottom right plot in Fig. 10, increases by roughly 13% in scenario (1), which can be contributed to the changes in perceived travel time with PAV and congestion effects. The increase for PCV trips only is lower with 8%. The introduction of SAV has an even stronger effect on travel times for cars, as there is a 21% increase for cars in scenario (2a) and a 15% increase for PCV only. In comparison, the mean distance per PCV trip is roughly the same in all three scenarios. This indicates that the additional vehicle volume due to SAV leads to higher congestion in the model.

Automation also has an effect on the road network, with changing traffic loads and subsequently, effects on travel times due to congestion effects. Figure 11, left plot, shows increases in mileage per square kilometer in the east and metro-regions around Berlin, Munich and Hamburg. For the remaining country, traffic volumes remain similar. Adding SAV, higher traffic loads in urban regions with these services can be observed due to SAV despite a lower modal share of car trips.

SAV fleet sizes, occupancy rates and cost per kilometer were determined for each urban region and service area with a scheduling algorithm for both SAVc and SAVr trips, as well as input from an industry analysis (see chapter "Business Analysis and Prognosis Regarding the Shared Autonomous Vehicle Market in Germany"). It is

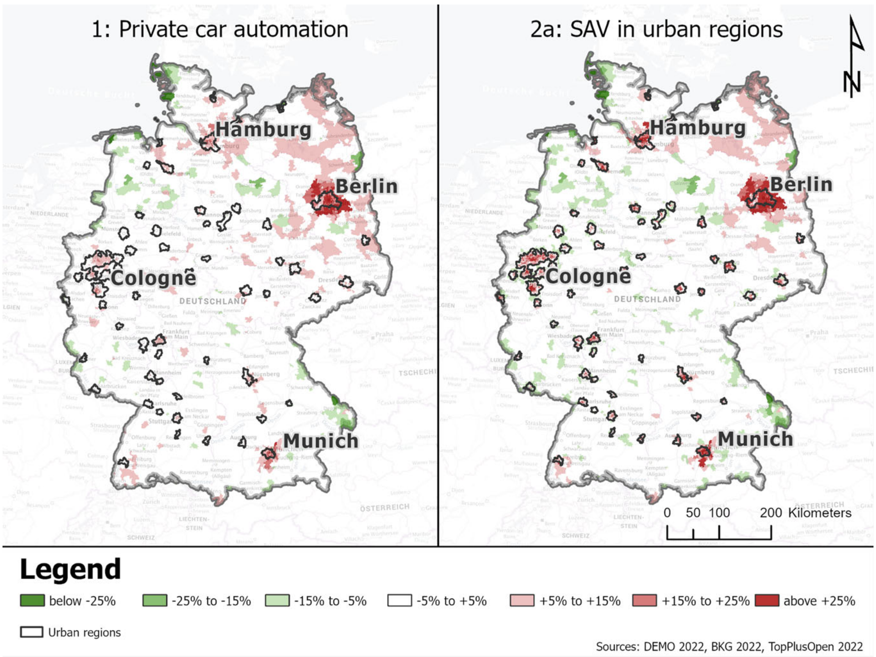

Fig. 11 Changes in mileage per square kilometer in the automated scenarios

Fig. 12 Distribution of cost per km and occupancy rates for (2a) SAV in urban regions in the service areas

assumed that the fee for SAVr trips is reduced by dividing the cost per kilometer by the occupancy rate. Overall, occupancy rates for SAVr trips range from 1.65 to 2.59, while overall occupancy including SAVc trips is between 1.19 and 1.36 (see Fig. 12). The fleet sizes are between 7.9 and 26.4 vehicles per 1,000 inhabitants, including a 10% reserve. This leads to costs of 0.55 €/km in the Rhine-Ruhr metropolitan region, including cities like Dortmund and Düsseldorf, up to 0.80 €/km in the mid-sized city Würzburg. The differences in SAV indicators between service areas can be attributed to the fact that the cities and service areas are heterogenous, with population sizes ranging from 100,000 to 4,000,000 inhabitants. This influences the number of trips, which ultimately affects fleet sizes and costs. Figure 12 shows the distribution of occupancy rates and costs among the service areas, including the mean values.

5 Discussion of Model Limitations

CAD affects car ownership, car stock, and travel demand in various ways. To quantify these aspects, a unique simulation framework of three consecutive models was developed. The benefit of combining the models lies in replacing assumptions regarding car availability when simulating travel behavior. Therefore, the model results are somewhat more realistic than those of separate models when planning for future scenarios of automation. Nevertheless, forecasting future situations contains several uncertainties as the real world and human behavior are very complex. These uncertainties come from limited or uncertain information on the future development of CAD and restrictions in the model methodologies.

Although the model framework reduces the number of assumptions by replacing them with modeled estimates, various influencing variables are still unknown. In terms of technology, it is uncertain when the different levels of automation will enter the market. Research studies vary between estimates of around 2025 and 2050, or even later for the implementation of PAV [55]. Within the car stock model (CAST), the market entry is set to 2035, leading to a vehicle stock of 44% automated vehicles in 2050. The earlier the market entry happens, the higher the share of PAV, the modal share, and vehicle kilometers—and vice versa.

Economic prognoses vary, referring to the additional costs of PAV and realistic costs of SAV for fleet operators. Concerning the latter, the chapter "Business Analysis and Prognosis Regarding the Shared Autonomous Vehicle Market in Germany" provides industry analyses and prognoses for the German market. For the purchase or leasing of private- or company cars, the cost of automation technology will make up considerable shares of vehicle prices, especially in the small and medium segments. As the willingness to pay greatly influences the adoption of automated vehicles [21], the model results react sensitively to different cost scenarios. Fewer costs will increase the speed of the market entry of PAV, such that the described results are likely to occur earlier than 2050.

Costs are not the only factor when speaking about the acceptance of PAV and SAV (e.g., see Literature review or chapter "Social Acceptance of CAD in Japan and Germany: Conceptual Issues and Empirical Insights"). It is impossible to accurately predict the uptake due to the complex interactions between the various acceptance determinants. To simplify this circumstance, the model framework assumes that all persons and households consider buying or riding automated vehicles. As a matter of fact, this assumption results in an overestimation of the effects of CAD as market shares and mode usage are presumably lower. Therefore, the proposed results should be considered as an upper boundary for the effects of CAD on transportation in Germany.

Furthermore, the simulation framework includes several simplifications to keep the models' interactions and calculation times within acceptable complexity. Accessibilities changing due to CAD are the key component of the car ownership model (COM). There are various methodologies to measure accessibility [4], but multiple analyses showed no considerable sensitivity in the model outcome. Thus, the current model version only uses cumulative opportunities, neglecting aspects such as accessible jobs or travel costs. Changes in accessibility might also result in household relocation. For example, if traveling by PAV will be easier than by PCV, people will live further away from the cities, resulting in urban sprawl and more vehicle kilometers in the transportation system [43]. However, this complex interaction does not enter the model framework due to simplification.

In the model framework, various choices concerning car ownership, car type, and mode usage are simulated. CAD adds new components to the choice sets. Observable and quantifiable variables such as travel times are possible to project, and thus form part of the model. However, unobservable attributes like safety concerns, or uncertain variables like safety distances between vehicles, which might either decrease through communication between the vehicles or increase due to safety concerns [24, 50], are neglected in the simulations. Therefore, the results inherit an uncertainty.

The model framework requires an interchange of information between the three models. As each model considers different input data concerning space and time, it is necessary to aggregate information. This step allows the combination of the models but also reduces the accuracy of the results. Nevertheless, the proposed model framework provides accurate results, as the key component of car availability is not assumed but modeled with respect to changes due to CAD.

6 Conclusion

Connected and automated driving (CAD), in the form of PAV and SAV, will transform the transportation system. Despite extensive research and technical testing, the impact of CAD is still unclear. The advantages, like a presumable reduction of car ownership or increased accessibility, oppose assumptions of increased urban sprawl and congestion. Thereby, the size of influence in each direction largely depends on the future concept of CAD. Economic considerations, societal implications, environmental restrictions, and political regulations build the framework for CAD. Thus, it is necessary to provide detailed knowledge about the impact of CAD in order to foster beneficial decisions.

The current study contributes to forecasting the impact of CAD on the transportation system by providing a simulation framework for Germany. It contains three consecutive models of car ownership (COM), car stock (CAST), and travel demand (DEMO). This model set allows combining long-term decisions of car ownership and type of automation with short-term decisions of travel behavior such as mode choice. Therefore, the simulation framework considers multiple effects of automation.

A total of four scenarios including automation are simulated to evaluate the results of different pathways. The first scenario analyses the influence of private car automation. It indicates only a minor increase of about 1% in car ownership. This small growth can be explained as accessibility by car is already very good, such that automation provides only a small additional benefit. Thereby, rural regions profit more than urban regions. Overall, the 2050 vehicle stock consists of 44% PAV. Thus, PCV and PAV drive as mixed traffic in the streets. Therefore, PAV cannot realize their full potential regarding safety and efficiency. In terms of the transportation system, PAV travel over 50% of the kilometers driven, which translates to an increase of 3% in total mileage. Overall, private car automation has a minor impact on car stock and ownership, but still leads to a disproportionate increase in vehicle kilometers driven. Further regulation could focus on discouraging driving longer distances.

The second scenario simulates automated door-to-door services in urban regions. The accessibility in these regions improves only slightly as public transit is already of good quality. Nevertheless, the number of private vehicles in urban regions reduces by 3.6% on average. However, the new transportation mode compensates for this effect by introducing new vehicles. As this service operates additionally in the transportation system, it attracts trips from all other existing means of transportation. As a result, the vehicle kilometers traveled increase by about 5%, which, especially in cities, might lead to further congestion. Therefore, introducing SAV should be closely monitored, and, if necessary, regulations such as limits on fleet size or operating hours should be implemented. A variation of the second scenario evaluates the

SAV fleet as a feeder to railway stations in rural regions. Such a service improves accessibility, especially in rural regions, but nearby urban regions also profit from better accessibility to their surroundings. Consequently, car ownership decreases in these regions by almost 3% on average. However, further analyses are necessary to evaluate whether the costs for such shared services outweigh the small benefits concerning reduced car ownership.

The third scenario implements full automation of PAV and SAV all over Germany. Therefore, it serves as the upper boundary of impacts due to CAD. Although vehicle ownership decreases on average by approximately 4%, the additional vehicles for the shared fleet might negate the reduction of private vehicles. Further research should analyze the cost structure in more detail.

The final model results forecast only a minor effect of CAD in reducing car ownership, and at the same time, an increase in SAV results in additional vehicle mileage in the transportation system. In order to create advantages from CAD, such as guaranteeing accessibility to further user groups including children, or persons with reduced mobility, and at the same time providing efficient transportation systems without increasing travel times due to congestion, further regulations on fleet size, operating hours, and areas are necessary. This research continues by modeling other regulatory frameworks, especially under the context of climate change.

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