

The impact of automated vehicles on long-distance travel in Germany

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1 Introduction

2 Automated vehicles (AV) might soon become reality, considering the rapid development of vehicle technologies
3 and data processing in the past years. Following the technological pathway and the complexity of driving tasks,
4 the highway pilot might be one of the first use cases of autonomous driving, since it requires a lower level of
5 automation (ERTRAC, 2017). According to experts, automated driving might change personal mobility and
6 mode choice decisions, as the driver being able to pursue other activities during the trip increases the comfort of
7 travelling (Anderson et al., 2014, Fraedrich et al., 2016). This is especially the case on long-distance trips, in
8 which driving is often seen as an exhausting and monotonous task (Trommer et al., 2016). Such trips are
9 particularly relevant due to a number of reasons. They are mostly rare events but amount to a large proportion of
10 the overall vehicle miles travelled (VMT), private car is dominating the modal split, and the total mileage
11 traveled on long-distance trips has continuously increased in past years, even though daily mobility remains
12 constant (Kuhnimhof et al., 2014). The share of the total VMT by car in Germany on highways is 28% (Bäumer
13 et al., 2017). These facts also indicate the high impact that long-distance car trips have on the environment in
14 general (Goeverden et al., 2016). It is therefore necessary to ascertain whether autonomous driving – even with
15 vehicles having lower automation (e.g. Level 3) – will impact on car VMT in the near future in order to provide
16 decision makers information for planning the transport system in accordance to the future challenges posed by
17 automation.

18
19 As highway pilots will likely be the first automated driving functions and drivers could benefit the most on long
20 journeys, the context of long-distance travel on highways in Germany was chosen in this study. We defined
21 long-distance travel as trips longer than 100 kilometer for all analysis steps. The time horizon of the study is the
22 year 2030, when the market ramp-up of AVs with mostly lower automation functions is expected to occur
23 (Trommer et al., 2018). With respect to the classification of automation (SAE, 2014) we defined that vehicles
24 with high automation (Level 4 or 5) can drive fully automated on highways at any time. In contrast, vehicles
25 with conditional automation (Level 3) need to be monitored by the driver in the automated driving mode. The
26 driver might be required to take over control of the vehicle in certain unforeseen situations, e.g. uncharted
27 roadworks or difficult light or weather conditions. The more often such take-over requests occur, the less will
28 drivers benefit from the additional comfort of automated driving. Finally, partial or non-automated vehicles
29 (Level 0-2) cannot drive autonomously, so drivers have to continuously concentrate on the driving task.

30 The aim of the paper is to quantify the perceived comfort improvements brought by vehicle automation to car
31 users, implement it into a travel demand model and estimate its impact on car travel demand for long-distance
32 trips in Germany in terms of VMT.

33 Methodology

34 In order to provide insights into the impact of autonomous driving on long-distance travel we combined four
35 analysis tools: An online survey including a stated preference experiment towards autonomous driving and mode
36 choice to estimate changes in the value of travel time savings (VTTS) when autonomous driving is available (1),
37 a technology diffusion model to determine the future fleet of privately owned vehicles and the share of AVs
38 within this fleet (2), a transport demand model to simulate mode and destination choices and thus changes in
39 VMT for each mode of transport (3), and finally a car traffic assignment model in which vehicles are
40 differentiated by their level of automation (4). The contribution of our study is to present a comprehensive
41 approach on the impact of vehicle automation on long-distance travel taking into account changes in user
42 behavior, the diffusion of different levels of AVs and its usage.

43

44 (1) Stated Preference Experiments on autonomous driving

45 As already mentioned, when driving autonomously the driver do not longer have to follow the driving task and
46 can instead engage other activities. This might lead to a change in the perception of time during the trip and
47 finally in a change of VTTS. For this reason we conducted an empirical study on the change in VTTS as an
48 online survey with a representative sample of approximately 500 participants in Germany. The study design was
49 a combination of Revealed Preference (RP) and Stated Preference (SP) methods with two stated Preference
50 experiments. In the first one, the participant had to choose between current available modes of transport: private
51 car, train, bus and airplane. In the second one, a future mode choice decision was created by presenting a private
52 car with autonomous driving function instead of the private car. According to the study design, the automated
53 private car could be either driven manually or autonomously. All SP experiments were created on the
54 information provided by the first part of the survey, in which the respondents reported detailed information about
55 their last long-distance trip, such as trip duration and length. The attributes of each alternative in the SP
56 experiments were the in-vehicle time, the arrival and departure time, the waiting time, travel/flight costs and the
57 total travel time.

58 A joint Mixed Logit, including both SP experiments with the current and the future choice set, was estimated
59 with the survey data using the software PythonBiogeme (Bierlaire, 2016). Based on the estimation results and its
60 time and cost parameters, different VTTS could be determined for each mode of transport. Due to the possibility
61 for the participant to choose between an autonomous or manual driving mode in the private car, different VTTS
62 could be calculated for driving a car manually or autonomously. The survey and study design, as well as
63 methodological approach including model estimation and calculation of the VTTS is described in details by
64 Kolarova and Steck (2019).

65

66 (2) Diffusion Model

67 The diffusion of AVs in the overall passenger car fleet is a crucial factor when analyzing the impact of
68 autonomous driving on the transport system. We adapted an existing technology diffusion model (Trommer et
69 al., 2018) in order to forecast the share and the number of AVs in the German passenger car fleet in 2030. We
70 differentiated the car fleet by automation level, age and segment in the following way:

71

- 72 – 3 automation levels: no automation (Level 0-2), conditional automation (Level 3) and full automation
73 (Level 4 or Level 5)
- 74 – 3 age categories: up to 3 years, 4 to 7 years and 8 years or older
- 75 – 4 vehicle segments: XS, S, M and L (an adapted version of the German Federal Motor Transport
76 Authority classification (KBA, 2018))

77

78 The diffusion rate of each automation level and each vehicle segment was calculated using a Gompertz function
79 (Gompertz, 1825). The year of introduction and the initial market penetration rate differs for each vehicle
80 segment and automation level, thus resulting in different overall diffusion levels. We derived the years of
81 introductions from a Roadmap towards autonomous driving (VDA, 2015).

82 For calculating the size of the German privately owned passenger car fleet in 2030 we considered the current
83 number of new passenger car registrations for each vehicle segment (KBA, 2018) and kept it constant for future
84 years. On the other hand, we implemented a dynamic rate of abolishment for privately owned vehicles, based on
85 the age distribution of the vehicle fleet in 2017. The result of this model is the total car fleet size differentiated
86 by automation level, age and vehicle segment for each year, beginning from 2018 and up to 2030.

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89 (3) Transport Demand Model

90 A multimodal, Germany-wide transport model (DEMO) was used to determine the effects of autonomous
91 driving on long-distance traffic throughout Germany (Winkler and Mocanu, 2017). DEMO consists of several
92 modules covering passenger and freight transport demand. For this study, only the long-distance passenger
93 transport module was employed. In this module, the destination and mode choice for trips with distances of over
94 100 km are modelled using a nested logit model. The utility function and the preference parameters towards
95 travel times and costs are derived from a German value of travel time study (Axhausen et al., 2014).

96 Travel demand for 2030 is based on the results of the Reference scenario from the DLR project “Transport and
97 the Environment” (Winkler and Mocanu, 2017). The Reference scenario foresees a business-as-usual
98 development of the transport system in terms of infrastructure, network quality, income growth, user costs etc.
99 and does not consider the effects of vehicle automation on travel demand. The scenarios presented in this paper
100 differ from the Reference scenario only by the explicit consideration of privately owned AVs.

101 In order to model the impact of automation on long-distance travel demand we used insights from the stated
102 preference experiment on autonomous driving (Kolarova et al., 2019) and implemented the VTTS reduction into
103 the car utility function. As only Level 3 (to some extent), Level 4 and Level 5 vehicles will benefit from this
104 VTTS reduction we based the travel demand calculation on a fictional car serving as weighted “average” over all
105 automation levels. The weights are given by the respective automation level shares in the vehicle fleet, as
106 estimated by the Diffusion Model. Furthermore, this VTTS reduction only applies on those journey segments
107 where autonomous driving is enabled, i.e. according to the scenario considered here on highways. The thus
108 modified utility affects both destination and mode choice in the Transport Demand Model. OD matrices and total
109 VMT by mode are the results of this model step.

110 As the benefit of automation by Level 3 depends on the frequency of users having to take-over control of the
111 vehicle during a trip, we set up a recent review on the number of take-over control on highways. Since no
112 verified numbers were found, a sensitivity analysis was done by varying the reduction of VTTS for different
113 automation levels. In the Reference Scenario (“No Benefit”) for all levels of automation no reduction of VTTS is
114 assumed. In Scenario 2 (“Partial Benefit”) the reduction of the VTTS is considered by 50% for Level 3,
115 indicating that with a higher number of take-overs the benefit of automation decrease. However, Level 4 or
116 higher generates the full benefit of automation. In Scenario 3 (“Full Benefit”) Level 3 also benefit by the total
117 reduction of VTTS by automation just as Level 4 and 5.

118 (4) Differentiated Car Assignment Model

119 The scenarios presented in this paper investigate the effects of enabling autonomous driving on highways only,
120 and assuming manual driving for all other road types. Therefore, a route choice model is required in order to
121 determine the proportion of travel time on AV-enabled roads, i.e. highways, for each OD pair. Furthermore, as
122 driving on highways becomes more attractive for users of AVs, this might also lead to different routes being
123 chosen compared to drivers of non-autonomous vehicles.

124 A multi-class assignment based on the DEMO network model (Winkler and Mocanu, 2017) was set up, with
125 each automation level representing an individual vehicle class. As the car trip matrices resulting from the
126 Transport Demand Model are not differentiated by automation levels, they were split up according to the
127 procedure proposed by Mocanu (2018) factoring in the vehicle fleet shares, the trip purpose and trip distance.
128 Results from the assignment model, i.e. impedance matrices for travel times (on highways only and overall) and
129 distance were fed back into the transport demand model to ensure consistency between the two model steps.
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131

132 **Results**

133 The combination of different analysis tools gives us the opportunity to investigate the impact of AV on the
134 transport system and address some specific questions. Crucial inputs for our transport demand model is VTTS
135 for each mode of transport as well as the composition of the private vehicle fleet. The model estimation on the
136 mode choice experiment including autonomous driving shows that participants perceive the in-vehicle time less
137 negatively if they rode a private car autonomously than participants driving their private car manually. The
138 results from the stated preference experiment indicate a reduction of the VTTS by 22 % for people riding their
139 private car autonomously instead of driving it manually. In more detail, the calculated VTTS of participants with
140 middle income is 16.20 €/h for riding a private car autonomously and 20.80 €/h for driving a private car
141 manually and is almost similar to the VTTS of using the train (15.60 €/h) (Kolarova and Steck, 2019).

142 This VTTS reduction is relevant only for cars having automation level 3 or higher. In 2030 the share of AVs in
143 the German privately owned car fleet is 17 %, whereby primarily vehicles of the segment M or L are automated.
144 In total the modelled car fleet consists of 45.46 million vehicles with 5.16 million and 2.46 million vehicles

145 having automation level 3 and 4 respectively. The latter ones are capable of driving fully automated on
146 highways, so the full reduction of VTTS by 22 % can be assumed for the travel time on these road segments.
147 The VTTS reduction leads to an increase in car travel demand, both in terms of mode shares and trip distances.
148 To sum this up, the impact of automation on long-distance travel demand in Germany is evaluated by means of
149 the total car VMT. In the Reference scenario (“No Benefit”), this amounts to 167 billion VMT per year. The
150 figure increases by 2.8 % in Scenario 2 (“Partial Benefit”) and 4.2 % in Scenario 3 (“Full Benefit”), highlighting
151 the impact that the uncertainty regarding the functionality of Level 3 automation has on the results. These
152 preliminary results indicate that, while automation will not radically change long-distance travel demand, it will
153 nevertheless lead to a noteworthy increase in car traffic.
154 Finally, the assignment model results show that, already in the Reference scenario, 87 % of the car VMT from
155 long-distance trips will occur on highways. This indicates that the German highway network is sufficiently dense
156 and accessible to attract the overwhelming majority of long-distance travel. The percentage increases slightly to
157 88 % in the automation scenarios. As expected, highways will attract a comparatively larger amount of
158 additional traffic, though this effect seems to be rather limited due to the already high levels in the Reference
159 scenario. The resulting overall VMT increase on highways will be of 5.1 % in Scenario 3.

160 **Conclusions**

161 The combination of the four analysis tools shows that even in the near future a partial automated vehicle fleet
162 with a low level of automation can influence the transport system significantly. The individual benefits for the
163 users by automation might lead to an increasing usage of the private car and consequently to more VMT by car.
164 On the one hand, users choose the private car instead of other modes of transports automation. On the other
165 hand, automation also induces additional transport. These negative effects on the transport system as well as on
166 the environment have to be investigated further on.
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168 **References**

- 169 Anderson, J. M., Nidhi, K., Stanley, K. D., Sorensen, P., Samaras, C., and Oluwatola, O. A. (2014).
170 Autonomous vehicle technology: A guide for policymakers. Rand Corporation.
- 171 Axhausen, K., Ehreke, I., Glemser, A., Hess, S., Jödden, C., Nagel, K., Sauer, A. and Weis, C. (2014)
172 Ermittlung von Bewertungsansätzen für Reisezeiten und Zuverlässigkeit auf der Basis eines Modells
173 für modale Verlagerungen im nicht-gewerblichen und gewerblichen Personenverkehr für die
174 Bundesverkehrswegeplanung. FE-Projekt-Nr. 96.996/2011, BMVBS, Berlin.
- 175 Bäumer, M., Hautzinger, H., Pfeiffer, M., Stock, W., Lenz, B., Kuhnimhof, T., and Köhler, K. (2017).
176 Fahrleistungserhebung 2014 – Inlandsfahrleistung und Unfallrisiko. Ed.: Bundesanstalt für
177 Straßenwesen, Bergisch Gladbach, Germany.
- 178 Bierlaire, M. (2016) PythonBiogeme: a short introduction. Report TRANSP-OR 160706, Series on
179 Biogeme. Transport and Mobility Laboratory, School of Architecture, Civil and Environmental
180 Engineering, Ecole Polytechnique Fédérale de Lausanne, Switzerland.
- 181 European Road Transport Research Advisory Council (ERTRAC) (2017). Automated Driving
182 Roadmap.
- 183 Fraedrich, E., Cyganski, R., Wolf, I., and Lenz, B. (2016). User perspectives on autonomous driving.
184 A use-case-driven study in Germany. Geographisches Institut, Humboldt-Universität zu Berlin,
185 Arbeitsbericht 187.
- 186 Gompertz B. (1825). On the nature of the function expressive of the law of human mortality, and on a
187 new mode of determining the value of life contingencies. Philosophical Transactions of the Royal
188 Society of London B: Biological Sciences.
- 189 KBA, 2018. Bestand an Personenkraftwagen nach Segmenten und Modellreihen am 1. Januar 2018
190 gegenüber 1. Januar 2017 (FZ 12). Hrsg.: Kraftfahrt-Bundesamt. Abrufbar unter:
191 https://www.kba.de/DE/Statistik/Fahrzeuge/Bestand/Segmente/segmente_node.html (last acces: 2018-
192 12-21).

- 193 Kolarova, V., and Steck, F. (2019). Estimating impact of autonomous driving on value of travel time
194 savings for long-distance trips using revealed and stated preference methods. In: Mapping the Travel
195 Behavior Genome. The Role of disruptive technologies, automation, and experimentation. Ed.
196 Goulias, K. and Davis, A. (in press).
- 197 Kuhnimhof, T., Frick, R., Grimm, B., and Phleps, P. (2014). Long distance mobility in central Europe:
198 Status quo and current trends. In: European Transport Conference 2014, Frankfurt, Germany.
- 199 Mocanu, T. (2018). What Types of Cars Will We Be Driving? Methods of Forecasting Car Travel
200 Demand by Vehicle Type. Transportation Research Record.
- 201 Trommer, S., Kolarova, V., Fraedrich, E., Kröger, L., Kickhöfer, B., Kuhnimhof, T., Lenz, B. and
202 Phleps, P. (2016). Autonomous driving: the impact of vehicle automation on mobility behaviour.
- 203 Trommer, S., Kröger, L., and Kuhnimhof, T. (2017). Potential Fleet Size of Private Autonomous
204 Vehicles in Germany and the US. In: Road Vehicle Automation 4, Berlin, Germany. Edt. Meyer, G.
205 and Beiker, S.
- 206 van Goeverden, K., van Arem, B., and van Nes, R. (2016). Volume and GHG emissions of long-
207 distance travelling by Western Europeans. Transportation Research Part D: Transportation and
208 Environment, 45, 28-47.
- 209 VDA (2015). Automatisierung - Vom Fahrassistenzsystemen zum automatisierten Fahren. VDA,
210 Berlin.
- 211 Winkler, C., and Mocanu, T. (2017). Methodology and Application of a German National Passenger
212 Transport Model for Future Transport Scenarios. In: Proceedings of the 45th European Transport
213 Conference, Barcelona, Spain.