Effects of Automated Vehicles on Traffic Flow With Different Levels of Automation

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ABSTRACT
Highly automated vehicles are regarded as the next revolution of the transport system. Automated vehicles include a spectrum from vehicles with driver assistance systems through to highly automated vehicles. These vehicles will only gradually appear in the overall vehicle fleet. Their impact as part of future traffic is of reference value for transport decision-makers. The present paper starts from assumptions for the shares of vehicles with different levels of automation in 2030 and 2050 (representing the near and far-distant future) and compares the effects of these automated vehicles on traffic flow using microscopic traffic simulations. The simulated vehicles include non-assisted vehicles, semi-automated vehicles with driver assistance systems, and fully autonomous vehicles. To obtain a more realistic result, a traffic scenario of the city of Duisburg is used in this thesis. With the support of the city administration, existing data of the origin/target matrix, detector data including induction loops, and cameras were available. Thus, the data of the origin/target matrix are used to generate the real traffic scenario and the detector data to investigate the accuracy of the generated traffic. The result shows that automated vehicles would have a positive impact on traffic, a proportion of automated vehicles can reduce the average travel time. For areas with different traffic conditions, the degree of impact of automated vehicles can be very different.

INDEX TERMS
Intelligent vehicles, simulation, microscopic traffic simulation, vehicle automation level.

I. INTRODUCTION
Automated vehicles may have great significance to cope with some of the negative impacts of the ever-growing traffic, such as traffic congestion, accidents, energy consumption, etc. The United Nations forecast that the proportion of the global urban population will increase from 55% in 2018 to 68% in 2050 [1]. The development of urbanization may increase the residents’ demand for urban mobility. Thus, the negative impacts could be more severe. Worldwide about 1.2 million people die in vehicle-related traffic accidents each year [2]. Most traffic accidents can be attributed to human error, such as driving under external influences, drowsiness, or distraction [3], [4]. Automated vehicle systems support or replace human drivers with sensors such as cameras and radar systems to provide the vehicle with visuals of its surroundings and help it detect the speed and distance of nearby objects. These devices cannot be drunk, do never suffer from the burn-out syndrome, and cannot be distracted. they may thus reduce or even eliminate the driver-related errors. In addition to reducing traffic accident deaths, automated vehicles can improve people’s quality of life [2], [5]. For energy consumption, automated vehicles might reduce greenhouse gas emissions and energy use by nearly half [6].

Due to the considerations of price and safety related to human error, road vehicles will gradually shift from low level to high-level degrees of automation. The choice of different types of vehicle owners and the transformation of urban alternative transportation modes (such as car-sharing and self-driving taxis) will result in a long mixture period of vehicles of various automation levels. From the perspective of travel demand, almost 85% of urban autonomous car-sharing trips can be covered using vehicles with significantly reduced requirements in the simulation scenario of the year 2035 [7]. Probably an increasing number of partly and fully automated vehicles will enter into public roads [8]. As the proportion of automated vehicles increases, how will these automated vehicles impact traffic flow in cities? Moreover, to get smoother traffic, is a fully autonomous vehicle necessary?
Previous works regarding the traffic flow effects of different degrees of automation focus on simple traffic scenarios like highways. Arem et al. [9] introduced a MIXIC (Microscopic Model for Simulation of Intelligent Cruise Control) simulation model for vehicles with CACC (Cooperative Adaptive Cruise Control) and conducted simulations in a highway scenario. They concluded that only a high-CACC-penetration rate (\(>60\%\)) has benefits on traffic stability while a low penetration rate of CACC (\(<40\%\)) does not influence traffic flow throughput. The highway scenario is a one-lane straight freeway and the simulation length is 1 hour. Reece and Shafer [10] introduced a computational driving model called Ulysses for autonomous vehicles and simulated the traffic in a simple intersection scenario. However, no comparison with vehicles of other degrees of automation is performed. Based on the previous studies, Talebpou et al. [11] introduced a car-following and lane-changing model for autonomous vehicles with limited sensors’ range and accuracy. Subsequently, the model is simulated with regular vehicle models in highway segments, to prove the benefits of reserved lanes for autonomous vehicles [12].

Instead of a simple traffic scenario such as a small highway or city area, this study implements a real high-mesh city network scenario of the entire city of Duisburg. Different from the comparison of two vehicle models (non-automated and automated) in precious works [13], this work compares vehicles with three degrees of automation, non-automated vehicles, vehicles with driver assistance systems, and fully autonomous vehicles. We use these three levels of automation to represent the major vehicle automation levels of the present, near future, and far-distant future. The vehicles with driver assistance systems addressed in this work include both horizontal and vertical assistance systems and belong to Level 2 automation in SAE classification [14]. The different penetration rates of vehicles with these three automation levels constitute traffic scenarios in the near as well as in the far-distant future.

II. METHODOLOGY

A. SIMULATION SCENARIO

On an international scale, the city of Duisburg is a medium-sized city with approximately 500,000 inhabitants [15]. Duisburg has the advantage of various transportation networks. For example, Duisburg has great connectivity to the national and European transport network in air, rail, and road aspects. In the transformation process to a smart city, smart mobility including road transportation is an indispensable part [16].

As a city with great transportation activities, the road network in the city of Duisburg is highly meshed. FIGURE 1 b) shows all motorways in the city of Duisburg, including highways and urban roads. The road network is imported from OSM (Open Street Map) and modified using Google street view. With the help of the city Duisburg officials and the WBD (Wirtschaftsbetriebe Duisburg in German), two kinds of data sources were provided: the OD (Origin-Destination) matrix data for the whole city and detector data for a specific area. The OD matrix describes people’s movement in a certain area, it is therefore nearly indispensable for modeling transport demand in rural and urban areas [17]. In principle, an OD matrix divides an area into smaller parts and describes the traffic volume among these parts. From an overall perspective, these small parts can be considered as points, which are then used for a point-to-point description of the traffic volume. The partition of the OD matrix of city Duisburg can be seen in FIGURE 1 c). Traffic flow data are recorded by the detectors, including induction loops installed below the roads and cameras located nearby the intersections. The principle of induction loops is that, when a vehicle passes by, the metal vehicle cuts magnetic induction lines, and the current changes. Multiple induction loops on the same section cannot only detect the number of vehicles, but also their speed. The detector data are relatively more accurate in a specific road compared to other data sources, but sufficient detector layout and reasonable pre-processing of data are the premises of ensuring accuracy.

FIGURE 1. The map, road network, and traffic partition of the City of Duisburg. a) City Duisburg in HERE map. b) Road network. c) Partition of OD matrix.

In this study, the OD matrix data are used as a traffic demand source. In addition, detector data are used to verify traffic volume. The generated traffic volume is compared with actual detector data like in our previous work [18]. Public means of transport such as buses and subways are neither included in the OD matrix data source nor the induction loops data. Therefore, in our simulation of this study, the emphasis is put on passenger cars and trucks.

B. ESTIMATION OF PENETRATION RATE OF AUTOMATED VEHICLES

Fully autonomous vehicles will not be an overnight addition to individual transport, but there will be a long-term phase of an evolutionary transition. The combination of (partially) automated and non-automated vehicles on the road is a common situation. The proportion of vehicles with different degrees of automation changes dynamically [19]. There are many obstacles on the way to the full-scale roll-out of automated vehicles. The future changes of these obstacles
will affect the market adoption, and thereby the penetration rate of automated vehicles. In general, four aspects are the most important in the way of large-scale market adoption of automated vehicles:

- **Policies:** The policies of automated vehicles’ road testing and insurance can reflect the attitude of the respective governments. Some countries already allow automated vehicle tests on public roads. As of 2018, over 80 manufacturers are testing over 1400 automated vehicles in at least 36 states in the U.S. [20]. As the center with the largest concentration of EU manufacturers, Germany approved automated vehicles’ testing on the A9 highway in 2015. In 2017, the German Federal Council (Bundesrat) created a legal framework for autonomous vehicles [21]. In China, some cities have also given automated vehicles permission for road testing. The UK’s government has modified the terms of mandatory liability insurance for motor vehicles, which let automated vehicles to be covered by insurance like traditional vehicles.

- **Technological development:** Many manufactures have announced that they have already finished the technological development for fully autonomous vehicles. From today’s perspective, however, the various systems in fully autonomous vehicles must be able to communicate and cooperate with each other. Moreover, many of the systems still need improvements, including navigation systems, global path planning, map matching, environment perception, vehicle control, etc. The automated vehicles must be able to detect other road users safely and accurately in real-time, which is still a challenge (Zhu et al. 2014). Incorrect and inaccurate detection has already led to accidents, some of them resulting in fatalities. Electronic security is also a problem that is worth worrying about. Large-scale mesh communication systems for V2V (Vehicle to Vehicle) and V2I (Vehicle to Infrastructure) may bring more possibilities for virus-like attacks.

- **Vehicle cost:** A survey shows that 20% of consumers would definitely/probably be willing to pay 3,000 U.S. dollars for autonomous driving applications [22]. However, a single system with advanced sensors, such as LIDAR, costs already tens of thousands of dollars [23]. The overall cost of the most current civilian and military automated vehicle applications could be over 100,000 dollars [24]. This would be unaffordable for most consumers. Fortunately, the costs are very likely to be reduced in the future. With mass production, the added costs per automated vehicle may fall to the price range between 25,000 and 50,000 dollars [24]. After 20 to 22 years, the cost could decline to 3,000 dollars [5]. Eventually, it may fall to 1,000 to 1,500 dollars per vehicle [23].

- **Public opinion:** The public opinion is also particularly important for the large-scale realization of automated vehicles. As long as there are no legal regulations, it is ultimately the individual customers who decide whether to buy automated vehicles or not. Many investigations of the public opinion on automated vehicles can be found. Generally, the public’s opinion differs between different gender, ages, education levels, income level, and current commuting methods [25]–[27]. People from developing countries with lower GDP, lower vehicle usage and ownership, greater numbers of road deaths, are more enthusiastic about autonomous vehicles [28]. The concerns about autonomous vehicles are mainly about safety related to machine error, legal issues, and privacy.

The estimation of time and percentage of automated vehicles penetrating the fleet differ between researchers. A survey during Automated Vehicle Symposium 2014 showed that experts expect conditionally automated vehicles and fully autonomous vehicles reach the market in 2019 and 2030 respectively [29]. An Internet-based questionnaire shows that 69% of respondents estimate that fully autonomous vehicles would reach a 50% penetration rate by 2050 [30]. Based on both optimistic and pessimistic aspects, an estimation of four scenarios is constructed for predicting the penetration rate for the years 2030 and 2050 [31]. The four scenarios assume supportive policies and high technological development, supportive policies and low technological development, restrictive policies and high technological development, and the most pessimistic situation, restrictive policies with low technological development, respectively. The estimation varies significantly in the four different scenarios. As of 2020, the technological assumption of the most optimistic scenario (supportive policies and high technological development) has already been realized. In 2017, Audi announced the first conditional automation system (automation level 3) in the new A8, and the realization is even one ear earlier than the most optimistic scenario. In 2018, Google Waymo’s driverless taxis launched in four Phoenix suburbs. With the rapid technological development, other relative aspects such as policies and public opinions also develop in a more optimistic direction. There are reasons to believe that the most optimistic scenario in the estimation is credible. Therefore, in this work, the penetration rate of fully autonomous vehicles is set to 11% and 61% for 2030 and 2050, respectively, as the estimation of the most optimistic scenario. As for the vehicles with driver assistance systems, they have reached the market for many years, not objected by policies or technical restrictions. Most barriers for large-scale market adoption are due to the price. Therefore, in the near and far-distant future, vehicles with driver assistance systems would be a common configuration. In this work, the assumption of the penetration rate of vehicles only with driver assistance systems is set to 40% and 30%, respectively. In total, the automated vehicles including vehicles with driver assistance systems and autonomous vehicles have an assumed share of 51% in 2030 and 91% in 2050 in this work. The penetration rate is directly reflected in the number of vehicles of different automation levels in the simulation. Since the
total number of vehicles in the simulations are the same, in the simulation scenario of 2050, 40% of non-automated vehicles will be replaced by automated vehicles than the scenario of 2030.

C. VEHICLE MODELS WITH DIFFERENT LEVELS OF AUTOMATION

In this study, a driver-vehicle model is used for the simulation, which consists of a vehicle model and a separate driver model. An obvious benefit of this kind of model is its flexibility. The driver model can be combined with different vehicle models (fuel, electric, hybrid, etc.), and the vehicle model can also combine with different driver models (autonomous driver, human driver, aggressive driver, etc.). As shown in FIGURE 2, the driver-vehicle model consists of three parts, where Model K represents the modified Krauss model, Model F represents the fuzzy control model and Model VM represents the vehicle model. The Model K takes traffic information including ego vehicle information, leading vehicle information, and road condition as input and outputs desired speed and actual speed. This part simulates a human driver sees the road conditions and reacts according to the status of the vehicle. The model F converts the desired speed and the actual speed into the gas pedal and brake pedal position through fuzzy control based on actual behavior of human drivers. This part simulates the human brain controlling the body to pedal. Model K and F are the two parts of the driver model, and the driver model and vehicle model are independent of each other and connected by data transmission.

The modified Krauss model can be expressed as:

\[
\begin{align*}
    v(t + \Delta t) &= \text{max}(0, V_n - \epsilon a\eta)
    \\
    V_n &= \min[V_s, V_{max}, v_n(t) + a\Delta t]
    \\
    v_s &= -\tau b + \sqrt{(\tau b)^2 + v_{n-1}(t)^2 + 2bg_n(t)}
    \\
    x(t + 1) &= x(t) + v_n(t) t_f
\end{align*}
\]

where \(v(t + \Delta t)\) represents the speed of the ego vehicle after time \(\Delta t\), \(V_n\) is the desired speed, \(\phi\) is a random perturbation to allow for deviations from optimal driving, \(\epsilon\) is the imperfection factor of the driver, \(a\) is the acceleration of the ego vehicle, \(\eta\) is a random number between 0 and 1, \(v_s\) is the safe speed, \(V_{max}\) is the allowed speed of the road, \(v_n(t)\) is the speed of the ego vehicle at time \(t\), \(a_n\) is the maximum acceleration, \(t_f\) is the time step of the simulation, \(\tau\) is the reaction time of the driver, \(v_{n-1}(t)\) is the speed of the leading vehicle, \(b\) is the maximum deceleration of the ego vehicle, \(g_n(t)\) is the gap between the leader and the follower, \(x(t)\) is the position of the ego vehicle at time \(t\), and \(x(t + 1)\) is the position of the ego vehicle at the next time step.

The fuzzy control model is established by a driving experiment with 34 human drivers in a driving simulator. [33] Based on the data transferred from the modified Krauss model, the desired speed of the driver \(V_n\) and the actual speed of the vehicle \(v_n(t)\), the fuzzy control model outputs gas pedal position \(p_g\) or brake pedal position \(p_b\) with human-like fuzzy rules. The vehicle model considers the characteristic of the vehicle transmission and the driving resistances and is optimized by the data from the driving experiment.

In this study, different levels of automation are reflected in the parameters of the modified Krauss model and fuzzy control model. For vehicles with different levels of automation, the most influential parameters are reaction time and different action points [34]. Three degrees of automation are selected for the vehicles in simulation, that is Level 0 (non-automated), Level 2 (partial automation level), and Level 5 (fully autonomous vehicle). To effectively distinguish the difference between Level 0 and Level 2, it is assumed that in the simulation Level 2 vehicles are in the driving assisted mode. The reaction time \(\tau\) and the randomness factor \(r\) are the two parameters distinguish the three levels. The reaction time in the modified Krauss model is set according to the different actors (human or machine) of the reaction task. For Level 0 and Level 2 models, the reaction task is taken by the human driver. Therefore, the human reaction time of 1 s is set for the Level 0 and Level 2 models. For Level 5 models, the reaction task is finished by the machine driver, and the machine reaction time of 0.5 s is set for the Level 5 models. The randomness factor \(r\) represents the randomness of human operation in this model. According to the analysis of the driving experiment results, the randomness factor \(r\) is set to 0.5 for Level 0, which means that the human driver will have a ±50% random value of the pedal position in the fuzzy control model. For Level 2 and Level 5 operated by the machine driver, the randomness factor is set to 0.

![Figure 2. Driver-vehicle model with different degrees of automation.](image-url)
III. CONFIGURATION OF THE SIMULATION MODEL
To simulate the traffic situation of the city of Duisburg in 2030 and 2050, an open-source microscopic traffic simulation software SUMO (Simulation of Urban MObility) [35] developed by the German Aerospace Center (DLR) is used. Compared with similar simulation software, SUMO has more possibilities of model extension with less complexity. Software with high complexity would have negative impacts with other models (like lane changing model, dynamic assignment model, etc.) which are not easy to be resolved [36]. Hence, the simulation software package SUMO is selected for this paper.

A. OD MATRIX TRAFFIC DEMAND
In the process of generating traffic demand from an OD matrix, the traffic volume from the divided zones (with different colors in FIGURE 1 c.) is assigned to roads in the area. There are in total of 596 inner-city traffic zones and 153 outer city traffic zones around the city of Duisburg. In this work, only the inner-city traffic zones are used. The OD matrix data was calibrated to an average working day of 24 hours, and there is no more specific data for the traffic volume per hour. Therefore, common daily timelines retrieved from cities in West Germany are used [37]. For passenger cars and trucks, timelines named TGw2_PKW and TGw_LKW are used separately for describing the traffic distribution on a workday. The overall process of generating traffic demand from the OD matrix is listed below:

- **Areas described by OD matrix transfer into polygons in SUMO:** The 596 areas described by the OD matrix data source are saved in shapefiles (a data format for geometric location information), and also described by geometry information (longitude and latitude). The most similar data format in SUMO are polygons. The boundary lines of polygons in SUMO can be also described by geometry points in order. In this step polycovvert in SUMO is used to transfer shapefiles into polygons.
- **Polygons to TAZ:** Traffic Assignment Zone (TAZ) is a district defined in SUMO and the vehicles can be coded to drive from one TAZ to another within a certain time. TAZ contains also districts based on points. For a better visualization, the geometry coordinate format is transferred to the XY coordinate system in SUMO. FIGURE 3 a) shows the TAZ distribution of the studied area, all the areas in OD matrix are marked with red boxes.
- **TAZ to edges/roads:** To distribute the traffic demand from the whole zone into edges/roads, a python program called edgesInDistricts.py is used. Depending on the length of the roads, the traffic demand is distributed with different weight. An example of one TAZ is shown in FIGURE 3 b), the grey dotted box is the range of the TAZ, and the lines in different colors represent the road in the TAZ.

B. TRAFFIC CONTROL INTERFACE
For the convenience of programming, the driver-vehicle model with different degrees of automation is written in MATLAB. Due to the simulation scenario being still implemented in SUMO, TraCI (Traffic Control Interface) is used as an interface between MATLAB and SUMO. For each time step, the simulation values such as ego velocity, time headway, the velocity of the leading vehicle, etc. are retrieved from SUMO. Based on these values, the Model K (modified Krauss model) calculate the desired velocity and transfer it to Model F (fuzzy control model). Model F calculates the pedal position and transfers it to Model VM (vehicle model). Model VM calculates the ego speed and velocity based on the pedal position. The whole calculating process happens in MATLAB, and through TraCI, the ego speed and position are sent back to SUMO.

C. VERIFICATION DATA
To compare the traffic situation in different simulation scenarios of 2030 and 2050, a comparative scenario of the current stage with non-automated vehicles is generated. Besides the different penetration rates of automated vehicles, all other parameters (total vehicle number, simulation time step, speed limitations, etc.) of the three simulations remain the same. Some road sections are chosen as the verification points. In the real world, different road sections with valid detector data in the northern, southern, western, and eastern parts of Duisburg are chosen.
IV. RESULTS AND DISCUSSION

In our previous work of traffic simulations with vehicles of different degrees of automation, the penetration rate is 100%. In a scenario of a simple intersection, the vehicles of automation Level 2 finish the driving task 9.1% faster than the non-automated group, and vehicles of automation Level 5 finish it 19.8% faster than the non-automated group. In a traffic scenario that only covers the inner ring area of the city of Duisburg, vehicles with different degrees of automation show little differences among themselves in the current traffic demand. However, if an additional traffic demand of 50% is added to the simulation, vehicles with a higher degree of automation show significantly more advantages.

In this study, the vehicle quantity of the three simulation scenarios of 2020, 2030, and 2050 varies largely according to different road sections. FIGURE 4 shows four examples of recorded road sections. The detectors of road sections in FIGURE 4 a), b) and c) show small differences in the three scenarios. The scenario of 2050 (red lines) have sometimes higher traffic volume than the other two lines, but in general, the difference between the three lines is not large for the three road sections. In the scenario of 2050, there are more 4.35%, 14.26%, 0.41% of vehicles passed the three road sections than scenario 2020, respectively. However, in some road sections as shown in FIGURE 4 d), the traffic volume of scenario 2050 (red line) is much higher than that of scenario 2030 (blue line) and scenario 2020 (black line). The traffic volume in the scenario of 2050 is on average 67.79% larger than in the scenario of 2020. The higher penetration rate of vehicles with higher automation levels shows greater positive effects on traffic for this road section. The different effects of the same model can be a result of the different degrees of traffic congestion of these road sections. For more congested roads, the higher penetration rate of vehicles with higher automation levels results in higher traffic flows.

For all 22 recorded verification road sections, the scenario of 2050 has an extra 22.08% vehicle quantity in the same period compared to scenario 2020. The scenario of 2030 shows an improvement of the vehicle quantity with a 21.93% proportion compared to scenario 2020. Compared with the current non-automated group, both scenario 2030 and scenario 2050, show an apparent increase in traffic volume for the same period and same traffic demand. But compared with each other, there is only a measurable positive impact of 2.54% on traffic of scenario 2050 compared to the scenario of 2030.

In addition, the average travel time of the trips in different scenarios is considered as a representative statistic. FIGURE 5 shows the comparison of the average travel time of a six-hour simulation. The bar graphs represent the distribution percentage of all travel time in the three scenarios.

FIGURE 4. Vehicle quantity at some road sections of the scenario 2020, 2030, and 2050. d) shows more effects than the other three road sections and can be the result of its congestion traffic situation.

FIGURE 5. Average travel time of different scenarios. Most of the travels over 60 minutes in scenario 2020 become less than 60 minutes in scenario 2030, all of them become less than 60 minutes in scenario 2050.
The median of the travel time of the scenario 2020, 2030, and 2050 are 8.37 min (SD σ = 61.45), 7.24 min (σ = 8.19), and 7.00 min (σ = 5.52), respectively. From the perspective of average travel time, scenario 2030 and 2050 reduced travel time by 13.5% and 16.4%, respectively.

**V. CONCLUSION**

In this work, the impact of future penetration rates of vehicles with different levels of automation in 2030 and 2050 is predicted based on a thorough simulation study. The simulated vehicles involve non-automated vehicles, partially automated vehicles with driver assistance systems, and fully autonomous vehicles. Based on the penetration rate, simulations of three different scenarios of city Duisburg in 2020, 2030, and 2050 are built. The effects of the different penetration rates of automated vehicles are compared to the simulation result recorded by detectors. For most parts of the city of Duisburg, the automated vehicles lead to a 21.93% improvement in traffic throughput in scenario 2030 with the same expansion of the road network, and in scenario 2050 the positive effect will increase to 22.08%. For some parts with heavy traffic congestion, the scenarios of 2030 and 2050 with a higher penetration rate of automated vehicles have a positive effect of up to 67% on the traffic flow. In the perspective of average travel time, scenario 2030 and 2050 have a 13.5% and 16.4% shorter travel time on average compared with scenario 2020.

It can be seen from the simulation results that, under the same traffic demand/travel flow, increasing the proportion of automated vehicles can significantly improve the traffic flow and shorten the average travel time. With a larger proportion of fully autonomous vehicles, the average travel time in scenario 2050 is slightly better than in scenario 2030. Replacing a certain proportion of non-automated vehicles with automated vehicles in the city can greatly improve the traffic conditions (scenario 2030 VS scenario 2020), but based on this circumstance, a higher proportion of fully autonomous vehicles on road will not significantly improve traffic conditions. (Scenario 2030 VS scenario 2050).

There are still some limitations to this work. First, the penetration rate of the automated vehicles uses an optimistic estimation, and the proportion of the automated vehicles in simulation is based on this optimistic estimation. Second, the traffic scenario of the city of Duisburg contains only passenger cars and trucks. Other road users such as pedestrians, cyclists, busses, subways are not included in the simulations. Last, the driver model used in this work uses parameters to distinguish different levels of automation of vehicles, not all the parameters in vehicles are considered. For future work, a simulation that includes more road users will better reproduce the real traffic. Furthermore, the effect of automated electric vehicles is an interesting topic worthy of exploration.

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