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REVIEW

Evidence on impacts of automated vehicles on traffic flow efficiency and emissions: Systematic review

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Abstract

Despite high expectations of driving automation improving road traffic, its practical implications on traffic flow and emissions are not yet definite. This study systematically reviewed literature on practical impacts of non-connected automation of passenger cars on motorway traffic efficiency. A conceptual framework showed the importance of understanding interactions between vehicles, both human-driven and automated, but they are not yet sufficiently known and reproduced by traffic models. Field studies have focused on equipped vehicles. Simulation studies have used different models and assumptions, narrow fleet compositions and road layouts, and covered the theoretical potential in ideal conditions rather than likely impacts in practice. Simulations with automated vehicle time gaps below 1.2 s have found throughput increases, but recent field experiments and simulations using commercial ACC vehicles indicate decreased traffic flow efficiency with increasing traffic volumes and penetration rates. Concluding implications for real traffic from available data is challenging. While benefits are possible for equipped vehicles in low traffic, results suggest negative implications for throughput and emissions at higher traffic volumes. Importantly, more differentiated discussion on the impacts of automated vehicles on traffic flow is needed, considering also the practical implications, such as tradeoffs with safety goals, if benefits are to be achieved.

1 | INTRODUCTION

1.1 | Motivation for research

While road transport is a core activity of society by enabling movement of people and goods, it is a major cause of greenhouse gas (GHG) emissions and air pollution, and traffic congestion is a tangible everyday concern for many road users in Europe [1] and around the world [2, 3]. At the same time, driving automation is facing high expectations of improving traffic flow efficiency and mitigating emissions [4, 5], in addition to road safety benefits [6]. The prevailing presumption is that were all or most vehicles automated, accidents and congestion would be eliminated or at least greatly reduced. Automated vehicles (AVs) have indeed gained considerable interest in the research field, however this interest has mainly been focused on technical development related to perception, localisation, motion planning, controllers and functional safety [7] of single vehicles, while impact assessment on the traffic level has focused on safety. Some researchers [8] suggest however that the effects of automated driving on traffic flow efficiency may be the most significant. To date, estimates of traffic flow efficiency and environmental impacts are scattered [9], especially as regards the likely impacts in the near future in mixed traffic in practice, and benefits for the collective traffic system are not self-evident.

In theory, the benefits of automation are apparent. With driving automation systems taking over (parts of) the dynamic driving task, the influence of the variety of individual driver characteristics, preferences and skills is reduced. Humans need time to perceive events such as change in speed of the predecessor, process the information, decide on a response, and enact the decision [10]. All these processes introduce a time delay. A common expected benefit of AVs is that they can react more quickly to actions of the predecessor, which would allow keeping smaller time gaps between vehicles, leading to more vehicles to fit on the road [11]. A related potential benefit of automation is a smoother and more homogeneous driving style [12]. Time gaps and speeds kept by human drivers are not constant and depend on driver and vehicle characteristics, often oscillating around the desired values. AVs have more efficient throttle control and thus less variation in longitudinal vehicle motion control, which can help curb energy demand and improve traffic flow efficiency. Further, human drivers regularly exceed the speed limit, which especially in motorway conditions leads to higher fuel consumption and emissions as well as larger speed differences with slower vehicles. In reality, however, benefits are not guaranteed, as the interrelationship between automated driving (AD) and traffic flow efficiency is complex and depends on many factors [13].

Due to the complexity and the fact that vehicles with driving automation systems beyond driver support (SAE L1, SAE [100]) and partial automation (SAE L2) are not yet on the market, potential impacts of longitudinal motion control of AVs have been studied by considering adaptive cruise control (ACC), which is a driver support system helping with the longitudinal vehicle motion control, while the driver remains responsible for monitoring the system performance at all times. ACC systems represent a first step in the path to automated driving [15], and ACC is assumed to be used as longitudinal vehicle motion control component in future automated vehicles [16] and can thus provide indications of the potential of AV impacts in these situations, as long as more specific data is lacking. The first widely available automation systems for private cars are likely to operate in the relatively restricted motorway environments [17]. In the following, the term AV is used to describe vehicles equipped with an automated driving system (SAE [100]) able to perform the entire dynamic driving task (SAE L3 and above).

1.2 | Previous review studies

A handful of review studies on the impacts of changed driving dynamics with AVs or ACC on traffic flow efficiency or emissions have been previously conducted. Wadud et al. [18] explored impact mechanisms of the carbon and energy impacts of automation and found that GHG emissions from road transport depend highly on the type of implementation and could either be reduced to half or doubled with automation. They considered a long-term scenario with high levels of automation and high penetration rates. Milakis et al. [19] explored potential impacts of AD on a range of society related areas with the ripple effect concept. Energy and efficiency impacts were included as one part of implications. Their conclusion, based on review of simulations and analytical studies, was that first-order impacts of AVs on road capacity, fuel efficiency and emissions are likely beneficial, but the balance between short- and long-term impacts remains an open question. Taiebat et al. [20] examined the interactions between CAV (connected automated vehicle) technology and the environment at four levels of increasing complexity: vehicle, transportation system, urban system, and society. They concluded that the net effects on emissions are uncertain due to the significant uncertainties on the changes to driving behaviour. Eilbert et al. [21] conducted a systematic review and meta-analysis of network performance and environmental impacts of ACC and CACC (cooperative adaptive cruise control). They found that impacts were highly sensitive to the time gap setting. Modest capacity improvements were found for ACC, and fuel savings were possible. Do et al. [22] reviewed CAV modelling studies on highways and classified the simulation models used. They found that the penetration rate is important in determining impacts. Benefits of CAV for capacity were considered marginal without connectivity. Further, they found that CAV models are usually not calibrated with field data. Narayanan et al. [23] identified four categories of traffic flow efficiency impacts of AVs and CAVs based on reviewing available literature: vehicle characteristics, travel behaviour, network characteristics and policies. They concluded that AV technology is a "double-edged sword" and highlight the need for policy regulation for best impacts as well as the need for policy makers to base decisions on studies involving field trials.

Common to these reviews and the studies they assessed is that most work on AV impacts concentrates on a few issues in isolation, omitting potential mutually countered, cumulative or synergistic impacts, and studies with a holistic approach are rare [24]. Although one review focused on mixed automation in the near term, most did not consider likely near-term impacts and presented combined results from studies with autonomous and connected AVs. Differences of the simulation models, assumptions that the results were based on as well as their implications for the results were not discussed in detail. Importantly, interest focused on equipped vehicles, and impacts on other road users or the traffic as a whole were not in focus. As vehicle interactions define traffic dynamics, forming a complete picture needs consideration of all road users, and little is yet known on how human drivers behave in the presence of AVs [13, 25]. The effects of behavioural adaptation of the AV user when driving manually are also not known. Little evidence is further available of automated lane changes on capacity [13] as most studies on automated vehicles focus on the longitudinal vehicle motion control.

Recently, the need for critical reviewing of assumptions and their applicability in practice has been expressed [5]. Comparing results and inferring general conclusions from present literature is challenging, as the terminology, assumptions, scenarios and evaluation criteria differ across studies [22] and the scope in terms of automation level addressed or inclusion of connectivity is not always made explicit [5]. The differences in the study assumptions and scope should be considered when forming conclusions from simulation studies [26], yet impact estimates from studies are often generalised as impacts of automation, although only a part of relevant aspects of the real traffic system were considered and the results are thus not easily generalisable. It becomes difficult to separate the impacts of increasing use of driving automation systems from other related factors. At a closer look, claims of increased traffic flow efficiency with driving automation are almost always based on studies considering connected automated systems [8, 20] or shared mobility [27]. In fact, achieving benefits of automation on road network performance is thought to come with rigid requirements, which are not certain to realise soon: full fleet automation, widespread vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication, and successful uptake of shared mobility [28, 29].

Besides considering theoretical benefits at high penetrations of high-level automation, it is important to be aware of the potential impacts on traffic dynamics also in the transition phase. While higher level driving automation has been declared "imminent" for several years, systems beyond partial automation are not yet available in production vehicles today, and vehicles with partial automation systems cover only a small subset of the European vehicle fleet. The transition period towards conditional (SAE L3) and high (SAE L4) automation at significant penetration rates is expected to be long [30, 31], possibly lasting several decades. The objective of this paper is to fill the research gap on the likely impacts of driving automation on traffic flow efficiency and emissions on motorways.

1.3 | Research objectives and scope

This article aims to answer the following research questions:

- What is known of likely impacts of (non-connected) automated passenger cars (AVs) on traffic flow efficiency and emissions in the near-term future on motorways?
- What are the main factors influencing these impacts and how have they been considered in previous studies?

The study focuses on privately owned automated passenger cars on motorways, specifically on impacts arising from the changes in the dynamic driving task, specifically the changes in longitudinal and lateral vehicle motion control. Although other simultaneous trends to automation, such as electrification and shared mobility, have larger potential to reduce emissions and congestion [32, 18], with effects enhanced through synergy with automation [20], the changes in lateral and longitudinal motion due to automation are of interest in themselves. Factors such as vehicle size, weight, engine, fleet composition, vehicle occupancy and mobility patterns are thus assumed constant.

The study does not address any specific levels of automation, but the focus is on the potential impacts in situations where the vehicle performs the entire dynamic driving task, including both lateral and longitudinal motion control and object and event detection and response. A frame of reference is provided by ERTRAC [17] and Wood et al. [33], which describe SAE L3/L4 motorway automation systems for speeds up to 130 km/h from entrance to exit including overtaking and lane changes when required. The system does not operate in adverse weather conditions and may either ask the driver to take over or carries out minimum risk manoeuvres, such as brings the vehicle to a safe stop. However, this study focuses on regular driving situations and assumes that the automated driving function is working as intended and the conditions are within its operational design domain (ODD). Therefore, the impacts of take over requests or minimal risk manoeuvres are out of scope.

Connectivity between vehicles is expected to improve the performance of AVs and ACC, for example, by enabling shorter time gaps and higher accuracy in car following [34]. Development, testing and standardisation efforts are ongoing, but it is still uncertain how connectivity will realise in the vehicle fleet [29]. A high share of V2V equipped CAVs is needed for benefits to show [35], as they need to directly follow another V2V equipped CAV to take advantage of the connectivity. When following non-connected vehicles, CAVs act as regular AVs. According to Shladover [36], 70% of V2V market penetration is needed to achieve half the benefits of full penetration. However, achieving a feasible fleet share is slow even if all new vehicles were connected [37]. A further concern for connectivity consists of potential risks regarding malevolent attacks, technology failures or network breakdown [35] and ensuring reliability and accuracy of provided data. Developers may be wary of trusting information provided by unverified external sources [36]. Users may not agree to their vehicles' movements being tracked and shared. Finally, even with connectivity in place, the AVs need to work safely also in case of malfunction or temporal unavailability of connectivity [33]. It is important to be aware of the implications in the situations where connectivity is not available. For these reasons, this study assumes that a significant penetration rate of V2V or V2I connectivity in AVs will not be achieved in the near future to have an impact on traffic, and the focus lies on impacts of autonomous, non-connected AVs, which are envisioned as self-sufficient within the existing physical infrastructure [11, 38]. They use the sensors embedded in the vehicle and do not rely on technology to communicate with other road users or the infrastructure. In the following, the methodology is introduced and a conceptual framework for assessing the practical impacts of driving automation on traffic dynamics is presented. Next, the evidence from literature is summarised. Finally, results are discussed and conclusions formed.

2 | Methodology

2.1 | Systematic review

Two systematic literature reviews were carried out in August 2021 on Scopus to identify the relevant journal articles and conference papers involving microscopic simulation studies and real traffic experiments of AVs or ACC equipped vehicles. Published estimates on impacts of ACC (SAE L1) are included because they provide an indication on the potential longitudinal behaviour of AVs. The reviews followed the PRISMA guidance [39].

The search terms used were the following:

1. automated vehicle(s), automated driving, autonomous vehicle(s), cruise control
2. capacity, traffic flow, throughput, emissions, CO_2, delay, congestion, energy consumption, energy demand, fuel consumption, GHG
3. impact*, assess*, evaluat*, influenc*, implicat*, effect*, poten*, affect*

4. model*, simulat*
5. empirical, naturalistic, field test, field operational test, FOT, real world, real traffic

Search terms within a row were connected with Boolean OR, and different rows were connected with Boolean AND. The aim of the first search was to find all relevant simulation studies, using the rows 1, 2, 3 and 4. The second search aimed to find empirical results and used the rows 1 and 5. In addition, potential documents not fitting in the search were scanned with Google Scholar and from the references of studies reviewed.

The titles and abstracts of resulting articles were reviewed for relevance and results on implications on traffic flow efficiency or emissions. The following eligibility criteria had to be fulfilled:

1. The study assesses non-connected automated driving or ACC. Regarding papers examining both connected and autonomous AVs, or both CACC and ACC, the results concerning the autonomous AVs or ACC systems are included.
2. The study focuses on impacts to be expected from wider use of the systems, that is, does not focus on controller design and theoretical investigations.
3. The study provides estimates on one of the indicators of interest, that is, road capacity or throughput, travel times or speeds, energy demand, fuel consumption or emissions.
4. The study covers motorways or similar two-carriageway roads.
5. For simulation studies, the underlying driver model and desired time gap of automated or ACC vehicles are specified.
6. The study is published in the English language.

2.2 | Study selection and data extraction

The search for simulation studies in August 2021 returned 2208 results and that for empirical studies 1582 results. Besides excluding studies from completely different fields and published in languages other than English, the most common reasons for excluding search results were the following:

- the scope of the article was to develop and/or validate a (ACC) controller or model created for specific purposes, often to fulfil a certain objective (e.g. optimised for string stability or energy efficiency)
- the study focused on connected or cooperative systems only or required the vehicle to have knowledge of the current traffic situation beyond what is available from its own sensors
- the study had a technological focus (such as specific sensor performance)

In total 12 unique simulation studies and 12 unique empirical studies were found relevant in the scope of this study. In addition, one empirical study was identified from the simulation category results, and 3 empirical studies were found from other sources, thus the numbers are 13 simulation studies and 15 field studies. Some studies combined empirical tests with simulations, by calibrating the car-following models in the real world. These are reported with the simulation studies.

Impact estimates on the indicators of interest (throughput, stability, emissions, fuel consumption or energy demand) were extracted from the simulation articles using the data provided or by estimating values from graphs (with graphreader.com) and categorised according to the corresponding time gap values and penetration rates assumed as well as the underlying car following models used. In some cases, additional information on the studies was included from additional sources, such as project reports.

2.3 | Conceptual framework

Several publications have described the relationships and impact mechanisms between automation and its impacts on traffic flow efficiency or emissions, among other impact areas [13, 20, 23, 40]. However, these frameworks are either on a general level, without going into sufficient details for traffic dynamics purposes, or focus on a single aspect of traffic dynamics, and are therefore not suitable for the purposes of this study. Consequently, a conceptual framework was developed to provide structure for capturing the holistic impacts of automation on motorway traffic operations in practice. Leaning on the work by Elefteriadou [[41], chapters 1 to 5], four categories are used to describe the traffic operations on a road: (1) Single vehicle behaviour, (2) interaction between vehicles, (3) traffic stream properties and (4) traffic stream performance. Traffic stream performance is considered to have the same meaning as the term “traffic flow efficiency and emissions”. The four categories are further described below.

Traffic dynamics result from single vehicle operations, describing the movements of several individual vehicle-driver-units and their interrelations [42]. These movements can be described by the fundamental equations of motion [41]. Vehicle characteristics differ in terms of physical dimensions, weight, powertrain, and performance, which all affect driving dynamics, in addition to environmental factors such as weather conditions. As the focus of this study is specifically on the effects of changed vehicle behaviour, that is, changes in longitudinal and lateral vehicle motion control, due to automation itself, vehicle characteristics and environmental conditions are out of the scope and considered constant. The main interest is thus on driver characteristics, which are defined here to describe the desired longitudinal and lateral motion of the vehicles, regardless of whether they are controlled by a human driver or by driving automation systems. Human drivers have different preferences related to desired speed, desired time gaps and minimum accepted gaps as well as different physical, psychological, and cognitive abilities [43, 44], and these differences lead to variance in driving behaviour such as both the desired and actually observed values of speed, acceleration, deceleration, and time gaps. With automation, the explicit or implicit settings of the driving automation systems, which have less variation, replace driver characteristics to a large extent.

Differences in driver preferences are most relevant in low traffic densities, where most vehicles are able to drive at their desired speeds and are not constrained by other vehicles. Thus, while single vehicle characteristics define the desired driving behaviour, vehicle interactions govern the actually observed driving behaviour. As the number of vehicles on the road increases, interactions between vehicles gain importance. Three basic forms of interaction are distinguished: Car following within the same lane, lane changes and gap acceptance. The latter two are interconnected in the motorway environment, where gap acceptance describes the gap between consecutive vehicles that a vehicle is willing to accept when changing lane. The car following process includes three main states: acceleration, deceleration and keeping a constant speed [45], thus it is governed by the throttle control. Car following situations can be described in terms of time gaps, speed and acceleration. Longitudinal vehicle motion control includes car following situations as well as driving without an immediately preceding vehicle on the lane (free driving).

Driving on a motorway involves uniform line sections and discontinuities. On uniform sections, driving conditions are mainly determined by the traffic demand and weather conditions, and differences in individual driving behaviour characterise traffic flow [46]. Near discontinuities, such as ramps or lane drops, more lane changes take place. Lane changes can reduce road capacity and cause disruptions due to the gap needed in the target lane and the gap left in the original lane [26]. The total number of lane changes on a motorway section depends on driver preferences as well as on the properties of the traffic in terms of speeds and speed differences, and on the available gaps between vehicles. With increased traffic density, lane change possibilities decrease due to lack of adequate time gaps and the need for lane changes decreases with more uniform speed across lanes. However, the lane change processes of human drivers are complex [47] and not yet fully understood. Indicators such as number of lane changes or amount of acceleration are rarely of interest in themselves, but they are relevant when considering traffic stream performance, as the amount of acceleration significantly affects emissions and energy demand. Traffic stream performance describes traffic flow efficiency in terms of the typical indicators of interest such as travel time, delay time and average vehicle throughput, as well as the resulting emissions or energy demand. The amount and nature of vehicle interactions determine the traffic stream properties for example in terms of the overall acceleration.

The developed framework on impacts of driving automation on a traffic stream level is presented in Figure 1. The four levels of traffic operations based on Elefteriadou [41] form the main boxes, with elements of one box influencing the elements of the following boxes. The remaining (grey) boxes represent other important factors that are out of scope of this study but need to be kept in mind when forming overall conclusions of automation on the road network. Complex feedback loops exist between all boxes. Traffic stream performance is directly affected by the elements of the other main boxes and therefore changes to all elements of the main boxes need to be considered simultaneously when studying impacts of changes in the traffic system on performance. The remaining elements affect traffic stream performance indirectly. For example, the available technology and regulation define the potential, and user acceptance and mobility patterns influence the overall traffic demand and the number of vehicles in the network.

3 | RESULTS

3.1 | Study characteristics

Two groups of studies were identified in the literature review: simulation studies and field tests. Simulations used mostly models with theoretical parameters from literature, but two studies calibrated the parameters with commercially available ACC vehicles in empirical field tests. Also, the field studies showed two distinct groups: studies concerning single equipped vehicles in naturalistic driving conditions (in the following referred to as single vehicle studies) and controlled studies examining several equipped vehicles following each other in ACC mode (referred to as vehicle string studies). An important difference in these is that single equipped studies include different types of driving situations and traffic states, including fuel-efficient free flow driving, while vehicle string studies focus only on car-following situations. Most studies focused on ACC systems and longitudinal vehicle motion. The results regarding simulation studies and field tests are elaborated in the following.

3.2 | Simulations

3.2.1 | Study characteristics

The literature search returned 13 relevant simulation studies dated between 1999 and 2021, summarised in Table 1. The studies differed in several ways, including the car following models used both for automated or ACC vehicles and manually driven vehicles as well as the simulation parameters, road layouts in terms of number of lanes and presence of ramps or other bottlenecks, traffic volumes and fleet composition and penetration rates. Studies considered motorway or highway driving with one or several lanes and used mostly fixed time gaps for AVs or ACC vehicles and manually driven vehicles (MVs). Three studies included heavy duty vehicles (HDVs). The main performance indicator used was throughput (12 studies). Two studies addressed CO_2 emissions, one addressed fuel consumption.

Three main car following models were used. The first is a linear controller designed to represent car following behaviour of ACC vehicles [14, 38, 48]. Different variations have been applied for example regarding inclusion or exclusion of the leading vehicle's length and differences in control gain values. Of the 13 simulation studies, six studies used a version of this model for ACC or automated vehicles. Eight studies used the intelligent driver model (IDM, [49]) or its enhancements, the improved IDM (IIDM, [50]) or IDM+ [51] and three studies used the Wiedemann99 model implemented in the Vissim simulation software [52]. The Wiedemann99 model and IDM

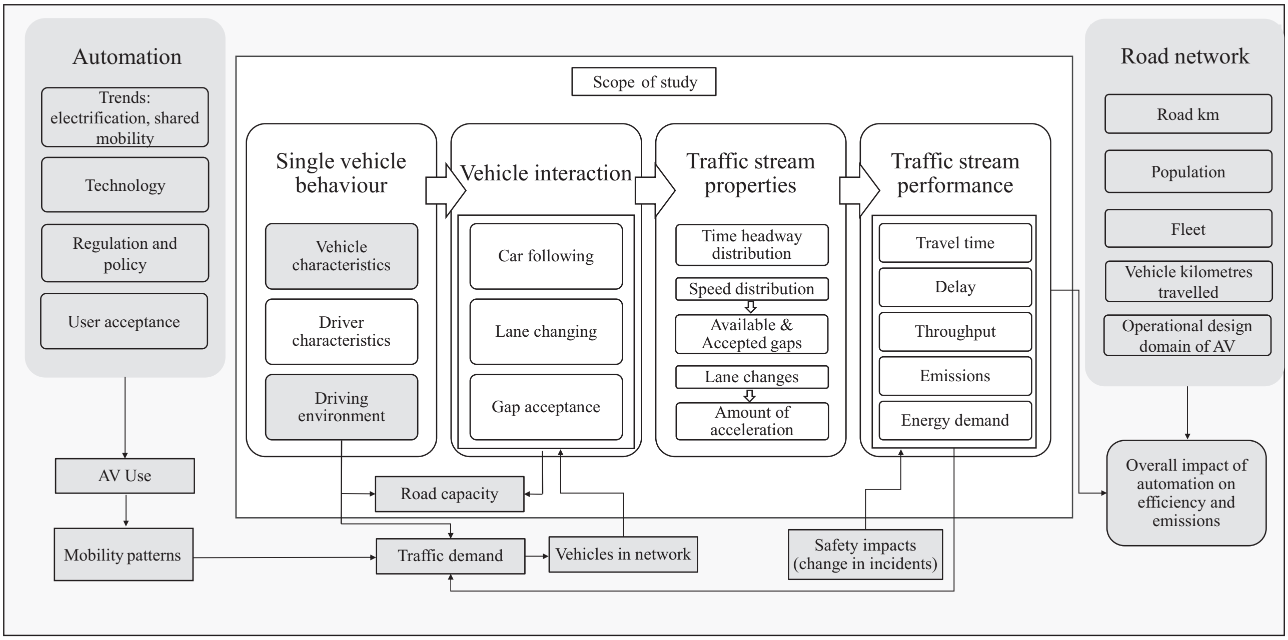

FIGURE 1 Framework for determining impacts of driving automation on a road network level and scope of study (white boxes). The four levels of traffic operations are based on Elefteriadou [41]

variants were originally developed to represent human driving behaviour. Vissim has been recently updated to better cater for automated vehicles by allowing to remove stochastic distributions in some input parameters [53], however not all studies used this new feature. Two studies conducted simulations with several models. Shang and Stern [54] studied both a theoretical controller model and a model calibrated with field tests of two commercially available controllers with both their minimum and maximum available time gap settings. James et al. [55] studied three linear ACC models and the IIDM with model parameters calibrated in field tests. These are also the only two studies using parameters fully calibrated with field tests of commercially available ACC systems.

The reviewed simulation studies were generally interested in car following behaviour of AVs or ACC vehicles and/or road capacity with human driven and automated or ACC vehicles, and thus considered mostly situations with high traffic volumes. Two studies [35, 56] simulated also lower traffic volumes. The changes in throughput were addressed in different ways. Seven studies considered maximum throughput on a road section before breakdown (named in the following capacity or C), five considered the bottleneck or queue discharge flow (named queue discharge capacity Q) and three studied other changes to throughput, for example, using empirical traffic volumes (named throughput T). Most studies used one single setting for the AV/ACC time gap in each simulation scenario. The desired gaps varied from 0.45 s to 2.1 s. Three studies ([26, 57], partly [55]) implemented a distribution of different time gaps among AVs or ACC vehicles within the same simulation. The desired time gaps of manual drivers in the models were generally in the range of 0.9–1.3 s, however not all studies reported the values they used.

3.2.2 | Throughput

The results of the simulation studies in terms of change in the throughput indicators with different time gaps and penetration rates are shown in Figure 2. To visualise the impact of increasing penetration rate, results are shown separately for the penetration rates 20–25% (low), 50–60% (medium) and 100% (full). The figure shows the percentual change of the throughput indicators (capacity C, queue discharge capacity Q and throughput T) for different desired time gaps compared to the baseline with all manual driving. A clear dependence of the change in throughput on the time gap of the ACC vehicles can be seen. Generally, throughput increases with small desired time gaps and decreases with larger desired time gaps. Larger effects, both positive and negative, are seen for larger penetration rates of ACC. Results per simulation study are shown in the Appendix.

For low penetration rates of 20–25% impacts are small. Throughputs that are high but below capacity (*T*) increase slightly (up to 8%) with a low penetration rate of AVs or ACC vehicles at all desired time gaps. Regarding capacity (*C*), a small increase (around 4%) in throughput is observed with low desired time gaps and a small decrease (around 8 %) with high time gaps. The changes in queue discharge capacity (*Q*) are negligible. With about half of the vehicles equipped (penetration rate 50–60%), larger impacts are seen. Throughputs below capacity (*T*) increase by up to 14% with low time gaps, and decrease by up to 14% with larger time gaps. Results are similar for capacity (*C*) and queue discharge capacity (*Q*), where increases of up to 20–23% are seen with small time gaps and decreases of 10–34% are seen with large time gaps. However, variation in queue discharge capacity is large. The largest effects are seen with all vehicles equipped. Throughput below capacity

TABLE 1 Overview of simulation studies. Where HDV were not mentioned in the articles, it was assumed that none were included in simulations. Throughput indicators: *C*: capacity, *Q*: queue discharge capacity, *T*: throughput. Model groups: *L*: linear ACC model, I/I+/II: IDM, IDM+, IIDM, *W*: Wiedemann99. Note that the desired time gaps in Wiedemann99 studies are slightly larger than reported as the standstill distance is not included; values between 0.4 and 2.5 m were used in the reported studies

Reference	Setup	Throughput indicator	ACC/AV model	ACC/AV time gap	MV model	MV time gap	Penetration rates (%)	HDV
[58]	two lanes, with ramps	*Q*	L	0.8, 1.0, 1.2 and 1.4 s	not specified / unclear	1.2 s	10, 20, 50, 100	10%
[59]	one lane, with ramps	*C*	L	1.0, 1.4, 1.55 and 2.0 s	not specified / unclear	1.1 s (mean)	20, 40, 60, 80, 100	-
[14]	one lane, no ramps	*C*	L	0.8, 0.9, 1.0, 1.1, 1.2, 1.5 and 2.0 s	not specified / unclear	not specified	25, 50, 75, 100	-
[26]	several, with ramps	*Q*, *C*	I+	between 0.5 and 1.9 s (calibrated) mean: 0.9 s; between 1.1 and 1.9 s (mean:1.5 s)	I+	between 0.3 and 1.9 s (calibrated) mean: 1. 1s	5, 10, 15, 20, 30, 40, 50, 60, 70, 80, 90, 100	6%
[35]	several, with ramps	-	L	1.1, 1.6 and 2.2 s	Gipps	not specified	20, 40, 60, 80, 100	9%
[60]	several, with ramps	*C*	L	1.0 s	Fritzsche	not specified	20, 40, 60, 80, 100	-
[57]	several, with ramps and lane drop	*Q*, *C*	I	between 0.8 and 2.2 s; mean 1.4 s, SD 0.3 s	I	between 0.68 and 1.67 s; mean 1.15 s, SD 0.26 s	5, 10, 20, 30, 60	-
[55]	several, no ramps or disruptions	*C*	L, II	0.9s, 1.1s*, distribution 1.1s to 2.2s (mean 1.54s*) *calibrated and non-calibrated	W	1.1 s	25, 50, 75, 100	-
[56]	several, with ramps	*T*	W	0.5 and 2.1 s (means of unspecified distribution)	W	not specified	100	-
[53]	one lane; two lanes w. ramps, two lanes w. gradient	*C*	W	0.9, 1.5 s and mix of both	W	0.9 s	10, 20, 30, 40, 50, 60, 70, 80, 90, 100	-
[61]	several, no ramps; bottleneck ahead	*Q*	II	1.0 s	II	1.3 s	10, 25, 50, 75, 90, 100	-
[62]	several, with ramps	*T*	W	0.45 and 0.9 s	W (assumed)	not specified	10, 20, 30, 40, 50, 60, 70, 80, 90, 100	-
[54]	one lane, with ramps	*Q*, *T*	I	1.5 s (theoretical) 1.0, 1.9 and 2.2 s (calibrated)	I	1.26 s	20, 40, 60, 80, 100	-

(*T*) increases by up to 26% with low time gaps and decreases by 21–39% with high time gaps. Queue discharge capacity (*Q*) shows large variation, but on average a small increase is seen at desired time gaps below 1 s and decreases of 20–30% with large time gaps. The capacity (*C*) increases on average by 10–15% with low time gaps and decreases by up to 22–40% with large desired time gaps. Absolute values for throughputs per lane per hour differ by study and throughput indicator. Values are highest for capacity throughput (*C*) and roughly similar for queue discharge capacity (*Q*) and throughput (*T*). Values decrease with desired ACC/AV time gap used.

Impacts thus depend largely on the desired time gap and penetration rate. Largest increases are seen for throughputs that are high yet below capacity (*T*), and largest decreases for capacity (*C*). With larger ACC/AV penetration, smaller time gaps are needed to achieve improvements to throughputs. In addition to the desired time gap of automated or ACC vehicles, the desired gap of manual vehicles in the model also likely plays a role in the simulation outcome. Therefore, effects were also plotted against the ratio of desired time gaps of AVs or ACC vehicles and human drivers for the studies where the desired time gap of human drivers was disclosed. No significant differences to the

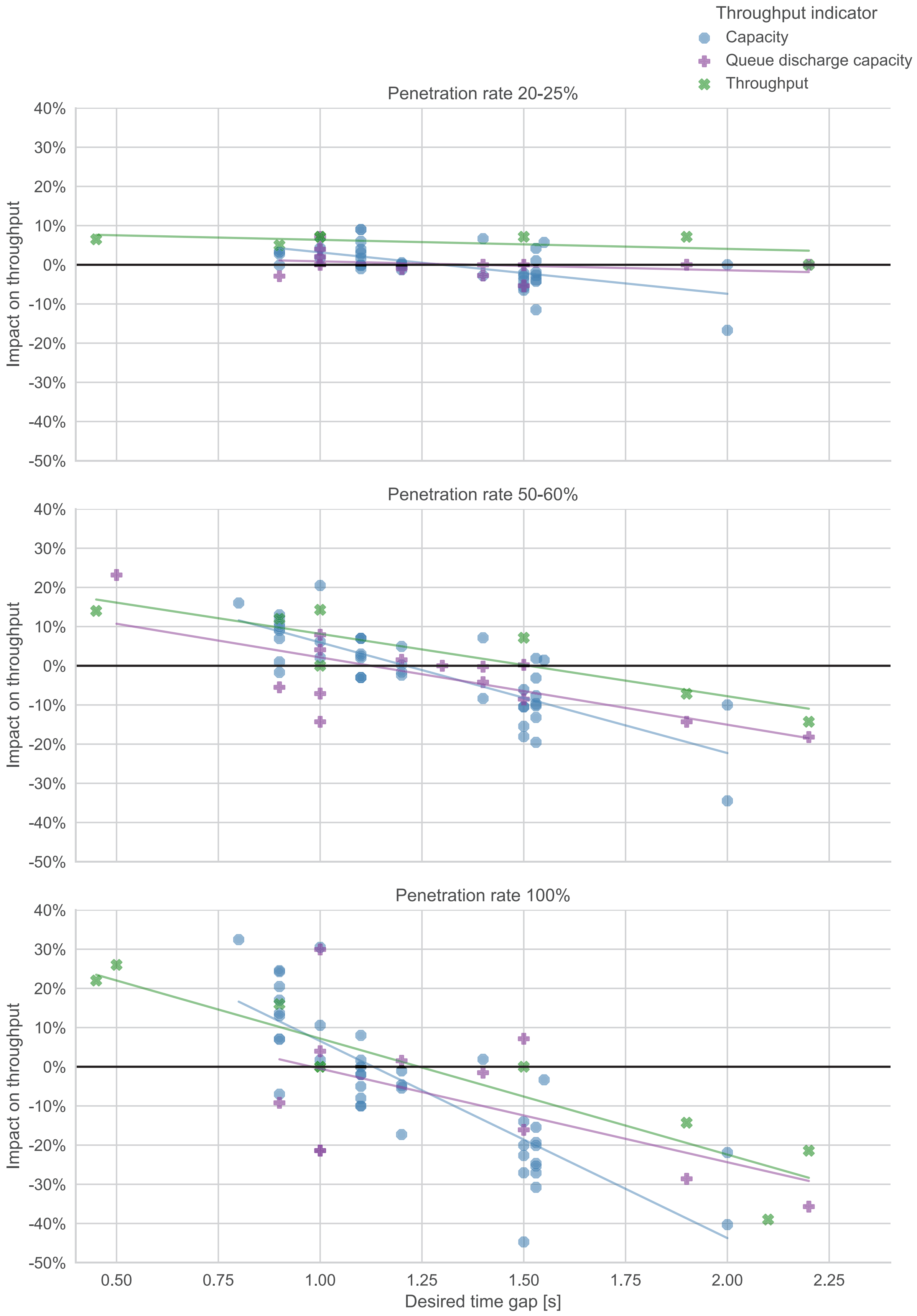

FIGURE 2 Simulation results from literature for impact on throughput by ACC/AV desired time gap with low, medium and full ACC/AV penetration, with fitted linear regression lines

reported results were found. Generally, changes in throughputs were positive with time gap ratios of 1 or below (desired gap of AV/ACC vehicles is equal to or smaller than that of manual vehicles) and negative with larger ratios, but there are exceptions in both directions. For the capacity throughput (*C*) indicator, throughput per lane increases with penetration rate when the time gap ratio is approximately 1.2 or less and decreases with larger ratios.

In the following, results are described from the different perspectives of calibrated and non-calibrated model parameters, road layouts and model types. Due to the small number of studies with similar configurations, the results are indicative only. Models with parameters calibrated with commercial ACC vehicles show generally less positive results than theoretical simulations in the medium and full penetration rates. Smaller desired time gaps are needed to achieve increases in the throughput indicators. Results are especially different for queue discharge flow, where results from simulations with non-calibrated parameters report small increases (~8%) for time gaps between 0.9 and 1.3 s and small decreases (~9%) with time gaps up to 1.5 s. However, calibrated models predict decreases of 7–18% with desired time gaps 1.0 to 2.25 s for the medium penetration rate and decreases of 21–36% for the full penetration rate. It needs to be noted that the number of studies using calibrated models is small.

Simulations using road layouts with one to four lanes without ramps show similar impacts. Only the throughput indicator capacity (*C*) was analysed in these studies. With low and medium penetration rates, capacity increases with desired time gaps of approximately 1.3 s and below. With all vehicles using driving automation systems, the desired time gap needed for improvements seems to be slightly lower for layouts with several lanes. Studies with a road layout of one lane and ramps show small increases in all throughput indicators. At low penetration rates, small increases (up to 7%) in throughput are observed. With moderate penetration rates the capacity indicator (*C*) shows increases of up to 20% with desired time gaps below 1.6 s and decreases of up to 10% above. The throughput indicator (*T*) increases by about 10% with time gaps below 1.5 s and decreases by 10% above. The queue discharge capacity (*Q*) shows decreases by about 8–14%. At full penetration, values are similar with larger values for increases (up to 30% for capacity *C*) and decreases (up to 36% for queue discharge capacity *Q*). It should be noted that in this layout, the results for capacity are mainly from non-calibrated models whereas the results for queue discharge capacity and throughput are from calibrated models. The confidence intervals are large.

Studies with road layouts of two to four lanes and ramps show similar results for all throughput indicators. A small increase (up to 7%) was found with a desired time gap below 1.2 s and small decrease (up to 6%) above with small penetration rates. With medium and full penetration rates, the capacity indicator shows significant increases (up to 26%) for desired time gaps below 1.2 s. Throughput decreases by up to 27–39% with larger time gaps. The three traffic model groups (linear ACC, IDM variants and Wiedemann 99) generally produce similar results with similar desired time gaps. Differences are largest in road layouts with ramps.

3.2.3 | Emissions, fuel consumption and travel time

Few studies were found regarding the impacts on CO_2 emissions or fuel consumption. Stogios et al. [56] studied emissions based on the vehicle trajectories from the simulations with the MOVES emissions model. They found that aggressive AVs with small desired time gaps (0.5 s) could reduce emissions by 2.6% and 26.3% per km driven in low and high traffic demand conditions respectively. For cautious AVs (desired time gap 2.1 s) emissions per km driven increased by 10.3% and 35.1%, in low and high demand respectively, due to larger gaps leading to accumulation of congestion. For aggressive AVs different penetration rates besides 100% were considered, showing that the emissions per km driven decrease approximately linearly with increasing penetration rate. Average delays decreased by 89% with aggressive AVs and increased by 230% with cautious AVs. Vehicle km driven in the network dropped by 23% with the cautious AVs, indicating that less vehicles were able to pass the network. With aggressive AVs no significant change in vehicle kilometres was observed.

Mattas et al. [35] estimated changes in CO_2 emissions with the COPERT emission model in peak hour demand as well as with 20 % less and more traffic with the desired time gap 1.6 s for AVs. At the low demand level (80% of peak hour demand) emissions decreased by about 2% with AV penetrations of 70% and above. At peak hour demand, AV penetration rates of 60% and above led to an increase of emissions by 2–6%. With the highest traffic demand (120% of peak hour demand) emissions increased by 2–11% with AV penetration rates over 35%. Emissions per km were lowest in low traffic demand with 70% or more AVs and at peak hour demand with 0–60% AVs. The authors explained the changes in emissions with changes in average speeds and the optimal speed intervals for internal combustion engine vehicles. Spiliopoulou et al. [57] studied fuel consumption and found increases of 0.4–4.0% at ACC penetration rates 5–60%, with the highest consumption at 40% penetration rate. Delays increased approximately linearly by 6–136% at penetration rates 5–60% when compared to all manual driving.

Calvert et al. [26] studied changes in travel time with two different desired time gap distributions for AVs. With the lower values (mean of distribution 0.9 s) travel times increased by 0–5.5% at penetration rates 5–80% and reduced by 25.8% at 100% penetration. With higher desired time gaps (mean of distribution 1.5 s), increases between 5% and 19% were found at penetration rates 10–90%, and a small decrease of 2% at 100% penetration rate.

TABLE 2 Overview of single vehicle ACC experiments identified from literature

Reference	Location	Focus	Participants and vehicles	Duration	Results
[67]	USA	human interaction, safety and comfort	108 volunteers, 10 vehicles	2–5 weeks	
[63]	Netherlands	impacts on traffic flow and environment	19 participants, 20 vehicles	5 months	3% decrease in FC (measured) Change in lane use, no change in average speed but more even speed distribution
[68]	Germany		140 vehicles	12 months	2.8% decrease in fuel consumption on motorways
[15]	Netherlands	traffic flow efficiency	8 participants volunteers, own vehicles, regular trips	4–5 weeks	reduction in lane changes; peaks in speed
[64]	Sweden, Gothenburg ring road	energy demand	93 vehicles, car manufacturer employees and family members	months	5–7% decrease in fuel consumption
[69]	USA	GHG emissions	51 vehicles, car manufacturer employees	62 days	1.7% decrease in fuel consumption

3.3 | Field studies

3.3.1 | Single equipped vehicles

In total, six studies reporting results from field tests with single equipped vehicles using commercial ACC systems were found. These were naturalistic driving studies with a number of equipped vehicles used by regular drivers or company employees on their daily trips during weeks or months. Car following situations thus occurred within normal driving in regular traffic and were not specifically set up.

A summary of studies and results is presented in Table 2. Results show that the chosen average time gaps in car following situations were longer in ACC mode than in manual driving. Schakel et al. [15] studied acceleration and deceleration behaviour and found that the ACC tested had higher speeds both when decelerating after a leading vehicle braked and accelerating after stops. Results further show [15, 63, 64] that the standard deviations of time gaps and accelerations were smaller (standard deviation of acceleration without ACC 0.26 and 0.29 m/s^2, with ACC 0.22 and 0.22 m/s^2 ([64] and [15], respectively). In congested conditions however the results were mixed.

Lane changes decreased by 19% in free flow and by 36% in congestion with ACC compared to manual driving in one [15] of two studies considering lane changes However, the number of participants in this study was low and the other study mentioning lane changes [63] did not observe changes in the number of lane changes with ACC enabled. Yet, Alkim et al. [63] found a change in the usage patterns of lanes such that drivers stayed longer on the left and middle lanes with ACC on compared to ACC off. The field test reported by Alkim et al. [63] was also the focus of separate studies on driving behaviour. It was found that drivers activate ACC for comfort reasons in regular, non-congested traffic situations and tend to disable the system to use shorter time gaps in dense traffic conditions [65, 66]. Four studies considered fuel consumption and reported a decrease in fuel consumption of the equipped vehicle, with decreases ranging from 1.7% to 7.0%. Schakel et al. [15] found that due to ACC accelerating faster than human drivers after leaving congestion or bottlenecks, ACC has potential to increase queue discharge rate and thus lead to faster dissipation of congestion.

3.3.2 | Vehicle string studies

Nine studies reporting results of field tests with strings of ACC vehicles were found. In some of these [70, 71], the focus was primarily on studying CACC performance, but ACC behaviour was reported for reference and the results concerning ACC are included in this study. The relevant studies involved strings of two to ten vehicles from different manufacturers with their factory equipped ACC systems following a lead vehicle driven manually or with cruise control. Six studies were conducted on public roads and three on test tracks. Different performance indicators were used. Most studies investigated the performance of following vehicles with speed perturbations of the leading vehicle, while two studies [72, 29] addressed naturalistic driving. Five studies investigating string stability of platoons found that ACC strings were string unstable, that is, perturbations of the lead vehicle (small changes in speed) were amplified with each following vehicle. In the field test by He et al. [72], three ACC vehicles were followed by a human driven vehicle, which did not aggravate the instability and was even able to reduce perturbations. Tiernan et al. [71] did not explicitly study string stability, but the results of the field test, with follower vehicles' reactions amplifying, point towards the same conclusion. Three more recent studies published in 2021 sought to explain the string instability observed with commercial ACC systems. The relevant studies are summarised in Table 3.

TABLE 3 Overview of ACC string experiments identified from literature

Reference	Setting	Study focus	Time gaps used	Results
[70]	USA, real traffic, 4 vehicles	controller performance	1.1s (smallest setting)	unstable
[71]	USA, closed track, 5 vehicles	test and evaluate platooning with prototype	1.1s (smallest setting)	delayed response
[29]	Netherlands, real traffic, 7 vehicles	effects of L2 platooning	smallest setting (varies by brand)	significantly amplified reaction by each vehicle; cut-ins of other traffic observed; considerably higher fuel consumption for last vehicle compared to first
[72]	Italy, real traffic, 3 ACC vehicles followed by MV	ACC driving behaviour, energy impact	not specified	unstable; amplifying perturbations; tractive energy demand 2.7–20.5% higher with ACC
[73]	Sweden, test track, 5 vehicles	ACC response time, string stability	minimum and maximum settings	THW variation increases with platoon; unstable; high response times of ACC (1.7 to 2.6s)
[79]	USA, real traffic, 8 vehicles	string stability	minimum gap setting	unstable, perturbations amplify
[16]	real traffic, 3 vehicles		minimum and medium settings	stability depends on headway setting, speed level, and stimulus
[76]	real traffic, 3 vehicles	tradeoffs between safety, efficiency, stability	four settings	unstable with low time gaps; tradeoff between time gap and stability
[75]	proving ground, 10 vehicles	impact on traffic flow	short, medium, long settings	string stability depends on time gap setting

Two studies examined fuel consumption. Knoop et al. [29] concluded that following vehicles in the string have higher fuel consumption, without quantifying. He et al. [72] found that the ACC vehicles' fuel consumption was 2.7–20.5% higher than that of a human driven vehicle, and the energy demand increased with each ACC vehicle in the string. High response times of ACC were reported by Makridis et al. ([73]; response times between 1.7 and 2.6 s), Li et al. ([16]; response times 1.3–1.4 s) and Tiernan et al. [71], confirmed by Lanaud et al. ([74]; mean response time 2.8 s with standard deviation of 1.6 s. Knoop et al. [29]) conducted their test of a platoon of seven vehicles on a public road and observed many cut-ins by manual vehicles despite using the smallest available ACC gaps. Li et al. [16] had to abandon tests with the highest time gap setting due to too many cut-ins, and the risk of cut-ins was high even with the medium time gap.

Studies with different vehicle makes and models [75, 76] found differences in behaviour of the respective commercial ACC controllers, indicating different design of the controllers. Differences in controllers between manufacturers have also been found by Makridis et al. [77] and Staiger and Calvert [78] who analysed results from several empirical studies. Li et al. [16] found that commercial ACC response to the leading vehicle's behaviour depends on the time gap setting, speed level and stimulus, such as the magnitude of deceleration of the leading vehicle. Amplification and overshoot by the following vehicles were higher in lower speeds.

4 | DISCUSSION

4.1 | General discussion

This study aimed to identify what is known on the likely impacts of non-connected automated driving on motorways on traffic flow efficiency and emissions, and how these impacts are formed. Results from a systematic literature review were reflected against a framework for traffic operations that helped determine the most important contributing factors and mechanisms. In short, the main finding is that not a lot is yet reliably known on the likely impacts of driving automation on overall traffic. Impacts largely depend on accurate representation of single vehicle motion as well as vehicle interactions, which both are challenging to study and model. Considering the attention directed towards automated driving and the increasing amount of research on the topic, the rather low number (28) of relevant studies on estimated impacts on motorway traffic flow efficiency and emissions is surprising. This finding confirms that interest has focused more on theoretical capabilities and technical developments than on practical traffic impacts on a network level. Simulation studies, field studies with single equipped vehicles in naturalistic driving situations and controlled field tests with strings of vehicles equipped with commercial ACC systems have been used for estimating AV impacts. Different study types are suitable for assessing different factors that affect traffic flow efficiency and emissions, and none is able to address all. Simulation studies have been focused on changes in throughput, while changes to road traffic emissions or fuel consumption of the traffic stream were considered in three studies only.

4.2 | Simulation studies

4.2.1 | Model limitations

In theory, simulations are a promising means for efficiently studying changes in traffic dynamics with increasing use of driving automation systems, as simulations allow for investigating a variety of performance indicators, both on single vehicle level and on overall traffic. However, this requires models able to: (1) Describe the movements of human-driven vehicles and vehicles equipped with driving automation, (2) the differences in behaviour or motion of different humans and different AVs or ACC equipped vehicles, as well as (3) the interactions between vehicles in free flow, car following and lane change situations. Although many of the existing traffic models can fairly accurately reproduce overall traffic flow characteristics, they do not necessarily accurately describe the dynamics of single vehicles [80]. In fact, most existing car following models produce ideal, collision free driving behaviour without sufficient consideration of the variation in human capabilities and preferences as well as variation in driving conditions [81, 77, 44], and thus practically represent automated vehicles better than human-driven vehicles. Current models lack detail to sufficiently describe the longitudinal and lateral response of human drivers in mixed traffic with vehicles equipped with driving automation systems [26, 5], and it is in fact not yet known how driving behaviour of human drivers might change over time when a significant share of vehicles are AVs. However, the responses of human drivers will affect the impacts of AVs on traffic flow efficiency. Models with better consideration for human factors are therefore needed [5, 25] to be able to capture the differences between AV and human driving behaviour and, with that, the impacts on traffic flow efficiency and emissions. Thus, although many studies have provided estimates on traffic stream performance indicators, such as changes in throughput and emissions with increasing automation, the results need to be interpreted with caution as the lower levels of the traffic operations framework, namely driver characteristics and vehicle interaction, are not necessarily depicted with sufficient accuracy in the underlying models.

Further, distinction is necessary between studies on theoretical or hypothetical models for how ACC or AVs should behave ideally [54] and studies, which try to estimate the likely impact of AVs on traffic flow efficiency or emissions. Results of single studies should not be directly compared, nor generalised, but must be considered within their specific context, assumptions and limitations. Unfortunately, this consideration is rarely made, and assumptions are not always specified. A related challenge is the fact that vehicle manufacturers are developing their own proprietary controllers for ACC systems and AVs, the logics of which are not publicly known. Therefore, traffic simulation studies reported in available literature have mostly been carried out with theoretical ACC models, or by adjusting parameters of existing car following and lane change models developed to represent human driven vehicles. Moreover, the variations in models and contexts applied in simulation studies complicate distinguishing the effect of automation from differences between models, as the number of relevant studies is low.

Most simulation studies consider rather homogeneous behaviour of the ACC or automated vehicles, with one type of controller implemented for each vehicle type. Considering the difference in liability between driver assistance systems (SAE L1–2) where drivers are responsible for safe completion of the dynamic driving task and automated driving (SAE L3–5) where the manufacturer is responsible, it is indeed not likely that drivers can choose the desired time gaps in the same way as they can in current ACC systems [53]. Different car manufacturers may however implement different settings, as shown in field studies with commercial ACC systems of several vehicle manufacturers [75, 76]. Therefore, heterogeneous driving behaviour may prevail even if all vehicles were automated. Further, the presence of other vehicle types such as heavy vehicles is rarely considered, although it adds to the heterogeneity of driving behaviours, especially speed differences, and influences traffic dynamics. In addition to the deficiencies of car following models, significant uncertainties exist in realistically modelling lane changes even with human drivers [26], and the lane change behaviour of AVs is not yet known and thus cannot be modelled accurately [5]. Generally, similar parameters are currently used for modelling lane change behaviour of AVs and human drivers [21]. However, there is reason to believe AVs will be more cautious to change lanes than human drivers, as they are expected to keep required gaps, which makes lane changes challenging in higher traffic volumes [82]. Further, AVs are not likely to force gaps and rely on other drivers to give way, as is common for human drivers. The consequences of the differences in lane change behaviour on traffic flow efficiency are not yet known [26], but efficiency may deteriorate for example in bottleneck situations where lane changes are required [35]. This suggests that results based on ACC studies in terms of throughput at merging areas and bottlenecks are likely too optimistic. In addition, existing lane change models consider only the equipped vehicle and do not account for the impact of lane changes on other vehicles [83].

4.2.2 | Time gaps and string stability

The time gap to the vehicle in front determines the amount of time available for a following vehicle to react to any changes to the behaviour of the preceding vehicle and is thus related to the reaction and response times of drivers and vehicles. In contrast to human drivers with reaction and response times commonly assumed in the order of 1 s [50], it is often expected that driving automation systems are able to react almost instantly with negligible response times [84, 11], an assumption used to justify the small desired time gaps of AVs and ACC vehicles in simulations.

The literature review on simulation studies found a negative linear relationship between ACC and AV time gaps and traffic throughput, with benefits to throughput occurring mostly at time gaps below 1.2 s when compared to the baseline case of no automation. However, these time gaps do not seem realistic for AVs at least in the near to medium term, for the following reasons. It has been shown that the minimum time gap for platoons of CACC vehicles in ideal conditions is 0.6 s [70, 5]. As ideal conditions do not exist in the real world where disturbances such as wind and uneven road surfaces are always present, and also possible communication errors need to be accounted for [5], even this value is likely to be larger in practice. In contrast to CACC, which allows for anticipation of events ahead through communication between vehicles, the control of ACC vehicles and AVs is feedback-based, and the future behaviour of the vehicle in front is not known. This implies that decisions on the future movements of the equipped vehicle are made based on the situation in the past [85], and a sufficient safety buffer to the vehicle in front is needed to prevent collisions even in the case that the preceding vehicle would suddenly come to a halt. Therefore, time gaps required by ACC vehicles and AVs are significantly larger than the theoretical minimum for CACC in ideal conditions. Another reason to expect relatively large time gaps for AVs are the recently formed recommendations by The United Nations Economic Commission for Europe [86] for Automated Lane Keeping Systems, which control the lateral and longitudinal vehicle motion for extended periods without further driver command, for the low-speed range (up to 60 km/h). Their recommended time gap increases with speed, and at 60 km/h the recommended minimum time gap is 1.6 s. While no recommendations yet exist for motorway speeds, it is in this light not likely for the recommended time gap for higher speeds to be lower. The value of 1.6 s is also better in line with the time gaps observed in commercial ACC systems than those in the theoretical models.

Further, as regards the benefits to throughput found in simulations with ACC/AV desired time gaps less than 1.2 s, it needs to be considered that 1.2 s is also close to the average desired time gap of the human driver models used in the simulations. Thus, it is in theory evident that with lower gaps more vehicles fit on the road. However, in reality it is not as straight forward due to string stability, an aggregate level characteristic arising from the behaviour of individual vehicles [54]. If small perturbations of a leading vehicle are amplified with each following vehicle, the string of vehicles shows unstable behaviour, leading to increased accelerations and decelerations and a decrease in road capacity, especially in congested conditions [54]. The fact that all the different commercial ACC controllers in vehicle string tests showed string unstable behaviour with low time gap settings is remarkable, when compared to theoretical ACC/AV benefits from literature. The string unstable behaviour indicates that ACC vehicles are not as good at reproducing driving style of the preceding vehicle than human drivers are, as they show larger reactions than humans for example when decelerating [87, 29]. In fact, the models used to describe ACC vehicle motion in simulation studies are usually designed to be string stable in the first place, as this is assumed to be a requirement for ACC systems, and are thus not able to reproduce the increases in braking and accelerating with each vehicle along the string. With low desired time gaps for AVs and ACC vehicles, simulation studies find that throughput increases with penetration rate. The finding that commercial ACC controllers are string unstable highlights a large contrast between the empirical findings and this assumption of simulations.

Attempts to explain the string instability of commercial ACC systems have recently been made by Zhou et al. [88] and Shi and Li [76]. Zhou et al. [88] found, based on study of an open source ACC system, that the gap between theory and practice of string stability of ACC platoons arises from the assumption of perfect performance of the lower level controller in the ACC system. Simulation studies usually omit the details of lower-level controllers that implement the acceleration calculated with the car following model by the upper-level controllers, and an immediate response of the vehicle is assumed. However, in reality the lower-level controllers have response delays leading to larger response times [88]. Two recent studies [75, 76] found that time gaps needed to absorb overshoots in ACC control are significantly larger than the minimum settings of commercial ACC systems. These overshoots describe to what extent the ACC vehicle's speed exceeds the leading vehicle speed when accelerating [16] and they arise from the response delays of the ACC systems [89] as well as the uncertainty of the leading vehicle's movements [76]. It was found that the overshoot is larger in low speeds, and therefore the time gap needed in low speed conditions is higher than at high speeds [76]. Human drivers on the other hand can anticipate speed changes of the preceding vehicles, and perturbations are absorbed instead of reinforced [77]. These findings are opposite to what has been assumed in many simulation studies, namely ACC being able to balance unstable human driving behaviour [90]. In addition, large time gaps may be partly implemented on purpose by manufacturers for comfort reasons and to avoid drivers disabling ACC if it responds too swiftly [10, 76]. However, these gaps are not long enough to guarantee string stability, as very large gaps would likely result in an inferior driving experience for example due to increased cut-ins [76].

To ensure string stable controllers, time gaps significantly larger than those currently used in simulations are likely needed (as high as 4–5 s estimated by [76]). Ciuffo et al. [75] suggest that a compromise could be found for a time gap which can provide sufficiently stable traffic while not deteriorating traffic flow efficiency too much. However, even this compromise time gap will be significantly larger than the minimum setting, and large enough to cause cut-ins by human driven vehicles, which in turn cause disruption to traffic. Therefore, this compromise time gap is likely not feasible at least before a sufficiently large penetration is achieved. With high penetrations the high gaps are likely to lead to congestion in peak times due to the decreased capacity.

4.3 | Field studies

Field tests enable studying the actual performance of equipped vehicles in a realistic environment and may provide more reliable results regarding car following behaviour, but are cost and labour intensive to arrange [77]. In single vehicle field tests, ACC systems are used in everyday driving of test participants over a prolonged period of time. Studies found that standard deviations of time gaps and accelerations were smaller with ACC on, confirming the general expectation that automated vehicles are, under stable traffic conditions, able to maintain their speed more accurately than manual vehicles, which leads to smoother driving and more homogeneous time gaps by the ACC vehicles. However, reactions to even small perturbations downstream can be inefficient and lead to unstable behaviour [77]. ACC equipped vehicles in single vehicle field tests had 2–7% fewer emissions when driving in ACC mode than in manual mode, but lane changes as well as impacts on other vehicles were out of the scope of these studies and no overall conclusions can be made. As pointed out by Knoop et al. [29], single field experiments are useful for the development of individual AVs, but cannot provide insights on the impacts on the collective traffic system. Rather, the objective in single studies is mostly to study the impacts that ACC has on the single equipped vehicle, in terms of the time gap, speed, acceleration and their differences between manual driving (ACC off) and driving with ACC activated. Vehicle string field studies allow for studying the car following performance of several equipped vehicles following each other. Here the environment is usually controlled, with some tests performed on real roads. Also, these studies produce results only for the car-following behaviour in strings of equipped vehicles. Vehicle string studies have been conducted to study the real-world behaviour of theoretical ACC controllers used in simulations and more recently also to investigate the performance of commercially available ACC vehicles.

The field test by Schakel et al. [15] indicated that ACC equipped vehicles may perform less lane changes than human driven vehicles, but lane changes by other vehicles were not studied. The implications are difficult to assess, as they depend on the actions taken by the human drivers, of which not enough is yet known. Human drivers may be induced to overtake the AVs in order to keep a higher speed, and the larger time gaps by AVs may invite other vehicles to cut in in front of them, as observed in some of the field tests [16]. Lane changes cause disturbance to traffic and cut-ins can cause AVs to slow down considerably in order to regain the desired headway. Consequently, acceleration is needed afterward to reach again the desired speeds.

4.4 | Expected impacts

The complexity of the real-world traffic system together with the inadequacies of simulation models and the uncertainties related to future AV behaviour hinder drawing definite conclusions on traffic flow efficiency and emissions with increasing driving automation. Overall traffic impacts are likely to depend on the traffic state of the network. Benefits are possible in low traffic volumes, where impacts are determined by individual driver characteristics, including preferred speed and time gap and smoothness of throttle control. According to the European Transport Safety Council [91], between 23% and 59% of observed vehicle speeds on motorways currently exceed the speed limit in the 14 European countries included. As automated vehicles are expected to obey the speed limit when the driver is not responsible for driving, a considerable decrease of average speeds is possible for equipped vehicles at low traffic volumes, inducing a decrease in emissions. For traffic flow efficiency, longer travel times due to a lower average speed in theory means a deterioration, however it is questionable whether increases in travel time due to adherence to the speed limit should be considered delay [92]. Further, with increased homogeneity of traffic and decreased speed differences, the travel time reliability may improve. The findings highlight the significance of the non-ideal conditions inevitably faced in the real world and often ignored in simulation studies where simplifications are necessary. Due to differences in vehicle and driver characteristics as well as small irregularities in external conditions, there are always causes for even small perturbations in vehicle motion, which can be amplified by following vehicles.

Lower average speeds can decrease energy demand and emissions of vehicles with driving automation systems in low traffic volumes. Field tests with single ACC equipped vehicles showed small reduction of emissions (2–7%). While most studies did not mention driving speed, one found that speeds with ACC on were on average 5 km/h above the speed limit. Therefore, the potential for emission reductions is larger with AVs obeying speed limits. Field tests by Mahdinia et al. [93] showed that when following automated vehicles compared to following manual vehicles, human drivers adapted their driving behaviour to that of the AV. Speeds and accelerations reduced, and the human driven vehicles consumed about 10% less fuel and caused 4% less emissions when following AVs compared to following other human drivers. More homogeneous flow may thus provide benefits in fuel consumption also for the non-equipped vehicles. It should be noted however that drivers in this study were instructed to follow the leading vehicle and did not have the possibility to overtake. In naturalistic ACC field tests, Schakel et al. [15] found that ACC vehicles were less likely to cause disturbances compared to human drivers, however the string stability of ACC was not assessed. Comparing results of four experiments, Makridis et al. [77] found that commercial ACC systems showed lower speed variation and more homogeneous time gap distributions compared to human driven vehicles. However, even small disturbances could lead to large decelerations of the ACC vehicles due to the lack of anticipation of downstream conditions [77], potentially causing shockwaves upstream. Li et al. [16] found that in steady-state driving during periods of 10–15 s, the magnitude of oscillations and overshoot by the ACC vehicles was much smaller than in situations with fast changes in speed. The field test by Ciuffo et al. [75] found that with a longer platoon of vehicles and longer duration of the situation, small perturbations in leading vehicle speed caused only by road geometry (small uphill gradient) can lead to stop and go traffic with instable platoons.

These results indicate that uncertainties in estimated impacts increase with traffic volume, as the interactions between vehicles become predominant. It is likely that AVs will have rather large desired time gaps, which by itself indicates a smaller road capacity. At small AV penetration rates, a small increase in the order of 5% of throughput below capacity and of queue discharge capacity are possible with desired time gaps larger than 1.5 s, as indicated by simulations with theoretical as well as those with calibrated parameters. With medium and large penetration rates, decreases in capacity are more likely with these time gaps. Simulations with theoretical parameters point to a small increase (about 8%) in throughput, while both calibrated and theoretical simulations indicate substantial decreases in queue discharge flow and road capacity (in the order of 5–10% in medium penetration rate and up to 20–30% with a homogeneous fleet of automated passenger cars). Also, the results of field experiments with strings of commercial ACC vehicles point to decreased capacity due to string instability of the controllers, as well as to a substantial increase in CO_2 emissions of equipped vehicles. The results from the simulation studies addressing CO_2 emissions also point towards increases in emissions of up to 35%, with a small reduction (2%) possible in lower traffic volumes.

There is indication that automation may improve the dissipation of congestion. Human drivers tend to be less attentive when accelerating than when decelerating, leading to larger gaps between vehicles and a decrease in capacity compared to the flow before breakdown. AVs or ACC vehicles may accelerate faster with smaller time gaps, as observed in the field test by Schakel et al. [15]. Therefore, if most controllers were set up this way, automation could help with dissolvement of traffic jams. However, results of simulation studies with calibrated parameters indicated that current commercial ACC systems are slower in acceleration than the manual vehicles in the simulations. Possibly the less attentive behaviour of human drivers when accelerating after congestion is not captured in the current driver models, leading to more fluent behaviour in simulations than in reality. On the other hand, the acceleration of some commercial ACC systems may be slower than in the field test by Schakel et al. [15]. Research is needed to investigate the reasons.

Returning to the conceptual framework in Figure 1, the literature review showed that only parts of the four categories defining traffic operations—single vehicle behaviour, vehicle interaction, traffic stream properties and traffic stream performance—are addressed with current studies. Field studies mainly provide insights on car following of AVs or ACC vehicles, with some indication of lane change behaviour provided. Simulation studies address all parts of the framework and include non-automated vehicles, but results are conditional on assumptions of the interactions between vehicles and model capabilities. In summary, the present study highlighted that due to the uncertainties and limitations of current literature, the changes in vehicle interactions and the resulting amount of acceleration in the traffic flow with the introduction of AVs are unknown, and consequently, changes on traffic flow efficiency and emissions are difficult to estimate.

Finally, in order to make conclusions on the overall impacts of AVs on motorway traffic flow efficiency and emissions, the field of potential needs to be considered: The proportion of driving on motorways or other roads where the automated system can operate, the proportion of time that automation can be used (fair weather conditions), and the proportion of time it is actually used, in case the driver can turn it off. Thus, to make conclusions on network level impacts, those factors should be studied in future work. More research is further needed to capture the potential impacts of automation in real traffic conditions. Due to the differences in traffic models, road layouts, traffic composition and performance indicators considered in current simulation studies, it is not easy to distinguish the effect of automation from the potential influence of these other differences between the studies.

4.5 | Policy implications and recommendations

Traffic flow efficiency has not traditionally been attributed a responsibility of vehicle manufacturers, but with increasing automation, the objectives of the automated driving systems call for consideration as well. The vehicle motion of AVs is not an inherent property, but AV controllers aim to optimise the vehicle's response according to some predefined control objective, such as safety or fuel efficiency. But these objectives and the criteria applied in current vehicles are not publicly declared [5]. For example, Makridis et al. [10] showed that commercial ACC controllers emphasise comfort and safety over traffic flow efficiency more than is assumed in models, and a rather cautious driving style was observed. This is plausible, as vehicle manufacturers primarily aim for systems adding to the selling qualities of their vehicles, while fulfilling traffic efficiency objectives has been the role of road operators and public authorities [94]. As formulated by Li [85], traffic instabilities (such as stop and go) are not easily attributed to one's own vehicle's behaviour, but rather to the behaviour of vehicles downstream. Therefore, manufacturers may be inclined to incorporate (lower) time gap settings as desired by customers rather than optimising for string stability. The lack of common standards for dynamic response of ACC vehicles and AVs means that different manufacturers apply different control objectives adjusted to their customers' preferences [5, 38], likely maximising comfort [78]. This heterogeneity in vehicle behaviour needs to be considered even in the case that all vehicles were automated [76]. A trade-off between the different objectives of road safety, driver comfort and traffic flow efficiency has been shown [76, 85]. So far, efficiency has not played a role in legal requirements for ACC systems or AVs. For example, no requirements to date exist related to string stability or traffic flow efficiency for ACC vehicles or AVs [75]. Yet due to the changes in driving behaviour that automation induces, there will be consequences for traffic flow efficiency and emissions as well. Mostly focused on ensuring safety, a stronger role of policy makers has recently been encouraged to avoid negative impacts of automation on traffic flow efficiency [75]. The results of this study support the recommendations of others [4, 23, 75] in that more differentiated discussion is needed to be able to achieve the envisioned benefits, for example regarding the tradeoffs between safety and efficiency and the implications of cautious AV behaviour in high traffic volumes. Gaps in knowledge concerning the reactions of human drivers to AVs as well as the fundamental flaws of the traffic models should be addressed so that more definite conclusions can be drawn and recommendations on the deployment of AVs made.

To facilitate differentiated discussion, the scope and assumptions of simulations should be clearly stated and discussed in publications. Driving automation systems comprise a variety of different functionalities from supporting the driver in restricted situations with keeping a certain speed and distance to a vehicle in front, to completely driverless vehicles transporting their passengers comfortably to any destination of choice. Within these functionalities, the driving behaviour can vary from cautious to aggressive. Further, the way AV operation and traffic management in general is organised, for example, with or without V2V or V2I, is relevant. Therefore, the type of automation considered, the driver models used and the assumptions made both in terms of the vehicle (main differences in driving behaviour of AVs and MVs at least in terms of desired speeds, time gaps and acceleration), infrastructure (type of road, speed limit) and traffic conditions (traffic volumes and vehicle types) should be made explicit in all publications and discussion.

4.6 | Limitations

This study has the following limitations. First, potential impacts of AVs have mostly been inferred from studies on the driver support system ACC. With the fundamental difference in responsibility for the dynamic driving task lying with the manufacturer when the automation is activated, liability is an important issue for manufacturers, who dedicate considerable effort on safe operation [33]. This implies that in contrast to most human drivers, AVs are expected to obey traffic rules and adhere to speed limits. It may be argued that sensors and algorithms will be further enhanced before more sophisticated automation systems such as the motorway function considered as reference in this study are introduced. What concerns the vehicle operations themselves however, the controllers determining the longitudinal vehicle motion are not necessarily significantly affected by this liability difference, and certain limitations due to physical laws of motion, for example regarding required braking distances of vehicles, are difficult to overcome even with improved technology. Anticipative and flexible driving behaviour is challenging to implement into AVs without communication abilities. As there is indication that ACC systems are purposefully more cautious than necessary [10], it is possible that manufacturers increase their interest in traffic flow efficiency impacts of the controllers in the long run, if with increasing penetration rate negative impacts on capacity start influencing user acceptance, but this is not likely to happen in the short term. Without policy intervention, manufacturers are likely to continue designing their products from the standpoint of appealing to their customers instead of optimal network performance [85]. For these reasons it is considered feasible to make inferences from ACC driving behaviour, as long as no better information is available.

Second, the study focuses only on situations inside the ODD of automation. Impacts caused by the transition of control between a human and the ADS as well as potential behavioural adaptation by drivers when outside of the ODD are out of scope. Authority transitions can significantly influence the driving dynamics of AVs, for example by driving at slower speeds during the transition phase. Varotto et al. [95] found in a simulator study that authority transitions between ACC and manual driving could even mitigate the expected benefits of ACC on traffic flow efficiency and lead to increased instability of traffic and congestion. In a controlled road experiment with 23 participants, Varotto et al. [96] found significant decreases in speed (decrease of 10.5 km/h over 4 s in high traffic volumes) after ACC deactivation, as well as significant increases in speed after overruling of ACC by the driver. This can lead to string instability at high penetration rates and negative impacts on capacity. In case the driver does not take over when requested, the vehicle may need to do a minimal risk manoeuvre and reduce speed significantly or stop, which would likely have more profound consequences for following vehicles.

Third, it is assumed that automation is used whenever possible. It is likely that at least in the near-term, AV drivers are able to take over control of the dynamic driving task at their preference. If AV driving behaviour is considered annoying or insufficient by drivers, or if they wish to drive faster than the speed limit allows, they may choose to disengage the automation and drive manually. In the field test by Schakel et al. [15], drivers tended to disable ACC in congested traffic. At higher penetration rates of automation (or with rigorous enforcement), human drivers may be more inclined to content with driving at the lower average speed of the flow [97], as speed choices are directly related to the speeds of other vehicles on the road [98]. Fourth, as the study considers only direct impacts due to driving dynamics, changes in amount of travel and mode choice are not included. Increased driving comfort may lead to increased travelling with personal vehicles [99], which has implications on traffic flow efficiency and emissions.

5 | CONCLUSION

While the reviewed simulation studies provide valuable insights within their respective contexts, their results cannot necessarily be interpreted as likely impacts of automation in the real world. The simplifications in vehicle fleets as well as the lack of reliable driver models make the validity of results in the real world uncertain. To summarise, present studies concluding benefits for traffic flow efficiency and emissions with increasing driving automation are optimistic for the following reasons. Current approaches are simplified in many ways and lack sufficient detail to model both human driven vehicles and vehicles with driving automation systems, as well as their interactions. First, the implemented driving behaviour is typically narrow and can at best describe the behaviour of very experienced and alert drivers or perfectly working automation. Studies mostly assume that time gaps as low as, and even lower than, the minimum time gaps of current ACC systems can be used by future AVs. This is unlikely, due to the fundamental difference in liability between ACC systems and higher levels of automation, as elaborated earlier. There is consensus in the research community that low time gaps with high automation can only be reached with V2V connectivity. Another common reasoning for short time gaps is the assumption of low response times of the controllers, which has been found not to apply to currently available commercial ACC systems. Simulations with longer time gaps in the order of what is expected to be the minimum legal requirement (1.6 s) point to significant decrease in throughput.

Second, modelling efforts are mostly concerned with longitudinal vehicle motion only. In the simulations, AVs are assumed to have the same lane change behaviour as human drivers, although AVs will likely be more cautious than humans when changing lanes. The lack of adequate lane changing models for human drivers as well as the lack of knowledge on lane change behaviour of AVs likely leads to overestimation of traffic flow efficiency in simulations. Third, simulations consider a limited range of vehicle types and road environments. Heavy vehicles are often excluded, although they have considerable impact on the traffic dynamics due to their lower speeds and slower acceleration. The same underlying driving dynamics are assumed for all ACC vehicles or AVs, and different ACC controller designs are not considered. Road environments in simulations are often simplified in terms of number of lanes, bottlenecks and road gradients considered. Impacts are mostly assessed for high traffic volume situations only. Little is known on the behaviour of manual vehicles in presence of AVs. Simulation studies on AV and ACC impacts on traffic flow efficiency use different models, environments and assumptions and consider a limited range of vehicles and driving behaviours. In reality, however, it is likely that AV driving behaviour will vary with manufacturers and possibly user preferences and interactions, while a variety of manual drivers with different characteristics and driving skills will be present for a long time.

These factors point to conclude that although variance in driving behaviour may be smaller with high penetrations of AVs, it will not be homogeneous, and results from studies with homogeneous vehicles and driving behaviour should be considered with care. While the aim of the studies with limited assumptions may have been to demonstrate what is possible if the systems and conditions were optimised for traffic flow efficiency, these limitations (and their implications in terms of tradeoffs with safety and comfort) are not sufficiently considered when these potential impacts are further cited and discussed.

Considering the results of the literature review in light of the conceptual framework provided in Figure 1, only indicative remarks can be made on the potential impacts of automation on traffic flow efficiency and emissions. Benefits are possible for equipped vehicles in low traffic volumes, where the overall impact on traffic is likely small. In high traffic volumes, impacts on traffic flow efficiency are likely negative with increasing AV penetration rate. Impacts largely depend on the actions of human drivers, the AV penetration rate and the implementation of AV controllers. If longitudinal vehicle motion control of AVs is implemented similarly to currently available ACC systems, the conditions in road segments prone to disturbances will likely deteriorate [16]. While benefits in form of more stable traffic are possible in theory, these are likely not achieved in practice, due to the lack of ideal conditions in real traffic, and AVs may induce more congestion in high traffic volumes and penetration rates.

In conclusion, many uncertainties regarding the implementation of driving automation, existing driver models as well as differences in approaches and assumptions of simulation studies inhibit forming reliable estimates on the likely impacts of non-connected automated passenger cars on traffic flow efficiency and emissions. Although simulation studies have indicated benefits, they have made several assumptions which do not seem feasible in the near to medium term, and results are influenced by simplifications related to drivers, vehicles and the road environments considered. Uncertainties prevail in terms of the implementation of AVs and the response of human drivers both within the vehicles and in other, non-equipped vehicles. Results of field experiments and simulations with parameters calibrated in the field suggest deterioration of traffic flow efficiency due to a tradeoff with safety, which has priority in controller design. Research has focused on the single-vehicle perspective of equipped vehicles rather than the implications on the collective traffic system. The underlying behaviour of single vehicles as well as the interactions between vehicles are important when considering impacts on traffic flow efficiency and emissions, but their estimation and representation are challenging with the knowledge and tools currently available. Therefore, the overall implications of driving automation on traffic flow efficiency and emissions are still unclear. More nuanced discussion and interpretation of the published literature is needed.

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CONFLICT OF INTEREST

The author declares no conflict of interest.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analysed in this study.

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REFERENCES

1. Alonso Raposo, M. (Ed.), Ciuffo, B. (Ed.), Ardente, F., Aurambout, J-P., Baldini, G., Braun, R., Christidis, P., Christodoulou, A., Duboz, A., Felici, S., Ferragut, J., Georgakaki, A., Gkoumas, K., Grosso, M., Iglesias, M., Julea, A., Krause, J., Martens, B., Mathieux, F., Menzel, G., Mondello, S., Navajas Cawood, E., Pekár, F., Raileanu, I-C., Scholz, H., Tamba, M., Tsakalidis, A., van Balen, M., Vandecasteele, I.: The future of road transport - Implications of automated, connected, low-carbon and shared

mobility. EUR 29748 EN, Publications Office of the European Union. European Commission, Luxembourg (2019)

2. Bellis, R., Davis, S., McCahill, C., Sundquist, E., Mangan, E., Osborne, B.: The congestion con: How more lanes and more money equals more traffic. Smart Growth America, Washington, DC (2020)
3. Reed, T.: Inrix global traffic scorecard. Inrix Res. 2019, p. 2 (2019)
4. Cohen, T., Cavoli, C.: Automated vehicles: Exploring possible consequences of government (non) intervention for congestion and accessibility. Transp. Rev. 39(1), 129–151 (2019). https://doi.org/10.1080/01441647.2018.1524401
5. Yu, H., Jiang, R., He, Z., Zheng, Z., Li, L., Liu, R., Chen, X.: Automated vehicle-involved traffic flow studies: A survey of assumptions, models, speculations, and perspectives. Transp. Res. Part C: Emerging Technol. 127, 103101 (2021). https://doi.org/10.1016/j.trc.2021.103101
6. ACEA: Vehicles in use – Europe 2019. European Automobile Manufacturers Association (2019). https://www.acea.auto/files/ACEA_Report_Vehicles_in_useEurope_2019–1.pdf. Accessed 25 March 2021.
7. Faisal, A., Yigitcanlar, T., Kamruzzaman, M., Paz, A.: Mapping two decades of autonomous vehicle research: A systematic scientometric analysis. J. Urban Technol. 28, 45–74 (2020). https://doi.org/10.1080/10630732.2020.1780868
8. Shladover, S.E.: Connected and automated vehicle systems: Introduction and overview. J. Intell. Transp. Syst. Technol. Plann. Oper. 22(3), 190–200 (2018). https://doi.org/10.1080/15472450.2017.1336053
9. Vahidi, A., Sciarretta, A.: Energy saving potentials of connected and automated vehicles. Transp. Res. Part C: Emerging Technol. 95, 822–843 (2018). https://doi.org/10.1016/j.trc.2018.09.001
10. Makridis, M., Mattas, K., Ciuffo, B.: Response time and time headway of an adaptive cruise control. An empirical characterization and potential impacts on road capacity. IEEE Trans. Intell. Transp. Syst. 21(4), 1677–1686 (2020)
11. Mahmassani, H.S.: 50th Anniversary invited article autonomous vehicles and connected vehicle systems: Flow and operations considerations. Transp. Sci. 50(4), 1140–1162 (2016). https://doi.org/10.1287/trsc.2016.0712
12. Lee, J., Kockelman, K.M.: Energy implications of self-driving vehicles. In: *98th Annual Meeting of the Transportation Research Board in Washington, DC.* Washington, DC (2019)
13. Hoogendoorn, R., van Arem, B., Hoogendoorn, S.: Automated driving, traffic flow efficiency, and human factors: Literature review. Transp. Res. Rec. 2422(1), 113–120 (2014). https://doi.org/10.3141/2422-13
14. Ntousakis, I.A., Nikolos, I.K., Papageorgiou, M.: On microscopic modelling of adaptive cruise control systems. Transp. Res. Procedia. 6, 111–127 (2015). https://doi.org/10.1016/j.trpro.2015.03.010
15. Schakel, W.J., Gorter, C.M., De Winter, J.C.F., Van Arem, B.: Driving characteristics and adaptive cruise control-A naturalistic driving study. IEEE Intell. Transp. Syst. Mag. 9(2), 17–24 (2017). https://doi.org/10.1109/MITS.2017.2666582
16. Li, T., Chen, D., Zhou, H., Laval, J., Xie, Y.: Car-following behavior characteristics of adaptive cruise control vehicles based on empirical experiments. Transp. Res. Part B: Methodol. 147, 67–91 (2021). https://doi.org/10.1016/j.trb.2021.03.003
17. ERTRAC: Connected Automated Driving Roadmap. ERTRAC Working Group “Connectivity and Automated Driving". Brussels, Belgium (2019)
18. Wadud, Z., MacKenzie, D., Leiby, P.: Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles. Transp. Res. Part A: Policy Pract. 86, 1–18 (2016). https://doi.org/10.1016/j.tra.2015.12.001
19. Milakis, D., Van Arem, B., Van Wee, B.: Policy and society related implications of automated driving: A review of literature and directions for future research. J. Intell. Transp. Syst. Technol. Plann. Oper. 21(4), 324–348 (2017). https://doi.org/10.1080/15472450.2017.1291351
20. Taiebat, M., Brown, A.L., Safford, H.R., Qu, S., Xu, M.: A review on energy, environmental, and sustainability implications of connected and automated vehicles. Environ. Sci. Technol. 52(20), 11449–11465 (2018). https://doi.org/10.1021/acs.est.8b00127
21. Eilbert, A., Berg, I., Smith, S.B.: Meta-Analysis of Adaptive Cruise Control Applications: Operational and Environmental Benefits (2019). https://rosap.ntl.bts.gov/view/dot/41929. Accessed 11 January 2021.
22. Do, W., Rouhani, O.M., Miranda-Moreno, L.: Simulation-based connected and automated vehicle models on highway sections: A literature review. J. Adv. Transp. 2019, 1–14 (2019). https://doi.org/10.1155/2019/9343705
23. Narayanan, S., Chaniotakis, E., Antoniou, C.: Factors affecting traffic flow efficiency implications of connected and autonomous vehicles: A review and policy recommendations. Adv. Transp. Policy Plann. 5, 1–50 (2020). https://doi.org/10.1016/bs.atpp.2020.02.004
24. Papa, E., Ferreira, A.: Sustainable accessibility and the implementation of automated vehicles: Identifying critical decisions. Urban Sci. 2(1), 5 (2018). https://doi.org/10.3390/urbansci2010005
25. van Lint, J.W.C., Calvert, S.C.: A generic multi-level framework for microscopic traffic simulation—Theory and an example case in modelling driver distraction. Transp. Res. Part B: Methodol. 117, 63–86 (2018). https://doi.org/10.1016/j.trb.2018.08.009
26. Calvert, S., Schakel, W.J., Van Lint, J.W.C.: Will automated vehicles negatively impact traffic flow? J. Adv. Transp. 2017, 1–17 (2017). https://doi.org/10.1155/2017/3082781
27. Martinez, L., Crist, P.: Urban mobility system upgrade—How shared self-driving cars could change city traffic. In: Corporate Partnership Board Report. International Transport Forum. Paris (2015)
28. Cavoli, C., Phillips, B., Cohen, T., Jones, P.: Social and behavioural questions associated with Automated Vehicles: A Literature Review. pp. 1–124. UCL Transport Institute. London (2017)
29. Knoop, V.L., Wang, M., Wilmink, I., Hoedemaeker, D.M., Maaskant, M., Van der Meer, E.J.: Platoon of SAE Level-2 automated vehicles on public roads: setup, traffic interactions, and stability. Transp. Res. Rec. 2673(9), 311–322 (2019). https://doi.org/10.1177/0361198119845885
30. KiM: Paths to a self-driving future—Five transition steps identified. KiM Netherlands Institute for Transport Policy Analysis. Ministry of Infrastructure and the Environment. Bezuidenhoutseweg, The Netherlands (2017)
31. Litman, T.: Autonomous vehicle implementation predictions: Implications for transport planning. Victoria Transport Institute, Victoria, BC (2021)
32. Gawron, J.H., Keoleian, G.A., De Kleine, R.D., Wallington, T.J., Kim, H.C.: Life cycle assessment of connected and automated vehicles: sensing and computing subsystem and vehicle level effects. Environ. Sci. Technol. 52(5), 3249–3256 (2018). https://doi.org/10.1021/acs.est.7b04576
33. Wood, M., Robbel, P., Maass, M., Tebbens, R.D., Meijs, M., et al., Schlicht, P.: Safety first for automated driving. White paper. (2019)
34. Bu, F., Chan, CY.: Adaptive and cooperative cruise control. In: Eskandarian A. (eds) Handbook of Intelligent Vehicles. Springer, London (2012). https://doi.org/10.1007/978-0-85729-085-4_9
35. Mattas, K., Makridis, M., Hallac, P., Raposo, M.A., Thiel, C., Toledo, T., Ciuffo, B.: Simulating deployment of connectivity and automation on the Antwerp ring road. IET Intell. Transport Syst. 12(9), 1036–1044 (2018). https://doi.org/10.1049/iet-its.2018.5287
36. Shladover, S.E.: Opportunities and challenges in cooperative road vehicle automation. IEEE Open J. Intell. Transp. Syst. 2, 216–224 (2021). https://doi.org/10.1109/OJITS.2021.3099976
37. Sjoberg, K., Andres, P., Buburuzan, T., Brakemeier, A.: Cooperative intelligent transport systems in Europe: Current deployment status and outlook. IEEE Veh. Technol. Mag. 12(2), 89–97 (2017). https://doi.org/10.1109/MVT.2017.2670018
38. Shladover, S.E., Su, D., Lu, X.Y.: Impacts of cooperative adaptive cruise control on freeway traffic flow. Transp. Res. Rec. 2324(1), 63–70 (2012). https://doi.org/10.3141/2324-08
39. Moher, D., Liberati, A., Tetzlaff, J., Altman, D.G.: The PRISMA Group. Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. BMJ. 339, b2535 (2009). https://doi.org/10.1136/bmj.b2535
40. Innamaa, S., Smith, S., Barnard, Y., Rainville, L., Rakoff, H., Horiguchi, R., Gellerman, H.: Trilateral Impact Assessment Framework for Automation in Road Transportation. Version 2.0. Connected Automated Driving Europe (2018). https://connectedautomateddriving.eu/wp-

content/uploads/2018/03/Trilateral_IA_Framework_April2018.pdf. Accessed 25 March 2021.

41. Elefteriadou, L.: An Introduction to Traffic Flow Theory. Vol. 84. Springer, New York (2014). https://doi.org/10.1007/978-1-4614-8435-6
42. Tampere, C., van Arem, B.: Traffic flow theory and its applications in automated vehicle control: a review. In: *ITSC 2001. 2001 IEEE Intelligent Transportation Systems. Proceedings (Cat. No. 01TH8585)*. Oakland, CA, pp. 391–397 (2001). https://doi.org/10.1109/ITSC.2001.948689
43. Ossen, S., Hoogendoorn, S.P.: Heterogeneity in car-following behavior: Theory and empirics. Transp. Res. Part C: Emerging Technol. 19(2), 182–195 (2011). https://doi.org/10.1016/j.trc.2010.05.006
44. Saifuzzaman, M., Zheng, Z.: Incorporating human-factors in car-following models: a review of recent developments and research needs. Transp. Res. Part C: Emerging Technol. 48, 379–403 (2014). https://doi.org/10.1016/j.trc.2014.09.008
45. Hamdar, S.H., Treiber, M., Mahmassani, H.S., Kesting, A.: Modeling driver behavior as sequential risk-taking task. Transp. Res. Rec. 2088, 208–217 (2008). https://doi.org/10.3141/2088-22
46. Ossen, S.: Longitudinal Driving Behavior: Theory and Empirics. Doctoral Thesis. TRAIL Thesis Series no. T2008/8. Delft University of Technology, Delft (2008)
47. Ferrara, A., Sacone, S., Siri, S.: Freeway Traffic Modelling and Control. Springer International Publishing, Berlin (2018). https://doi.org/10.1007/978-3-319-75961-6
48. Ioannou, P., Xu, T.: Throttle and brake control. IVHS J. 1(4), 345–377 (1994)
49. Treiber, M., Hennecke, A., Helbing, D.: Congested traffic states in empirical observations and microscopic simulations. Phys. Rev. E 62(2), 1805 (2000). https://doi.org/10.1103/PhysRevE.62.1805
50. Treiber, M., Kesting, A.: Traffic Flow Dynamics: Data, Models and Simulation. Springer, Berlin (2013)
51. Schakel, W.J., Van Arem, B., Netten, B.D.: Effects of cooperative adaptive cruise control on traffic flow stability. In: *13th International IEEE Conference on Intelligent Transportation Systems*. Funchal, Portugal, pp. 759–764 (2010). https://doi.org/10.1109/ITSC.2010.5625133
52. PTV. PTV VISSIM 2020 User manual. PTV AG. Karlsruhe, Germany (2020)
53. Olstam, J., Johansson, F., Alessandrini, A., Sukennik, P., Lohmiller, J., Friedrich, M.: An approach for handling uncertainties related to behaviour and vehicle mixes in traffic simulation experiments with automated vehicles. J. Adv. Transp. 2020, 1–17 (2020). https://doi.org/10.1155/2020/8850591
54. Shang, M., Stern, R.E.: Impacts of commercially available adaptive cruise control vehicles on highway stability and throughput. Transp. Res. Part C: Emerging Technol. 122, 102897 (2021). https://doi.org/10.1016/j.trc.2020.102897
55. James, R.M., Melson, C., Hu, J., Bared, J.: Characterizing the impact of production adaptive cruise control on traffic flow: An investigation. Transportmetrica B. 7(1), 992–1012 (2019). https://doi.org/10.1080/21680566.2018.1540951
56. Stogios, C., Kasraian, D., Roorda, M.J., Hatzopoulou, M.: Simulating impacts of automated driving behavior and traffic conditions on vehicle emissions. Transp. Res. Part D: Transp. Environ. 76, 176–192 (2019). https://doi.org/10.1016/j.trd.2019.09.020
57. Spiliopoulou, A., Manolis, D., Vandorou, F., Papageorgiou, M.: Adaptive cruise control operation for improved motorway traffic flow. Transp. Res. Rec. 2672(22), 24–35 (2018). https://doi.org/10.1177/0361198118796020
58. Minderhoud, M.M., Bovy, P.H.L.: Impact of intelligent cruise control on motorway capacity. Transp. Res. Rec. 1679, 1–9 (1999). https://doi.org/10.3141/1679-01
59. VanderWerf, J., Shladover, S.E., Miller, M.A., Kourjanskaia, N.: Effects of adaptive cruise control systems on highway traffic flow capacity. Transp. Res. Rec. 1800, 78–84 (2002). https://doi.org/10.3141/1800-10
60. Olia, A., Razavi, S., Abdulhai, B., Abdelgawad, H.: Traffic capacity implications of automated vehicles mixed with regular vehicles. J. Intell. Transp. Syst. Technol. Plann. Oper. 22(3), 244–262 (2018). https://doi.org/10.1080/15472450.2017.1404680
61. Carrone, A.P., Rich, J., Vandet, C.A., An, K.: Autonomous vehicles in mixed motorway traffic: capacity utilisation, impact and policy implications. Transportation. 48(6), 2907–2938 (2021). https://doi.org/10.1007/s11116-020-10154-4
62. Rezaei, A., Caulfield, B.: Simulating a transition to autonomous mobility. Simul. Modell. Pract. Theory. 106, 102175 (2021). https://doi.org/10.1016/j.simpat.2020.102175
63. Alkim, T.P., Bootsma, G., Hoogendoorn, S.P.: Field operational test “ the assisted driver". In: 2007 IEEE Intelligent Vehicles Symposium. Istanbul, Turkey, pp. 1198–1203 (2007)
64. Zhu, L., Gonder, J., Bjarkvik, E., Pourabdollah, M., Lindenberg, B.: An automated vehicle fuel economy benefits evaluation framework using real-world travel and traffic data. IEEE Intell. Transp. Syst. Mag. 11(3), 29–41 (2019). https://doi.org/10.1109/mits.2019.2919537
65. Pauwelussen, J., Feenstra, P.J.: Driver behavior analysis during ACC activation and deactivation in a real traffic environment. IEEE Trans. Intell. Transp. Syst. 11(2), 329–338 (2010). https://doi.org/10.1109/TITS.2010.2043099
66. Viti, F., Hoogendoorn, S.P., Alkim, T.P., Bootsma, G.: Driving behavior interaction with ACC: Results from a field operational test in the Netherlands. In: *2008 IEEE Intelligent Vehicles Symposium*. Eindhoven, Netherlands, pp. 745–750 (2008). https://doi.org/10.1109/IVS.2008.4621199
67. Fancher, P., Ervin, R., Sayer, J., Hagan, M., Bogard, S., Bareket, Z., Mefford, M., Haugen, J.: *Intelligent cruise control field operational test* (No. UMTRI-97-11). National Highway Traffic Administration. Washington, DC (1998)
68. Benmimoun, M., Pütz, A., Zlocki, A., Eckstein, L.: Effects of ACC and FCW on speed, fuel consumption, and driving safety. In: IEEE Vehicular Technological Conference. Quebec City, QC. pp. 1–6 (2012). https://doi.org/10.1109/VTCFall.2012.6399173
69. Dvorkin, W., King, J., Gray, M., Jao, S.: Determining the greenhouse gas emissions benefit of an adaptive cruise control system using real-world driving data. SAE Technical Papers, 2019–01–0310, 1–9 (2019). https://doi.org/10.4271/2019-01-0310
70. Milanés, V., Shladover, S.E., Spring, J., Nowakowski, C., Kawazoe, H., Nakamura, M.: Cooperative adaptive cruise control in real traffic situations. IEEE Trans. Intell. Transp. Syst. 15(1), 296–305 (2014). https://doi.org/10.1109/TITS.2013.2278494
71. Tiernan, T.A., Richardson, N., Azeredo, P., Najm, W.G., Lochrane, T.: Test and Evaluation of Vehicle Platooning Proof-of-Concept Based on Cooperative Adaptive Cruise Control Final Report. pp. 1–112. US Department of Transportation, Southeast, Washington, DC (2017)
72. He, Y., Makridis, M., Fontaras, G., Mattas, K., Xu, H., Ciuffo, B.: The energy impact of adaptive cruise control in real-world highway multiple-car-following scenarios. Eur. Transp. Res. Rev. 12(1), 17 (2020). https://doi.org/10.1186/s12544-020-00406-w
73. Makridis, M., Mattas, K., Ciuffo, B., Re, F., Kriston, A., Minarini, F., Rognelund, G.: Empirical study on the properties of adaptive cruise control systems and their impact on traffic flow and string stability. Transp. Res. Rec.: J. Transp. Res. Board. 2674, 471 (2020a). https://doi.org/10.1177/0361198120911047
74. Lanaud, E., Ladino, A., Buisson, C.: First observations about response times and connectivity in a vehicles platooning experiment. Transport Findings (2021). https://doi.org/10.32866/001c.21190
75. Ciuffo, B., Mattas, K., Makridis, M., Albano, G., Anesiadou, A., He, Y., Josvai, S., Komnos, D., Pataki, M., Vass, S., Szalay, Z.: Requiem on the positive effects of commercial adaptive cruise control on motorway traffic and recommendations for future automated driving systems. Transp. Res. Part C: Emerging Technol. 130, 103305 (2021). https://doi.org/10.1016/j.trc.2021.103305
76. Shi, X., Li, X.: Empirical study on car-following characteristics of commercial automated vehicles with different headway settings. Transp. Res. Part C: Emerging Technol. 128, 103134 (2021). https://doi.org/10.1016/j.trc.2021.103134

77. Makridis, M., Mattas, K., Anesiadou, A., Ciuffo, B.: OpenACC. An open database of car-following experiments to study the properties of commercial ACC systems. Transp. Res. Part C: Emerging Technol. 125, 103047 (2021). https://doi.org/10.1016/j.trc.2021.103047
78. Staiger, J., Calvert, S.C.: Empirical analysis of longitudinal and lateral vehicle dynamics of automated vehicles. In: 100th Transportation Research Board Annual Meeting. Washington, DC (2021)
79. Gunter, G., Gloudemans, D., Stern, R.E., McQuade, S., Bhadani, R., Bunting, M., Delle Monache, M., Lysecky, R., Seibold, B., Sprinkle, J., Piccoli, B. Work, D.: Are commercially implemented adaptive cruise control systems string stable?. IEEE Trans. Intell. Transp. Syst. 22, 6992–7003 (2020). https://doi.org/10.1109/TITS.2020.3000682
80. Ciuffo, B., Makridis, M., Toledo, T., Fontaras, G.: Capability of current car-following models to reproduce vehicle free-flow acceleration dynamics. IEEE Trans. Intell. Transp. Syst. 19(11), 3594–3603 (2018). https://doi.org/10.1109/TITS.2018.2866271
81. Calvert, S.C., van Arem, B.: A generic multi-level framework for microscopic traffic simulation with automated vehicles in mixed traffic. Transp. Res. Part C: Emerging Technol. 110, 291–311 (2020). https://doi.org/10.1016/j.trc.2019.11.019
82. Chandru, R., Selvaraj, Y., Brännström, M., Kianfar, R., Murgovski, N.: Safe autonomous lane changes in dense traffic. In: *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*. Yokohama, pp. 1–6 (2017). https://doi.org/10.1109/ITSC.2017.8317590
83. Zheng, Z.: Recent developments and research needs in modeling lane changing. Transp. Res. Part B: Methodological. 60, 16–32 (2014). https://doi.org/10.1016/j.trb.2013.11.009
84. Davis, L.C.: Effect of adaptive cruise control systems on traffic flow. Phys. Rev. E. 69(6), 066110 (2004). https://doi.org/10.1103/PhysRevE.69.066110
85. Li, X.: Trade-off between safety, mobility and stability in automated vehicle following control: An analytical method. *Preprint*, (2020). DOI: 10.13140/RG.2.2.28804.35204
86. UNECE.: Proposal for a new UN Regulation on uniform provisions concerning the approval of vehicles with regards to Automated Lane Keeping System. United Nations Economic and Social Council. World Forum for Harmonization of Vehicle Regulations. https://undocs.org/ECE/TRANS/WP.29/2020/81. (2020). Accessed 11 January 2021
87. He, Y., Wang, P., Chan, C.Y.: Understanding lane change behavior under dynamic driving environment based on real-world traffic dataset. In: *2019 5th International Conference on Transportation Information and Safety (ICTIS)*. Liverpool, UK, pp. 1092–1097 (2019). https://doi.org/10.1109/ICTIS.2019.8883687.
88. Zhou, H., Zhou, A., Li, T., Chen, D., Peeta, S., Laval, J.: Significance of low-level controller for string stability under adaptive cruise control. arXiv preprint (2021). http://arxiv.org/abs/2104.07726.
89. Milanés, V., Shladover, S.E.: Modeling cooperative and autonomous adaptive cruise control dynamic responses using experimental data. Transp. Res. Part C: Emerging Technol. 48, 285–300 (2014). https://doi.org/10.1016/j.trc.2014.09.001
90. Bose, A., Ioannou, P.: Evaluation of the environmental effects of intelligent cruise control vehicles. Transp. Res. Rec. 1774(1), 90–97 (2001). https://doi.org/10.3141/1774-11
91. ETSC: Reducing speeding in Europe. PIN Flash report 36. European Transport Safety Council (2019). https://etsc.eu/wp-content/uploads/PIN-flash-report-36-Final.pdf. Accessed 25 March 2021.
92. Carsten, O.M., Tate, F.N.: Intelligent speed adaptation: accident savings and cost–benefit analysis. Accid. Anal. Prev. 37(3), 407–416 (2005). https://doi.org/10.1016/j.aap.2004.02.007
93. Mahdinia, I., Mohammadnazar, A., Arvin, R., Khattak, A.J.: Integration of automated vehicles in mixed traffic: Evaluating changes in performance of following human-driven vehicles. Accid. Anal. Prev. 152, 106006 (2021). https://doi.org/10.1016/j.aap.2021.106006.
94. Marsden, G., McDonald, M., Brackstone, M.: Towards an understanding of adaptive cruise control. Transp. Res. Part C: Emerging Technol. 9(1), 33–51 (2001). https://doi.org/10.1016/S0968-090X(00)00022-X
95. Varotto, S.F., Hoogendoorn, R.G., van Arem, B., Hoogendoorn, S.P.: Empirical longitudinal driving behavior in authority transitions between adaptive cruise control and manual driving. Transp. Res. Rec. 2489(1), 105–114 (2015). https://doi.org/10.3141/2489-12
96. Varotto, S.F., Farah, H., Bogenberger, K., van Arem, B., Hoogendoorn, S.P.: Adaptations in driver behaviour characteristics during control transitions from full-range Adaptive Cruise Control to manual driving: an on-road study. Transportmetrica A: Transp. Sci. 16(3), 776–806 (2020). https://doi.org/10.1080/23249935.2020.1720856
97. Strand, N., Nilsson, J., Karlsson, I.C.M., Nilsson, L.: Exploring end-user experiences: self-perceived notions on use of adaptive cruise control systems. IET Intell. Transp. Syst. 5(2), 134–140 (2011). https://doi.org/10.1049/iet-its.2010.0116
98. Haglund, M., Åberg, L.: Speed choice in relation to speed limit and influences from other drivers. Transp. Res. Part F: Traffic Psychol. Behav. 3(1), 39–51 (2000). https://doi.org/10.1016/S1369-8478(00)00014-0
99. Lehtonen, E., Malin, F., Innamaa, S., Nordhoff, S., Louw, T., Bjorvatn, A., Merat, N.: Are multimodal travellers going to abandon sustainable travel for L3 automated vehicles?. Transp. Res. Interdiscip. Perspect. 10, 100380 (2021). https://doi.org/10.1016/j.trip.2021.100380
100. SAE International: Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles (2021). https://doi.org/10.4271/J3016_202104

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APPENDIX

Results of the literature review per simulation study are shown for the indicators capacity throughput, queue discharge throughput and throughput in Figure A1, Figure A2 and Figure A3, respectively.

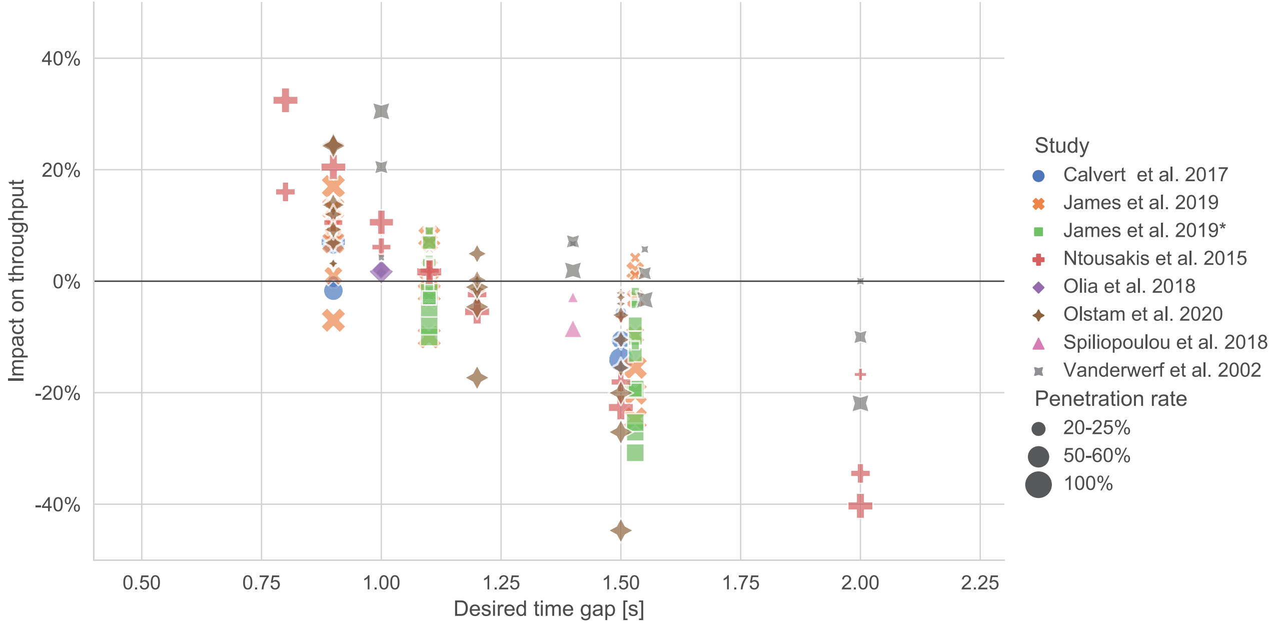

FIGURE A1 Simulation results from literature for impact on capacity throughput (C) by ACC/AV desired time gap with low, medium and full ACC/AV penetration, *Model calibrated with parameters from field experiment

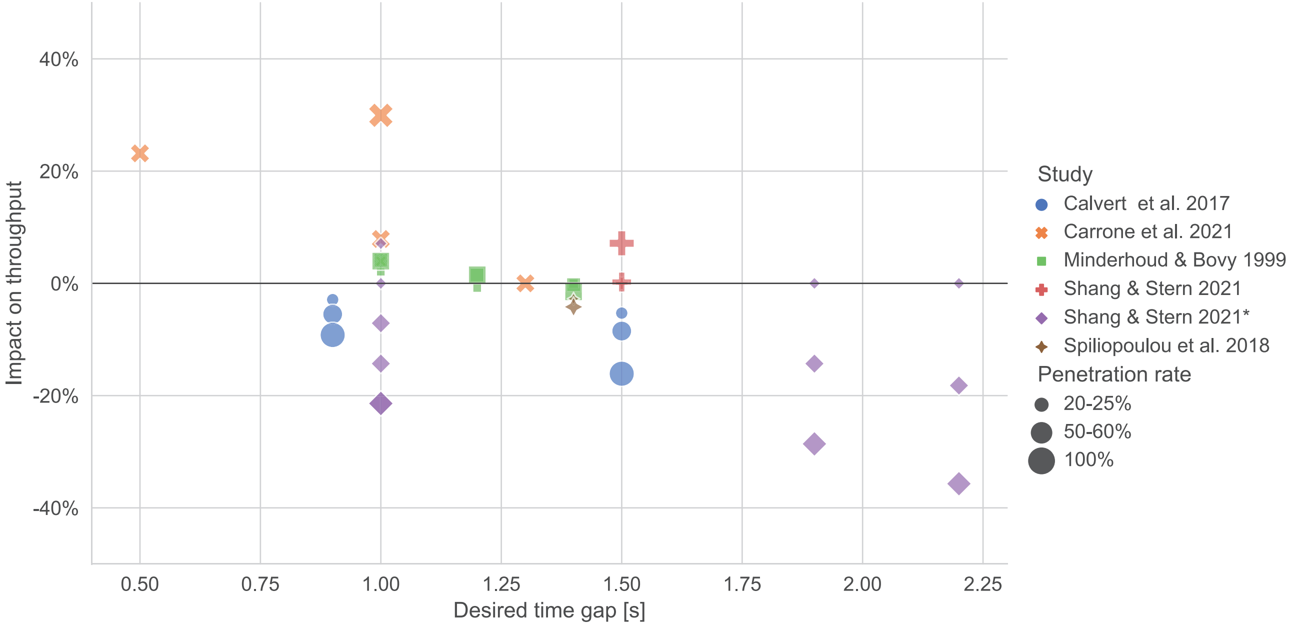

FIGURE A2 Simulation results from literature for impact on queue discharge capacity (Q) by ACC/AV desired time gap with low, medium and full ACC/AV penetration, *Model calibrated with parameters from field experiment

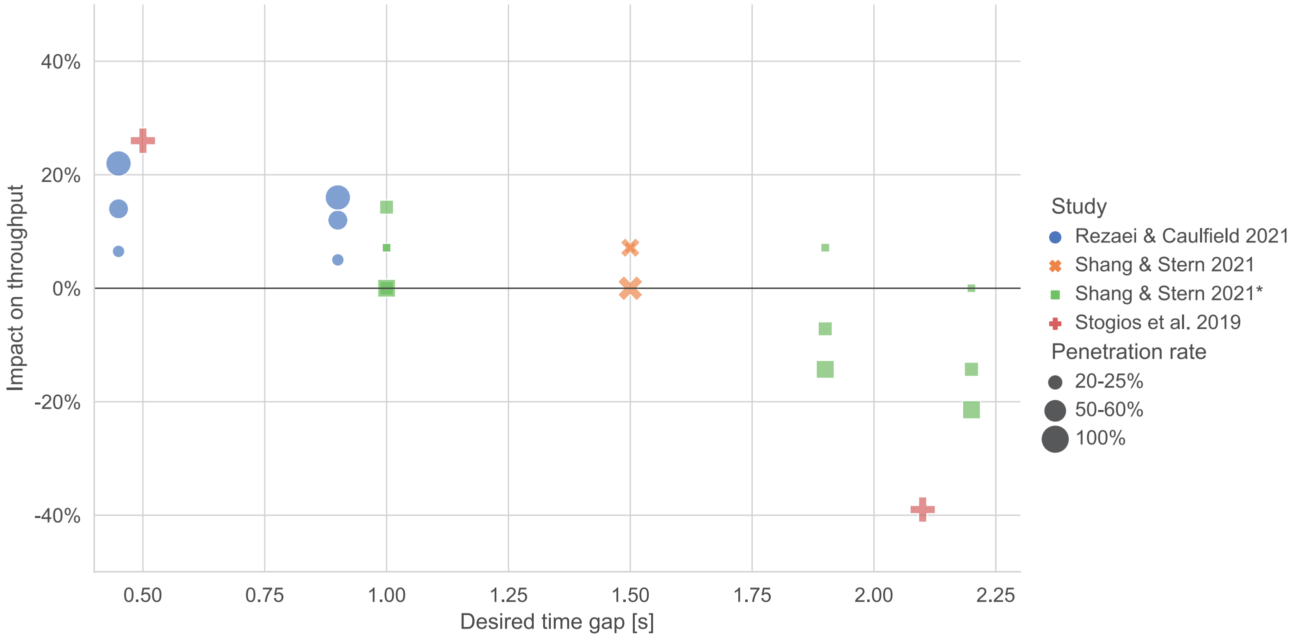

FIGURE A3 Simulation results from literature for impact on throughput (*T*) by ACC/AV desired time gap with low, medium and full ACC/AV penetration, *Model calibrated with parameters from field experiment