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Policy and society related implications of automated driving: A review of literature and directions for future research

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ABSTRACT

In this paper, the potential effects of automated driving that are relevant to policy and society are explored, findings discussed in literature about those effects are reviewed and areas for future research are identified. The structure of our review is based on the ripple effect concept, which represents the implications of automated vehicles at three different stages: first-order (traffic, travel cost, and travel choices), second-order (vehicle ownership and sharing, location choices and land use, and transport infrastructure), and third-order (energy consumption, air pollution, safety, social equity, economy, and public health). Our review shows that first-order impacts on road capacity, fuel efficiency, emissions, and accidents risk are expected to be beneficial. The magnitude of these benefits will likely increase with the level of automation and cooperation and with the penetration rate of these systems. The synergistic effects between vehicle automation, sharing, and electrification can multiply these benefits. However, studies confirm that automated vehicles can induce additional travel demand because of more and longer vehicle trips. Potential land use changes have not been included in these estimations about excessive travel demand. Other third-order benefits on safety, economy, public health and social equity still remain unclear. Therefore, the balance between the short-term benefits and long-term impacts of vehicle automation remains an open question.

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Introduction

Automated driving is considered to be one of those technologies that could signal an evolution toward a major change in (car) mobility. Estimations about the extent of this change can be inferred by answering the following two questions: (a) what are the potential changes in mobility and the implications for society associated with the introduction of automated driving and, (b) to what extent are these changes synchronized with broader concurrent societal transformations that could enhance the radical dynamic of such mobility technology? Examples of social transformations could be the digital and sharing economy, the livability and environmental awareness movement and the connectivity, networking, and personalized consumption trends.

In this paper, the focus is on the first question, aiming to (a) explore the potential effects of automated driving relevant to policy and society, (b) review findings discussed in literature about these effects, and (c) identify areas for future research. Thus far, scholarly efforts have been mainly concentrated on the technological aspects of vehicle automation (i.e. road environment perception and motion planning) and on the implications for driver and traffic flow characteristics. Accordingly, review efforts have focused on the development and operation of vehicle automation systems and the associated technologies (see Gerónimo, López, Sappa, & Graf, 2010; González, Pérez, Milanés, & Nashashibi, 2016; Piao & McDonald, 2008; Shladover, 2005; Shladover, 1995; Sun, Bebis, & Miller, 2006; Turner & Austin, 2000; Vahidi & Eskandarian, 2003; Xiao & Gao, 2010). Several review studies have also focused on the first-order impacts of vehicle automation with a special emphasis on traffic flow efficiency (see Diakaki, Papageorgiou, Papamichail, & Nikolos, 2015; Hoogendoorn, van Arem, & Hoogendoorn, 2014; Hounsell, Shrestha, Piao, & McDonald, 2009; Scarinci & Heydecker, 2014) and human factor aspects such as behavioral adaptation, driver's workload, and situation awareness (see Brookhuis, de Waard, & Janssen, 2001; de Winter, Happee, Martens, & Stanton, 2014; Stanton & Young, 1998). A partial overview of the wider implications of automated vehicles has been recently made by Fagnant and Kockelman (2015) with the aim to provide an order-of-magnitude estimation about the possible

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economic impacts of automated vehicles in the US context.

The remainder of this paper is structured as follows. Our methodology is first described (Section 2) and then a simplified concept, to represent the areas of possible policy and society related implications of automated vehicles, is presented (Section 3). In Sections 4–6 the results of our analysis about the first, second, and third order implications of automated driving are presented, respectively. Every sub-section in Sections 4–6 is structured in two parts. The first part presents the analysis about the possible implications of automated driving and their mechanisms (assumptions) and the second part is the review of the respective results found in existing literature (literature results). Section 7 presents conclusions and summarizes directions for future research.

Methodology

Our methodology involves two steps. First, a simplified concept is developed in a structured and holistic way, representing what the possible implications of automated vehicles are. Then, (a) the impacts of automated driving and their respective mechanisms, (b) existing literature results about these implications, and (c) research gaps between possible impacts and existing literature results are identified.

The impacts of automated driving and their respective mechanisms are explored, based on our own analytical thinking. Then, the literature results about the implications of automated driving are reviewed based on Scopus and Web of Science listed peer-reviewed journal articles. Included in our review were articles dated up to January 2017 containing in the title, abstract, or keywords any combination of the following keywords: advanced driver assistance system(s), [cooperative (C)] adaptive cruise control (ACC), vehicle automation, autonomous vehicle(s), autonomous car(s), self-driving vehicle(s), self-driving car(s), driverless vehicle(s), driverless car(s), automated vehicle(s), automated car(s), automated driving, robocar(s), and the keywords appearing in Table 1 for each area of implication. We primarily limited our review to peer-reviewed academic literature for two reasons: (a) the number of articles is already very high and (b) explicit review is an indication of quality. This does not mean that other literature does not have sufficient quality. Therefore, in the case of very limited or no results for specific implications of automated vehicles, our search was expanded to Google and Google Scholar, aiming to identify any unpublished reports of systematic studies. We did not include any policy reports on automated vehicles produced by governments or other institutions in our review.

Table 1. Keywords used to identify scholarly articles about the implications of automated vehicles.

Implication	Keyword
Travel cost	Cost, travel time, comfort, value of time, travel time reliability
Road capacity	Capacity, congestion, traffic flow
Travel choices	Travel choice(s), mode choice(s), travel behavior, travel distance, vehicle kilometers traveled, vehicle miles traveled, modal shift
Vehicle ownership and sharing	Vehicle ownership, car ownership, vehicle sharing, car sharing, ride sharing, shared vehicle(s)
Location choices and land use	Location choice(s), land use(s), accessibility, residential density, urban form, urban structure, urban design
Transport infrastructure	Road infrastructure(s), road planning, road design, intersection design, parking infrastructure(s), public transport service(s), transit service(s), cycle lane(s), cycle path(s), sidewalk(s), pavement(s)
Energy consumption and air pollution	Fuel, energy, emissions, pollution
Safety	Safety, accident(s), crash(es), risk, cyberattack(s)
Social equity	Social equity, social impact(s), vulnerable social group(s), social exclusion
Economy	Economy, productivity, business(es)
Public health	Public health, human health, morbidity, mortality

This paper focuses on passenger transport and employs the Society of Automotive Engineers (SAE) International (2016) taxonomy, which defines five levels of vehicle automation. In level 1 (driver assistance) and level 2 (partial driving automation), the human driver monitors the driving environment and is assisted by a driving automation system for execution of either the lateral or longitudinal motion control (level 1) or both motion controls (level 2). In level 3 (conditional driving automation), an automated driving system performs all dynamic tasks of driving (monitoring of the environment and motion control), but the human driver is expected to be available for occasional control of the vehicle. In level 4 (high driving automation) and level 5 (full driving automation) an automated driving system performs all dynamic tasks of driving, without any human intervention at any time. In level 4, the automated driving system controls the vehicle within a prescribed operational domain (e.g. high-speed freeway cruising, closed campus shuttle). In level 5, the automated driving system can operate the vehicle under all on-road conditions with no design-based restrictions.

The ripple effect of automated driving

The ripple model was used to conceptualize the sequential effects that automated driving might bring to several aspects of mobility and society (see Milakis, van Arem,

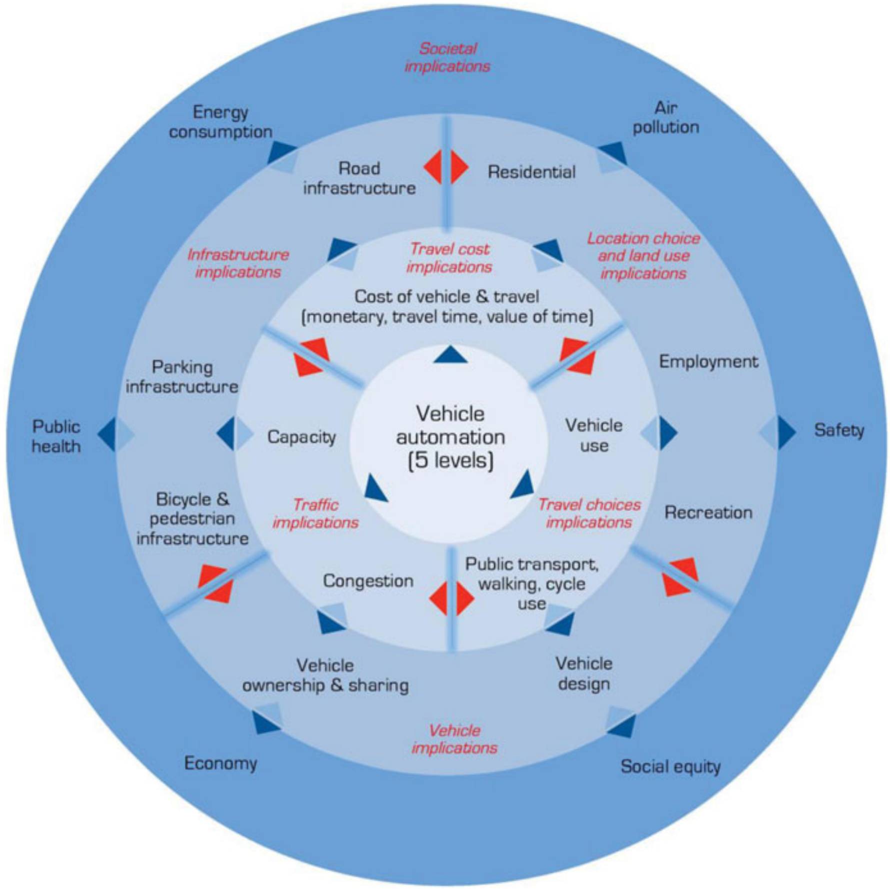

Figure 1. The ripple effect of automated driving.

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& van Wee, 2015). The "ripple effect" has been widely used to describe the sequentially spreading effects of events in various fields including economics, psychology, computer science, supply chain management, and bibliometric analysis of science (see e.g. Barsade, 2002; Black, 2001; Cooper, Orford, Webster, & Jones, 2013; Frandsen & Nicolaisen, 2013; Ivanov, Sokolov, & Dolgui, 2014; Meen, 1999). The ripple model of automated driving is presented in Figure 1. Driving automation is placed in the center of the graph to reflect the source of the sequential first, second, and third order effects in the outer ripples. The first ripple comprises the implications of automated driving on traffic, travel cost, and travel choices. The second ripple includes implications of automated driving with respect to vehicle ownership and sharing, location choices and land use, and transport infrastructure. The third ripple contains the wider societal implications (i.e. energy consumption, air pollution, safety, social equity, economy, and public health) of the introduction of automated vehicles.

The ripple model of automated driving does not hold the exact same properties as the respective ripple model in physics that describes the diffusion of waves as a function of time and distance. Therefore, the ripple model of automated driving should not be taken too strictly. Feedbacks can occur in our model. For example, changes in travel cost (first ripple) might influence accessibility, then subsequently location choices, land use planning, and real estate investment decisions (second ripple), which in turn could affect travel decisions (e.g. vehicle use) and traffic (first ripple). Also, there might be no time lag between sequential effects. For example, vehicle use changes will immediately result in safety or air pollution changes. Finally, it should be clear that effects on fuel consumption, emissions and accidents risk can occur soon after the introduction of automated vehicles, yet the wider (societal) impacts on energy consumption, air pollution, and safety (third ripple) can be evaluated only after changes in the first two ripples are taken into account.

First-order implications of automated driving

In this section the first-order implications of automated driving on travel cost, road capacity, and travel choices are explored (see also Table 2 for an overview of studies on first-order implications for automated vehicles).

Travel cost

Assumptions

Potential implications for both the fixed (capital) cost of owning an automated vehicle and the generalized transport cost (GTC), which comprises effort, travel time,

Table 2. Summary of literature review results.

Possible effect of automated vehicles	Effect	Comments	Source
First-order implications			
Travel cost			
Fixed cost of automated vehicles	+	Current automated vehicle applications cost several times the price of a conventional vehicle in the US, but the price could be gradually reduced to $3000 or even lower with mass production and the technological advances of automated vehicles.	Fagnant & Kockelman, 2015
Travel comfort	?	Comfort has been incorporated in trajectory planning and ACC algorithms as the optimizing metric. Motion sickness, apparent safety and natural human-like paths could be included in path planning systems. Time headway between vehicles below 1.5–2.0 seconds can influence comfort.	Dang, Wang, Li, & Li, 2015 Elbanhawi et al., 2015; Glaser et al., 2010; Lewis-Evans et al., 2010; Li et al., 2011; Luo et al., 2015; Moon et al., 2009; Raimondi & Melluso, 2008; Siebert et al., 2014; Bellem et al., 2016; Diels & Bos, 2016; Lefèvre et al., 2016
Travel time	−	Vehicle automation can reduce delays on highways, at intersections and in contexts involving shared automated vehicles.	Arnaout & Arnaout, 2014; Dresner & Stone, 2008; Fajardo et al., 2012; Ilgin Guler et al., 2014; International Transport Forum, 2015; Kesting et al., 2008; Khondaker & Kattan, 2015; Levin et al., 2016; Li et al., 2013; Ngoduy, 2012; Yang et al., 2016; Zohdy & Rakha, 2016
Value of time	?	Automated vehicles (level 3 and higher) could reduce the value of time. Yet, value of time could increase for users of automated vehicles as egress mode to train trips. The ability to work on the move is not perceived as a major advantage of an automated vehicle.	Cyganski, Fraedrich, & Lenz, 2015; Milakis et al., 2017; Yap et al., 2016
Road capacity			
Highway capacity	+	The higher the level of automation, cooperation and penetration rate, and the higher the positive impact on road capacity. A 40% penetration rate of CACC appears to be a critical threshold for realizing significant benefits on capacity (>10%), while a 100% penetration rate of CACC could theoretically double capacity. Capacity impacts at level 3 or higher levels of vehicle automation and more advanced levels of cooperation among vehicles, but also between vehicles and infrastructure, could well exceed this theoretical threshold. Capacity might be affected by vehicle heterogeneity. Capacity could decrease in entrance/exit of automated highway systems.	Arnaout & Bowling, 2011; Arnaout & Arnaout, 2014; Delis, Nikolos, & Papageorgiou, 2015; Fernandes, Nunes, & Member, 2015; Grumert, Ma, & Tapani, 2015; Hoogendoorn, van Arem, & Hoogendoorn, 2014; Huang, Ren, & Chan, 2000; Michael, Godbole, Lygeros, & Sengupta, 1998; Monteil, Nantes, Billot, Sau, & El Faouzi, 2014; Ngoduy, 2013; Rajamani & Shladover, 2001; Shladover, Su, & Lu, 2012; van Arem, van Driel, & Visser, 2006; Yang, Liu, Sun, & Li, 2013; Carbaugh et al., 1998; Hall et al., 2001; Le Vine et al., 2015; Michael et al., 1998; Talebpour & Mahmassani, 2016; Wang et al., 2016a, b; Xie et al., 2016; Zhou et al., 2016)
Intersection capacity	+	Significant capacity benefits (more than 100%, under certain conditions) are expected from automated intersection control systems.	Clement, Taylor, & Yue, 2004 Kamal et al., 2015
Travel choices			
Vehicle miles traveled	+	Automated vehicles could induce an increase in travel demand of between 3% and 27% due to changes in destination choice (i.e. longer trips), mode choice (i.e. modal shift from public transport and walking to car), and mobility (i.e. more trips, especially from people currently experiencing travel restrictions; e.g. elderly). Shared automated vehicles could result in additional VMT because of their need to move or relocate with no one in them to serve the next traveler. Extra VMT are expected to be lower for dynamic ride-sharing systems.	Childress, Nichols, & Coe, 2015 Fagnant & Kockelman, 2014, 2015; Gucwa, 2014; International Transport Forum, 2015; Malokin et al., 2015; Correia, de, & van Arem, 2016; Fagnant & Kockelman, 2016; Lamondia et al., 2016; Levin & Boyles, 2015; Milakis et al., 2017; Vogt et al., 2015; Zmud et al., 2016
Second-order implications			
Vehicle ownership	−	Shared automated vehicles could replace from about 67% up to over 90% of conventional vehicles delivering equal mobility levels. The overall reduction of the conventional vehicle fleet could vary according to the automated mode (vehicle-sharing, ride-sharing, shared electric vehicle), the penetration rate of shared automated vehicles and the presence or absence of public transport.	Fagnant & Kockelman, 2014; International Transport Forum, 2015; Spieser et al., 2014; Boesch, Ciari, & Axhausen, 2016; Chen et al., 2016; Fagnant & Kockelman, 2016; Zhang et al., 2015
Location choices and land use	?	Automated vehicles could enhance accessibility citywide, especially in remote rural areas, triggering further urban expansion. Automated vehicles could also have a positive impact on the density of economic activity at the center of the cities. Parking demand for automated vehicles could be shifted to peripheral zones. Parking demand for shared automated vehicles can be high in city centers, if empty cruising is not allowed.	Childress et al., 2015; Zakharenko, 2016; Zhang et al., 2015

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Table 2. (Continued)

Possible effect of automated vehicles	Effect	Comments	Source
Transport infrastructure	−	Shared automated vehicles could significantly reduce parking space requirements up to over 90%. The overall reduction of parking spaces could vary according to the automated mode (vehicle-sharing, ride-sharing, shared electric vehicle), the penetration rate of shared automated vehicles and the presence or absence of public transport. Less wheel wander and increased capacity because of automated vehicles could accelerate pavement-rutting damage. Increase in speed of automated vehicles could compensate for such negative effect by decreasing rut depth.	Fagnant & Kockelman, 2014, 2016; International Transport Forum, 2015; Boesch et al., 2016; Chen et al., 2016; Chen et al., 2016; Spieser et al., 2014; Zhang et al., 2015
Third-order implications			
Energy consumption and air pollution			
Fuel efficiency	+	Significant fuel savings can be achieved by various longitudinal, lateral (up to 31%), and intersection control (up to 45%) algorithms and optimization systems for automated vehicles. Higher level of automation, cooperation, and penetration rate could lead to higher fuel savings.	Asadi & Vahidi, 2011; Kamal et al., 2016; Kamalanathsharma & Rakha, 2016; Khondaker & Kattan, 2015; Li et al., 2012; Luo et al., 2010; Manzie et al., 2007; Rios-torres & Malikopoulos, 2016; Vajedi & Azad, 2015; Wang et al., 2014; Wu et al., 2011; Zohdy & Rakha, 2016
Energy consumption (long term)	?	Battery electric shared automated vehicles are associated with significant energy savings (90–100%) in the long term. The energy gains are attributed to more efficient travel and electrification. Several factors could lead to increased energy use (e.g. longer travel distances and increased travel by underserved populations such as youth, disabled, and elderly). Thus, the net effect of vehicle automation on energy consumption remains uncertain.	Brown et al., 2014; Greenblatt & Saxena, 2015; Wadud et al., 2016
Emissions	−	Vehicle automation can lead to lower emissions of NOx, CO, and CO2. Higher level of automation, cooperation and penetration rates could lead to even lower emissions. Shared use of automated vehicles could further reduce emissions (VOC and CO in particular) because of lower number of times vehicles start.	Choi & Bae, 2013; Fagnant & Kockelman, 2014; Grumert et al., 2015; Ioannou & Stefanovic, 2005; Wang et al., 2015; Bose & Ioannou, 2001
Air pollution (long term)	?	Long-term impacts of battery electric shared automated vehicles are associated with up to 94% less GHG. Yet, the net effect of vehicle automation on GHG emissions remains uncertain.	Greenblatt & Saxena, 2015; Wadud et al., 2016; Fagnant & Kockelman, 2014
Safety	+	Advanced driver assistance systems and higher levels of automation (level 3 or higher) can enhance traffic safety. Behavioral adaptation, cyberattacks, maliciously controlled vehicles and software vulnerabilities can compromise traffic safety benefits. Fully automated vehicles might not deliver high safety benefits until high penetration rates of these vehicles are realized.	Dresner & Stone, 2008; Ferguson, Howard, & Likhachev, 2008; Hayashi, Isogai, Raksincharoensak, & Nagai, 2012; Hou, Edara, & Sun, 2015; Khondaker & Kattan, 2015; Kuwata et al., 2009; Lee, Choi, Yi, Shin, & Ko, 2014; K.-R. Li, Juang, & Lin, 2014; Liebner, Klanner, Baumann, Ruhhammer, & Stiller, 2013; Martinez & Canudas-de-Wit, 2007; Shim, Adireddy, & Yuan, 2012; M. Wang, Hoogendoorn, Daamen, van Arem, & Happee, 2015; Carbaugh et al., 1998; Spyropoulou, Penttinen, Karlaftis, Vaa, & Golias, 2008; Amoozadeh et al., 2015; Brookhuis et al., 2001; Gerdes et al., 2013; Gouy et al., 2014; Hoedemaeker & Brookhuis, 1998; Markvollrath et al., 2011; Petit & Shladover, 2015; Rudin-Brown & Parker, 2004; Strand et al., 2014; Xiong et al., 2012; Young & Stanton, 2007; Dixit et al., 2016; Gong et al., 2016; Naranjo et al., 2016
Social equity	?	In-vehicle technologies can have positive effects (i.e. avoiding crashes, enhancing easiness and comfort of driving, increasing place, and temporal accessibility) for elderly. Automated vehicles could induce up to 14% additional travel demand from the non-driving, elderly, and people with travel-restrictive medical conditions. Automated vehicles offer the opportunity to incorporate social justice aspects in future traffic control systems.	Harper, Hendrickson, Mangones, & Samaras, 2016; Eby et al., 2016; Mladenovic & McPherson, 2016
Economy	?	Social benefits per automated vehicle per year could reach $3900 when there's a 90% market share of automated vehicles. Jobs in the transportation and logistics sectors have a high probability of being replaced by computer automation within the next two decades.	Fagnant & Kockelman, 2015; Frey & Osborne, 2017
Public health	?	No systematic studies were found about the implications of automated vehicles for public health.	

Note. Effects are described with the following symbols: '+': positive/increase, '−': negative/decrease, '?': uncertain/limited evidence

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and financial costs of a trip, are explored. The fixed costs of automated vehicles will very likely be higher than for conventional vehicles due to the advanced hardware and software technology involved. The increased fixed cost could influence the penetration rate and subsequently the magnitude of the effects of automated vehicles. The GTC, on the other hand, is expected to decrease because of lower effort, time, and money needed to travel. First, more travel comfort, enhanced travel safety, higher travel time reliability, and the possibility to perform activities other than driving (like working, meeting, eating, or sleeping) while on the move will likely lead to lower values of time. Second, less congestion delays because of increased road capacity and reduced (or even eliminated) search time for parking owing to self-parking capability, but also increased use of shared vehicles, would possibly require less travel time. Third, enhanced efficiency of traffic flow along with more fuel-efficient vehicles because of their lighter design (owing to less risk of having an accident) could also reduce the monetary cost of travel. Due to shorter headways, air resistance will possibly decrease, further reducing fuel use and costs. However, potential increase of vehicle travel demand because of enhanced road capacity, reduced GTC, and/or proliferation of vehicle sharing systems and urban expansion in the longer term, could compromise travel time and cost savings. The counter effects of increased vehicle demand could include increased congestion delays, longer trips, and more fuel costs.

Literature results

Fagnant and Kockelman (2015) report estimations that current automated vehicle applications cost several times the price of a conventional vehicle in the US. However, they estimate that this difference in cost could be gradually reduced to $3000 or even lower with mass production and the technological advances of automated vehicles. Looking at the components of GTC, several studies have incorporated comfort in terms of longitudinal and lateral acceleration as the optimizing metric in their trajectory-planning algorithms (see e.g. Glaser, Vanholme, Mammar, Gruyer, & Nouvelière, 2010; Raimondi & Melluso, 2008). Moreover, multi-objective ACC algorithms usually incorporate ride comfort (measured in terms of vehicle acceleration) along with safety and fuel consumption as system constraints (see e.g. Dang, Wang, Li, & Li, 2015; Li, Li, Rajamani, & Wang, 2011; Luo, Chen, Zhang, & Li, 2015; Moon, Moon, & Yi, 2009). Bellem, Schönenberg, Krems, and Schrauf (2016) suggested several maneuver-specific metrics such as acceleration, jerk, quickness, and headway distance to assess comfort of automated driving style. However, Elbanhawi, Simic, and Jazar (2015) argue in their review paper that several factors of human comfort are largely ignored in research for autonomous path planning systems [i.e. motion sickness, see also Diels & Bos, 2016; apparent safety (the feeling of safe operation of the automated vehicle); natural, human-like paths]. A more recent study (Lefèvre, Carvalho, & Borrelli, 2016) developed a learning-based approach for automated vehicles with the aim to replicate human-like driving styles (i.e. velocity control). Moreover, research has shown that comfort is not only influenced by vehicle acceleration but also by the time headway when the driver is still in the loop. Both Lewis-Evans, De Waard, and Brookhuis (2010) and Siebert, Oehl, and Pfister (2014) identified in driver simulator experiments a critical threshold for time headway in the area of 1.5–2.0 seconds below which a driver's perception of comfort reduces significantly.

Limited evidence exists on the impacts of automated vehicles on the travellers' value of time. Yap, Correia, and van Arem (2016) found a higher value of time for using fully automated (level 5) compared to manually driven vehicles as egress mode of train trips in a stated preference survey in the Netherlands. These researchers attributed this result to the possible uncomfortable feeling of travelers with the idea of riding an automated vehicle, the lack of any real-life experience with automated vehicles, and the fact that an egress trip is typically a short trip not allowing the travelers to fully experience potential benefits of automated vehicles such as travel safety. Cyganski et al., (2015) reported that only a minor percentage of the respondents in their questionnaire survey in Germany declared as an advantage the ability to work on the move in an automated vehicle (level 3 and higher). On the contrary, most respondents agreed that activities that they usually undertake while driving conventional vehicles (e.g. gazing, conversing, or listening to music) would continue to be important when riding an automated vehicle. Respondents working in their current commute were found to be more likely to wish to work in an automated vehicle as well. Milakis, Snelder, van Arem, van Wee, and Correia (2017) reported a possible decrease of the value of time between 1% and 31% for users of automated vehicles (level 3 and higher) in various scenarios of development of automated vehicles in the Netherlands.

Several studies have reported results about travel time and fuel savings based on simulation of various control algorithms for automated car-following scenarios and automated intersection management. Studies about fuel savings are presented later in this article. Considering travel time, Arnaout and Arnaout (2014) simulated a four-lane highway involving several scenarios of penetration rates for cars equipped with CACC and a fixed percentage for trucks (10%). They found that travel time decreased substantially with the increase of CACC penetration rate. Ngoduy (2012) reported that a 30% penetration rate of ACC could significantly reduce oscillation waves and stabilize traffic near a bottleneck, thus reducing

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travel time by up to 35%. Kesting, Treiber, Schönhof, and Helbing (2008) identified travel time improvements even with relatively low ACC penetration rates. Also, Khondaker and Kattan (2015) showed that their proposed variable speed limit control algorithm could reduce travel time by up to 20% in a context of connected vehicles compared to an uncontrolled scenario. However, travel time improvements were lower when a 50% penetration rate of connected vehicles was simulated. Zohdy and Rakha (2016) developed an intersection controller that optimizes the movement of vehicles equipped with CACC. Their simulation results showed that the average intersection delay in their system (assuming 100% market penetration of fully automated vehicles, level 4 or 5) was significantly lower compared to the traffic signal and all-way-stop control scenarios. Similarly, Dresner and Stone (2008) proposed a multi-agent, reservation-based control system for efficient management of fully automated vehicles (level 4 or 5) in intersections that could widely outperform current control systems like traffic lights and stop signs. According to these researchers, this system could offer near-to optimal delays (up to 0.35 seconds); about ten times lower than the delays observed in conventional control systems. The efficiency of reservation-based intersection controls in reducing delays was also demonstrated by Fajardo, Au, Waller, Stone, and Yang (2012), Li, Chitturi, Zheng, Bill, and Noyce (2013) and Levin, Fritz, and Boyles (2016). Yet, Levin, Boyles, and Patel (2016) indicated some cases that optimized signals can outperform reservation-based intersection controls (e.g. in local road-arterial intersections) and thus, these researchers recommended a network-based analysis before any decision about replacement of traffic signals is taken. Ilgin Guler, Menendez, and Meier (2014) assumed that only a portion of the vehicles were equipped with their intersection control algorithm and tested the impacts on delays for two one-way-streets. Their simulations revealed a decrease by up to 60% in the average delay per car when the penetration rate of the control system-equipped vehicles increased by up to 60%. These researchers reported further decrease of the delays by an improved version of their intersection controller (Yang, Guler, & Menendez, 2016). Chen, Bell, and Bogenberger (2010) proposed a navigation algorithm for automated vehicles that accounts not only for travel time but also for travel time reliability. Thus, this algorithm can search for the most reliable path within certain travel time constraints using either dynamic or no traffic information. Finally, when considering the impacts of shared automated vehicles on travel time, the International Transport Forum (2015) reported a reduction of up to 37.9% compared to the current travel time of private cars in Lisbon, Portugal, based on a simulation study.

Road capacity

Assumptions

Automated vehicles could have a positive influence on free flow capacity, the distribution of vehicles across lanes and traffic flow stability by providing recommendations (or even determining in level 3 or higher levels of automation) about time gaps, speed and lane changes. Enhanced free flow capacity and decreased capacity drops (i.e. fewer episodes of reduced queue discharge rate) could increase the road capacity and thus reduce congestion delays. Nevertheless, benefits in traffic flow efficiency will very likely be highly dependent on the level of automation, the connectivity between vehicles and their respective penetration rates, the deployment path (e.g. dedicated lanes versus integrated, mixed traffic) as well as human factors (i.e. behavioral adaptation). Moreover, increased vehicle travel demand could have a negative impact on road capacity owing to more congestion delays and subsequently increased capacity drops. Thus, although the benefits of automated vehicles in the short term are expected to be important, the long-term implications are uncertain and highly dependent on the evolution of vehicle travel demand.

Literature results

Hoogendoorn, van Arem, and Hoogendoorn (2014) concluded in their review study that automated driving might be able to reduce congestion by 50%, while this reduction could go even higher with the help of vehicle-to-vehicle and vehicle-to-infrastructure communication. Several studies have explored the traffic impacts of longitudinal automation (i.e. ACC and CACC), based on simulations. Results suggest that ACC can only have a slight impact on capacity (Arnaout & Arnaout, 2014). CACC, on the other hand, showed positive impacts on capacity (van Arem, van Driel, & Visser, 2006) but these will probably only be important (e.g. >10%) if relatively high penetration rates are realized (>40%) (Arnaout & Bowling, 2011; Shladover, Su, & Lu, 2012). A 100% penetration rate of CACC could theoretically result in double capacity compared to a scenario of all manually driven vehicles (Shladover et al., 2012). Ngoduy (2013) and Delis, Nikolos, and Papageorgiou (2015) have also confirmed that CACC performs better than ACC with respect to both traffic stability and capacity.

Several other studies have confirmed the beneficial effects of different types and levels of vehicle automation and cooperation on capacity in various traffic scenarios (see e.g. Talebpour & Mahmassani, 2016). In particular, Fernandes, Nunes, and Member (2015) proposed an algorithm for positioning and the cooperative behavior of multiplatooning leaders in dedicated lanes. Their

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simulations showed that the proposed platooning system can achieve high traffic capacity (up to 7200 vehicles/hour) and outperform bus and light rail in terms of capacity and travel time. Huang, Ren, and Chan (2000) designed a controller for automated vehicles that requires information only from vehicle sensors. Their simulations in mixed traffic conditions that involved both automated and human controlled vehicles showed that peak flow could reach 5000 vehicles/hour when 70% of the vehicles are automated. Moreover, Michael, Godbole, Lygeros, and Sengupta (1998) showed, via the simulation of a single lane automated highway system, that capacity increases as the level of cooperation between vehicles and platoon length increases. Several other studies have not only reported enhanced traffic flow efficiency because of cooperation and exchange of information between vehicles (e.g. Monteil, Nantes, Billot, Sau, & El Faouzi, 2014; Wang, Daamen, Hoogendoorn, & van Arem, 2016b; Xie, Zhang, Gartner, & Arsava, 2016; Yang, Liu, Sun, & Li, 2013; Zhou, Qu, & Jin, 2016) but also between vehicles and infrastructure (e.g. variable speed limits, see Grumert, Ma, & Tapani, 2015; Wang, Daamen, Hoogendoorn, & van Arem, 2016a). Rajamani and Shladover (2001) compared the performance of autonomous control systems and cooperative longitudinal control systems (with and without inter vehicle communication respectively). These researchers showed analytically that the autonomous control system could indeed deliver capacity benefits reaching a theoretical maximum traffic flow of 3000 vehicles/hour. However, a cooperative system comprising 10-vehicle platoons with a distance between the vehicles of 6.5 m was far more efficient, achieving a theoretical traffic flow of 6400 vehicle/hour. Theoretical traffic flow of the cooperative system could increase to 8400 vehicles/hour if the distance between the vehicles in the platoons was further reduced to 2 m.

Another group of studies identify significant capacity benefits from using automated intersection control systems. Clement, Taylor, and Yue (2004) proposed one of these conceptual systems whereby vehicles can move in closely spaced platoons when the lights turn to green at signalized intersections. These researchers showed analytically that this system could increase throughput by 163% compared to current road intersections even when they used quite conservative values for vehicle spacing in the platoons (i.e. 7.2 m). Kamal, Imura, Hayakawa, Ohata, and Aihara (2015) developed a control system which coordinates connected vehicles so they can safely and smoothly cross an intersection with no traffic lights. Both their estimations and simulations showed an almost 100% increase in capacity compared to the performance of a traditional signalized intersection. It should be noted that both Clement, Taylor, and Yue (2004) and Kamal, Imura, Hayakawa, Ohata, and Aihara (2015) assumed in their studies 100% market penetration of fully automated vehicles (level 4 or 5), no other road users (bicyclists or pedestrians), and perfect control performance (no errors).

However, some studies have identified possible tradeoffs between increases in capacity and various aspects of automated vehicles. Le Vine, Zolfaghari, and Polak (2015) identified a possible trade-off between comfort level and intersection capacity. These researchers showed that if the passengers of automated vehicles were to enjoy comfort levels similar to light rail or high-speed rail (in terms of longitudinal and lateral acceleration/deceleration), intersection capacity reduction could reach 53% and delays could increase by up to 1924%. Van den Berg and Verhoef (2016) showed that automated vehicles could have both positive and negative externalities through increases in capacity and parallel decreases in the value of time, although net positive externalities seem more likely according to their analysis. Moreover, Carbaugh, Godbole, and Sengupta (1998) showed that the probability of rear-end crashes in automated highway system platoons (level 4) increases as capacity increases, especially when intra-platoon spacing becomes very small (e.g. 1 m). Yet, collision severity tends to decrease because speed differences associated with crashes become smaller in higher capacity. The results of this study refer to the first rear-end crash between two vehicles and not to secondary crashes in a platoon of vehicles. Also, Hall, Nowroozi, and Tsao (2001) pointed to possible capacity reductions in entrance/exit of automated highway systems relative to the ideal 'pipeline' capacity without any entrances or exits, while Michael, Godbole, Lygeros, and Sengupta (1998) showed that capacity in automated highway systems could decrease compared with passengers cars, when trucks and buses are added.

Travel choices

Assumptions

In the short term, the increase of road capacity, the subsequent congestion relief and the decrease in GTC could lead to an increase of vehicle travel demand. However, vehicle travel demand might also increase because of transfers, pick-ups, drop-offs, and repositions of ride-sharing and vehicle-sharing vehicles. Moreover, the decrease of GTC could enhance the accessibility of more distant locations, thus allowing people to choose such destinations to live, work, shop, recreate, and subsequently increase the amount of their daily vehicle use. The increase in vehicle use might also be the result of a modal shift from conventional public transport. For example, buses could be gradually replaced by more flexible, less costly, and easier to operate automated ride-sharing and vehicle-sharing services. The use of high capacity public transport systems, such as trains, metro, and light rail might also drop after the introduction of automated vehicles, if ride-sharing or vehicle-sharing could adequately serve high-demand corridors. Finally, the increase of ride-sharing and vehicle-sharing systems might negatively influence the use of active modes, since automated shared vehicles could effectively serve short distance trips or feeder trips to public transportation. Also, further diffusion of the activities across the city might deter walking and bicycle use. However, the possibility that people still prefer active modes for short and medium distances for exercise and health reasons or simply because they like cycling or because cycling is cheaper, cannot be excluded. Moreover, enhanced road safety might also improve (the perception of) the safety of bicycling and subsequently positively influence cycle use, especially among the more vulnerable cycling groups (e.g. the elderly, children, and women; see Xing, Handy, & Mokhtarian, 2010; Milakis, 2015).

Literature results

Fagnant and Kockelman (2015) estimated a 26% increase of system-wide vehicle miles traveled (VMT) using a 90% market penetration rate of automated vehicles. This estimation was based on a comparison with induced travel demand caused by enhancement of road capacity after the expansion of road infrastructures. Milakis et al. (2017) reported a possible VMT increase between 3% and 27% for various scenarios of development of automated vehicles in the Netherlands. Higher VMT levels because of automated vehicles were identified by Vogt, Wang, Gregor, and Bettinardi (2015) through a fuzzy cognitive mapping approach that accounted for interactions among several factors including emerging mobility concepts (e.g. demand responsive services and intelligent infrastructure). Also, Gucwa (2014) reported an increase in VMT between 4% and 8% using different scenarios of road capacity and value of time changes through the introduction of automated vehicles. His scenario simulations in the San Francisco Bay area involved increases in road capacity of between 10% and 100% and decreases in value of time to the level of a high quality train or to half the current (in-vehicle) value of time. In the extreme scenario of zero time cost for traveling in an automated vehicle the increase of VMT was 14.5%. Additional vehicle travel demand in this study was due to changes in destination and mode choices. Correia, and van Arem (2016) reported an increase of 17% in VMT after replacing all private conventional vehicles by automated ones in simulations of the city of Delft, The Netherlands. Increase in VMT was the result of more automated vehicle trips either occupied (shifted from public transport) or unoccupied (moving vehicles to find parking places with lower cost). Another study showed that a modal shift of up to 1%, mainly from local public transport (bus, light rail, subway) and bicycle, to drive-alone and shared-ride modes could be possible because of the ability to multitask in automated vehicles (Malokin, Circella, & Mokhtarian, 2015). Levin and Boyles (2015) confirmed the possibility of increased modal shift from public transport to automated vehicles especially when these vehicles become widely available to travellers with lower value of time. Lamondia, Fagnant, Qu, Barrett, and Kockelman (2016) focused on possible modal shift from personal vehicles and airlines to automated vehicles for long distance travel using Michigan State as case study. These researchers found a modal shift of up to 36.7% and 34.9% from personal vehicles and airlines respectively to automated vehicles for trips less than 500 miles. For trips longer than 500 miles, automated vehicles appeared to draw mainly from personal vehicles (at a rate of about 20%) and much less from airlines. Childress, Nichols, and Coe (2015) used the Seattle region's activity-based travel model to explore the impacts of automated vehicles on travel demand. They simulated four different scenarios with respect to the AV penetration rate and changes in capacity, value of time, parking and operation costs. They concluded that an increase of VMT between 4% and 20% is likely in the first three scenarios that assumed capacity increases of 30%. Additional VMT was the result of both more and longer trips and also because of a modal shift from public transport and walking to car. Congestion delays appeared in only one of the first three scenarios that assumed a universal decline of value of time by 35% along with reduced parking costs. In the other two scenarios (with no or limited impact on the value of time), capacity increases offset additional travel demand, offering higher network speeds. In the fourth and final scenario, a shared autonomous vehicles-based transportation system with users bearing all costs of driving was assumed. Simulation results in this case showed that VMT could be reduced by 35% with less congestion delays. Significantly higher user costs per mile (up to about 11 times) induced shorter trip lengths, lower single-occupant vehicle share and an increase of public transport use and walking by 140% and 50%, respectively.

Fagnant and Kockelman (2014), on the other hand, indicated in their agent-based simulation study that automated vehicle-sharing schemes could result in 10% more VMT compared to conventional vehicles. The reason is that shared automated vehicles will need to move or relocate with no one in them to serve the next traveler. Yet, extra VMT was found to be around 4.5% when dynamic ride-sharing services were included in the simulation

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(Fagnant & Kockelman, 2016). Extra VMT was even lower when the ride-matching parameter (i.e. max time from initial request to final drop off at destination) for ride sharing travelers was increased. Also, in their simulation study for Lisbon, Portugal, the International Transport Forum (2015) reported an increase in VMT over the course of a day that could vary between 6.4% and 90.9% depending on the mode (vehicle-sharing or ride-sharing automated vehicles), the penetration rate, and the availability of high-capacity public transport. It should be noted that these studies did not take into account any potential changes in travel demand because of the introduction of automated vehicles. For example, Harper, Hendrickson, Mangones, and Samaras (2016) estimated that light-duty VMT could increase by up to 14% in the US, only through the additional travel demand of the non-driving, elderly, and people with travel-restrictive medical conditions because of automated vehicles.

Finally, Zmud, Sener, and Wagner (2016) explored impacts of automated vehicles on travel behavior using face-to-face interviews with 44 respondents from Austin, Texas. Contrary to the above modeling estimates, most of the participants (66%) stated that their annual VMT would remain the same if they would use an automated vehicle, because they would not change their routines, routes, activities, or housing location. Twenty-five percent of the participants responded that they would increase their annual VMT adding more long-distance, leisure, and local trips to their existing travel patterns.

Second-order implications of automated driving

In this section the second-order implications of automated driving for vehicle ownership and sharing, location choices and land use, and transport infrastructure are explored (see also Table 2 for an overview of studies on second-order implications of automated vehicles).

Vehicle ownership and sharing

Assumptions

The introduction of automated vehicles could facilitate the development of ride-sharing and vehicle-sharing services. Automated vehicles could significantly reduce operational costs (e.g. no driver costs) for ride-sharing and vehicle-sharing services. Such schemes could effectively meet individuals' travel demand needs with lower cost and higher flexibility compared to what today's bus and taxi systems offer to passengers. Subsequently, urban residents could decide to reduce the number of cars they own or even live car-free, avoiding the fixed costs associated with car ownership as well. However, shared automated vehicles might be utilized more intensively (e.g. additional travel to access travellers or to relocate) than conventional cars. We may thus expect shared automated vehicles to wear out faster and to be replaced more frequently.

Literature results

Several studies have simulated transport systems to explore the possibility of automated vehicles substituting conventional vehicles. Fagnant and Kockelman (2014; 2016) simulated the operation of shared automated vehicles (automated vehicles offering vehicle-sharing and dynamic ride-sharing services) in an idealized mid-size grid-based urban area and in Austin, Texas' coded network. These researchers reported that each shared automated vehicle could replace around eleven conventional vehicles. This rate dropped to around nine in a scenario of significantly increased peak hour demand. Also, Zhang, Guhathakurta, Fang, and Zhang (2015) and Boesch, Ciari, and Axhausen (2016) indicated in hypothetical and real city simulations (Zurich, Switzerland) that every shared automated vehicle could replace around ten and fourteen conventional vehicles, respectively. However, according to Chen, Kockelman, and Hanna (2016) if vehicle charging is also taken into account in the case of shared, electric, automated vehicles then the replacement rate of privately owned vehicles drops between 3.7 and 6.8. The International Transport Forum (2015) simulated different scenarios of automated modes (automated vehicles for ride-sharing and vehicle-sharing services), penetration rates, and availability of high-capacity public transport. This report indicated that shared automated vehicles could replace all conventional vehicles, delivering equal mobility levels with up to 89.6% (65% at peak-hours) less vehicles in the streets (scenario of automated ride-sharing services with high capacity public transport). Another conclusion of this study is that less automated ride-sharing than vehicle-sharing vehicles could replace all conventional vehicles. The reductions in fleet size were much lower (varying between 18% and 21.8%) when the penetration rate of shared automated vehicles was assumed at a 50% level and high-capacity public transport was also available. Finally, Spieser et al. (2014) estimated that only one third of the total number of passenger vehicles would be needed to meet travel demand needs if all modes of personal transportation vehicles were replaced by shared automated vehicles (automated vehicles offering vehicle-sharing services). These researchers used analytical techniques and actual transportation data in the case of Singapore for their study.

Location choices and land use

Assumptions

Automated vehicles could have an impact on both the macro (regional) and micro (local) spatial scale. At regional level, automated vehicles could enhance

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accessibility by affecting its transportation, individual and temporal components (see Geurs & van Wee, 2004 for an analysis of the accessibility components). Less travel effort, travel time, and cost and thus lower GTC could have an impact on the transportation component of accessibility. People without access to a car (not owning a car or not being able to drive) may travel to activities using (shared) automated vehicles, thus influencing the individual component of accessibility. Moreover, (fully) automated vehicles could perform certain activities themselves (e.g. pick up the children from school or the groceries from the supermarket). This could overcome any constraints resulting from the temporal availability of opportunities (e.g. stores opening/closing times) and individuals' available time. Enhanced regional accessibility might allow people to compensate lower travel costs with living, working, shopping, or recreating further away. Thus, an ex-urbanization wave to rural areas of former inner city and suburban residents could be possible, subject to land availability and land use policies. Enhanced accessibility may also affect the development of new centers. For example, former suburban employment centers could evolve into significant peripheral growth poles, serving the increased demand for employment and consumption of new ex-urban residents. The possibility to eliminate extensive parking lots in these kinds of centers because of the self-parking capability of (fully) automated vehicles could further enhance the potential of mixed-use growth in these areas. At the local level, automated vehicles could trigger changes in streetscape, building landscape design and land uses. First, the capability of self-parking and the opportunity of increased vehicle-sharing services because of automated vehicles could reduce demand for on-street and off-street parking, respectively. Subsequently, parking lanes could be converted into high occupancy vehicle lanes, bus lanes, and cycle lanes or to new public spaces (e.g. green spaces or wider sidewalks). A reduction of off-street parking requirements could bring changes in land use (infill residential or commercial development) and in building design (i.e. access lanes, landscaping). Moreover, surface parking lots and multi-story parking garages in central areas could be significantly reduced, enhancing infill development potential for people-friendly land use.

Literature results

Childress et al. (2015) identified potential changes in households' accessibility patterns in Seattle, WA, in a scenario where the transportation system of this region is entirely based on automated vehicles. This scenario not only assumed that driving is easier and more enjoyable (increased capacity by 30% and decreased value of time by 35%), but also cheaper because of lower parking costs. An analysis was performed on an activity-based model for a typical household type, using aggregate logsums to measure accessibility changes compared to a 2010 baseline scenario. Results showed that the perceived accessibility was universally enhanced across the whole region. The highest increase in accessibility was observed for households living in more remote rural areas. Changes to accessibility were also associated with an average increase of 20% in total VMT. The increase in travel demand was far higher (up to 30.6%) in outlying areas. Zakharenko (2016) analyzed the effects of fully automated vehicles on urban form from an urban economics perspective. This researcher developed a model of a monocentric two-dimensional city of half-circular shape that was calibrated to a representative US city. He assumed that workers could choose among no commute, traditional vehicle commuting and commuting by an automated vehicle taking into account variable, parking and fixed costs of each choice. According to the results, about 97% of the daily parking demand would be shifted to a "dedicated parking zone" in the periphery of the city center. This in turn would have a positive impact on the density of economic activity at the center of the city driving land rents 34% higher. On the other hand, reduced transportation costs because of automated vehicles would cause the city to expand and land rents to decline about 40% outside the city center. Finally, Zhang et al. (2015) showed in their agent-based simulation of a hypothetical city that the longer the empty cruising of shared automated vehicles the more evenly distributed the parking demand of these vehicles would be throughout the study area. If no empty cruising is allowed then parking demand of shared automated vehicles tended to be concentrated in the center of the study area.

Transport infrastructure

Assumptions

Increased road capacity because of automated vehicles could reduce future needs for new roads. However, induced travel demand resulting from enhanced road capacity, reduced GTC, and/or the proliferation of vehicle sharing systems and urban expansion may reduce or even cancel out or more than offset initial road capacity benefits. In the last case (more than offset), additional road capacity may be required to accommodate new travel demand. Automated vehicles will also be likely to reduce demand for parking, thus, probably, fewer parking infrastructures—either on-street or off-street—will be required. Moreover, a reduced need for public transport services in some areas (especially those with low and medium densities) could also lead to public transport service cuts. Pedestrians and cyclists could benefit from more space after the introduction of automated vehicles

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as a result of road capacity improvements. Finally, changes in ownership, organizational structure and operation of transport infrastructures might appear when fully automated vehicles (level 4 or 5) increase considerably their share in the vehicle fleet. According to Van Arem and Smits (1997) these changes could include a segmentation of the road network, operation and maintenance by private organizations and the emergence of transportation providers that could guarantee trip quality, regardless of the travel mode.

Literature results

International Transport Forum (2015) reported that both on-street and off-street parking spaces could be significantly reduced (between 84% and 94%) in all simulated scenarios that assumed a 100% shared automated vehicle fleet in the city of Lisbon, Portugal. Yet, the reduction was only incremental or even non-existent when these researchers tested scenarios with a 50% mix between shared automated and conventional vehicles. Also, Chen, Balieu, and Kringos (2016), Boesch, Ciari, and Axhausen (2016) Fagnant and Kockelman (2014, 2016), Zhang et al. (2015) and Spieser et al. (2014) offered estimations about a replacement rate of conventional vehicles by shared automated vehicles that varies between three and fourteen. Thus, parking demand could be reduced from about 67% up to over 90%.

Concerning the impact of automated vehicles on the long-term service performance of road infrastructures, Chen, Balieu, and Kringos (2016) showed that less wheel wander and increased capacity could accelerate pavement rutting damage, but potential increase in speed of automated vehicles could compensate for such negative effect by decreasing rut depth.

Third-order implications of automated driving

In this section the third-order implications of automated driving on energy consumption and air pollution, safety, social equity, economy, and public health are explored (see also Table 2 for an overview of studies on third-order implications of automated vehicles).

Energy consumption and air pollution

Assumptions

The introduction of automated vehicles might result in energy and emission benefits because of reduced congestion, more homogeneous traffic flows, reduced air resistance due to shorter headways, lighter vehicles (a result of enhanced safety), and less idling (a result of less congestion delays). Also, automated vehicles may require less powerful engines because high speeds and very rapid acceleration will not be needed for a large share of the fleet (e.g. shared automated vehicles). This could further improve the fuel efficiency and limit emissions. Yet, privately owned automated vehicles could still offer the possibility of mimicking different human driving styles (e.g. fast, slow, and aggressive). Moreover, the possibility that automated vehicles will be larger than conventional vehicles, serving passengers' needs to perform various activities while on the move, cannot be excluded. For example, extra space might be needed to facilitate office-like work (table and docking stations), face-to-face discussions (meeting table) or sleeping, and relaxing (couch, bed). Larger vehicles may limit fuel efficiency gains in this case. Shorter search time for parking and reduced needs for construction and maintenance of parking infrastructures can also lead to environmental benefits. However, shared automated vehicles may be programmed to drive continuously until the next call rather than try to find parking in a downtown area, generating more emissions. Additionally, an automated vehicle may be programmed to drive itself outside of the downtown center to an area where parking is cheaper or free, thus consuming more energy, producing more emissions and creating more traffic congestion. Finally, a smaller fleet size could be associated with lower energy and emissions for car manufacturing and road infrastructure development. Nevertheless, the potential environmental benefits of automated vehicles could be significantly mitigated by increased travel demand in the long term.

Literature results

Several studies have reported fuel savings from vehicle automation systems. Wu, Zhao, and Ou (2011) demonstrated a fuel economy optimization system that provides human drivers or automated systems with advice about optimal acceleration/deceleration values, taking into account vehicle speed and acceleration, but also current speed limit, headway spacing, traffic lights, and signs. Their driving simulator experiment in urban conditions with signalized intersections revealed a decrease in fuel consumption of up to 31% for the drivers who used the system. Khondaker and Kattan (2015) reported fuel savings of up to 16% for their proposed variable speed limit control algorithm compared with an uncontrolled scenario. Their control system incorporated real-time information about individual driver behavior (i.e. acceleration/deceleration and level of compliance with the set speed limit) in a context of 100% connected vehicles. Yet, fuel savings were lower when the penetration rate of connected vehicles was assumed at a 50% level. Also, Li, Peng, Li, and Wang (2012) showed that the application of a Pulse-and-Gliding (PnG) controller could result in fuel savings of up to 20% compared to a linear quadratic

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(LQ)-based controller in automated car-following scenarios. Other studies have also reported significant fuel consumption savings in field and simulation tests of their ACC and CACC control algorithms (see e.g. Eben Li, Li, & Wang, 2013; Kamal, Taguchi, & Yoshimura, 2016; Luo, Liu, Li, & Wang, 2010; Rios-torres & Malikopoulos, 2016; Wang, Hoogendoorn, Daamen, & van Arem, 2014) including controllers for hybrid electric vehicles (Luo, Chen, Zhang, & Li, 2015; Vajedi & Azad, 2015)

In a context where there are intersections, the controller proposed by Zohdy and Rakha (2016) provides advice about the optimum course of vehicles equipped with CACC. These researchers reported fuel savings of, on average, 33%, 45%, and 11% for their system compared with the conventional intersection control approaches of a traffic signal, all-way-stop, and roundabout, respectively. Moreover, Ala, Yang, and Rakha (2016), Kamalanathsharma and Rakha (2016) and Asadi and Vahidi (2011) reported fuel savings up to 19%, 30%, and 47%, respectively, for their cooperative adaptive cruise controller that uses vehicle-to-infrastructure (traffic signal in this case) communication to optimize a vehicle's trajectory in the vicinity of signalized intersections. Finally, Manzie, Watson, and Halgamuge (2007) showed that vehicles exchanging traffic flow information through sensors and inter-vehicle communication could achieve the same (i.e. 15–25%) or even more (i.e. up to 33%, depending on the amount of traffic information they can process) reductions in fuel consumption compared to hybrid-electric vehicles.

Looking at the implications of vehicle automation for air pollution, Grumert et al. (2015) reported a reduction in NOx and Hydrocarbon (HC) emissions from the application of a cooperative variable speed limit system that uses infrastructure-to-vehicle communication to attach individualized speed limits to each vehicle. Emissions were found to decrease with higher penetration rates with this system. Wang, Chen, Ouyang, and Li (2015) also found that a higher penetration rate of intelligent vehicles (i.e. vehicles equipped with their proposed longitudinal controller) in a congested platoon was associated with lower emissions of NOx. Moreover, Bose and Ioannou (2001) found, through using simulation and field experiments, that emissions could be reduced from 1.5% (NOx) to 60.6% (CO and CO_2) during rapid acceleration transients with the presence of 10% ACC equipped vehicles. Choi and Bae (2013) compared CO_2 emissions for lane changing of connected and manual vehicles. They found that connected vehicles can emit up to 7.1% less CO_2 through changing from a faster to a slower lane and up to 11.8% less CO_2 through changing from a slower to a faster lane. Environmental benefits from the smooth reaction of ACC vehicles in traffic disturbances caused by high-acceleration maneuvers, lane cut-ins, and lane exiting were also confirmed by Ioannou and Stefanovic (2005).

In a larger scale agent-based study, Fagnant and Kockelman (2014) simulated a scenario of a mid-sized city where about 3.5% of the trips in day are served by shared automated vehicles. These researchers reported that environmental benefits of shared automated vehicles could be very important in all of the pollutant indicators examined (i.e. SO_2, CO, NOx, Volatile organic compounds [VOC] PM_{10}, and GHG [Greenhouse gas]). VOC and CO showed the highest reductions, mainly because of the significantly less number of times a vehicle starts, while the impact on Particulate matter with effective diameter under 10 μm (PM_{10}), and GHG was relatively small, mainly because of the additional travel shared vehicles have to undertake in order to access travelers or to relocate. It should be noted that this simulation study assumed that shared automated vehicle users would not make more or longer trips and that the fleet (both automated and conventional vehicles) would not be electric, hybrid-electric or using alternative fuels. Finally, in another study focusing on the long-term effects of automated vehicles, Greenblatt and Saxena (2015) estimated that autonomous taxis (i.e. battery electric shared automated vehicles) in 2030 could reduce GHG emissions per vehicle per mile (a) by 87–94% compared to the emissions of internal combustion conventional vehicles in 2014 and (b) by 63–82% compared to the estimated emissions for hybrid-electric vehicles in 2030. According to these researchers, a significant increase in travel demand for autonomous taxis makes battery electric vehicle technology more cost-efficient compared to internal combustion or hybrid-electric vehicle technologies. Lower GHG intensity of electricity and smaller vehicle sizes explain the significant reductions of GHG for (battery) electric autonomous taxis. Furthermore, these researchers indicated that autonomous taxis could offer almost 100% reduction in oil consumption per mile compared to conventional vehicles because oil provides less than 1% of electricity generation in the US. Large energy savings of up to 91% per automated vehicle in 2030 were also estimated by Brown, Gonder, and Repac (2014) in a scenario that accounted for maximum impact of factors that could lead to energy savings (e.g. efficient travel, lighter vehicles, and electrification) and increased energy use (e.g. longer travel distances and increased travel by underserved populations such as youth, disabled, and elderly). However, it remains uncertain which of these factors and to what extent will they be realized in the future. Therefore, the balance between energy savings and increased energy use from automated vehicles could vary significantly. Similar uncertainty about the net effect of vehicle automation

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on emissions and energy consumption was reported by Wadud, MacKenzie, and Leiby (2016).

Safety

Assumptions

Over 90% of crashes are attributed to human driver (National Highway Traffic Safety Administration, 2008; data for the US context). Typical reasons include, in descending order, errors of recognition (e.g. inattention), decision (e.g. driving aggressively), performance (e.g. improper directional control), and non-performance (e.g. sleep). The advent of automated vehicles could significantly reduce traffic accidents attributed to the human driver by gradually removing the control from the driver's hands. This can be achieved through advanced technologies applied to automated vehicles with respect to perception of the environment and motion planning, identification and avoidance of moving obstacles, longitudinal, lateral and intersection control, and automatic parking systems, for example. However, any unexpected behavioral changes by a driver because of vehicle automation systems, human limitation in monitoring automation or in taking control when necessary, along with possible cyberattacks, maliciously controlled vehicles and software vulnerabilities might compromise the safety levels of automated vehicles.

Literature results

A significant amount of studies have proposed a wide variety of advanced driver assistance systems that could enhance traffic safety levels. These systems include collision avoidance (see e.g. Hayashi, Isogai, Raksincharoensak, & Nagai, 2012; Li, Juang, & Lin, 2014; Shim, Adireddy, & Yuan, 2012; Naranjo, Jiménez, Anaya, Talavera, & Gómez, 2016), lane keeping (see e.g. Lee, Choi, Yi, Shin, & Ko, 2014) and lane change assistance (see e.g. Hou, Edara, & Sun, 2015; Luo, Xiang, Cao, & Li, 2016), longitudinal speed assistance (see e.g. Martinez & Canudas-de-Wit, 2007), and intersection assistance (see e.g. Liebner, Klanner, Baumann, Ruhhammer, & Stiller, 2013). Several other studies suggested that greater levels of safety could be secured by advanced longitudinal or lateral multi-objective optimization controllers (see e.g. Gong, Shen, & Du, 2016; Khondaker & Kattan, 2015; Wang, Hoogendoorn, Daamen, van Arem, & Happee, 2015), intersection controllers (see e.g. Dresner & Stone, 2008) and path planning algorithms (see e.g. Ferguson, Howard, & Likhachev, 2008; Kuwata et al., 2009) with specific safety requirements.

Although advanced driver assistance systems can reduce accident exposure and improve driver behavior (see Spyropoulou, Penttinen, Karlaftis, Vaa, & Golias, 2008), adaptive behavior (i.e. the adoption of riskier behavior because of over-reliance on the system) may have adverse effects on traffic safety (see Brookhuis et al., 2001). For example, Hoedemaeker and Brookhuis (1998) showed that the use of ACC may induce the adoption of higher speed, smaller minimum time headway and larger brake force. Rudin-Brown and Parker (2004) indicated lower performance in brake light reaction time and lane keeping for ACC users. Markvollrath, Schleicher, and Gelau (2011) reported delayed reactions (i.e. speed reduction) for ACC users when approaching curves or entering fog, while Dixit, Chand, and Nair (2016) showed that reaction times in taking control of the vehicle after disengagement of the autonomous mode increases with vehicle miles travelled. Xiong, Boyle, Moeckli, Dow, and Brown (2012) showed that drivers' adaptive behavior—and therefore the safety implications of ACC—is related to trust in automation, driving styles, understanding of system operations and the driver's personality. Furthermore, safety levels might not substantially increase (or even decrease) until high penetration rates of fully automated vehicles are realized. For example, human driving performance could degrade in level 3 of automation because people have limitations when monitoring automation and taking over control when required (see e.g. Strand, Nilsson, Karlsson, & Nilsson, 2014; Young & Stanton, 2007). Moreover, automated vehicles might negatively influence a driver's behavior when using conventional vehicles in mixed traffic situations by making them adopt unsafe time headways (contagion effect; see Gouy, Wiedemann, Stevens, Brunett, & Reed, 2014).

Cyberattacks could also be an important threat for traffic safety. According to Petit and Shladover (2015), global navigation satellite systems (GNSS) spoofing and injection of fake messages into the communication between vehicles are the two most likely and most severe attacks for vehicle automation. Amoozadeh et al. (2015) simulated message falsification and radio jamming attacks in a CACC vehicle stream, influencing the vehicles' acceleration and space gap, respectively. These researchers showed that security attacks could compromise traffic safety, causing stream instability and rear-end collisions. Also, Gerdes, Winstead, and Heaslip (2013) showed that the energy expenditure of a platooning system could increase by up to 300% through the attack of a malicious vehicle, influencing the motion (braking and acceleration) of surrounding vehicles.

Social equity

Assumptions

The social impacts and distribution effects of a transport system can be significant. Vulnerable social groups, such

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as the poorest people, children, younger, older, and disabled people can suffer more from these impacts, resulting in their limited participation in society and potentially, in social exclusion (Lucas & Jones, 2012). The introduction of automated vehicles could have both positive and negative implications for social equity. Automated vehicles could offer the social groups that are currently unable to own or drive a car (e.g. younger, older and disabled people) the opportunity to overcome their current accessibility limitations. For example, not only people with physical and sensory (vision, hearing) disabilities, but also younger and older people, could use automated (shared) on demand services to reach their destinations. However, the first automated vehicles in the market are likely to be quite expensive, thus limiting these benefits to only the wealthier members of these groups for certain time. Safety benefits might also be unevenly distributed among different social groups. Owners of automated vehicles will probably enjoy higher levels of travel safety compared to drivers of conventional vehicles. Moreover, potential spread of urban activities and possible reduction of public transport services (especially buses) might further limit access to activities for poorer social groups. On the other hand, potential conversion of redundant road space to bicycle and pedestrian infrastructures (especially infrastructures that connect with high capacity public transport) could offer accessibility benefits to vulnerable population groups. Finally, the increase of vehicle-sharing services and the subsequent possible decrease of the requirements for construction of off-street parking spaces could increase housing affordability.

Literature results

Eby et al. (2016) reported, in their review paper, a positive effect (i.e. avoiding crashes, enhancing easiness and comfort of driving, increasing place, and temporal accessibility) of many in-vehicle technologies (e.g. lane departure warning, forward collision warning/mitigation, blind spot warning, parking assist systems, navigation assistance, and ACC) for older drivers. Such improvements could allow older adults to drive for more years despite declining of their functional abilities. Harper et al. (2016) estimated the extent to which total travel demand could increase in the US because of an increase in travel demand by the non-driving, elderly, and people with travel-restrictive medical conditions. They assumed that in a fully automated vehicle context, people currently facing mobility restrictions would travel just as much as normal drivers within each age group and gender. They found that the combined increase in travel demand from different social groups could result in a 14% increase in annual light-duty VMT for the US population. Finally, Mladenovic and McPherson (2016) analyzed the opportunities arising from vehicle automation to incorporate social justice in future traffic control systems in terms of efficiency and equal access.

Economy

Assumptions

Automated vehicles could bring significant economic benefits to individuals, society and businesses, but they may also induce restructuring and possible losses in some industries as well. The effects on GTC are distinguished from other effects that are relevant for the economy. Looking at the GTC effects, improved traffic safety could prevent accidents, thus avoiding the costs to society of accidents, such as human capital losses, medical expenses, lost productivity and quality of life, property damage, insurance, and crash prevention costs. A reduction in congestion delays would mean less travel costs for individuals and reduced direct production costs for businesses. Moreover, less congestion delays, along with increased potential for performing other activities (e.g. working or meeting) while on the move, could result in productivity gains. Finally, an increase in shared automated vehicle services would save individuals significant (fixed) costs associated with car ownership without compromising their mobility needs.

Other effects are now discussed. The reduction of off-street parking requirements (ground floor level parking, parking lots or multi-story parking garages) could allow the development of more economically productive activities (e.g. residential, commercial or recreational). However, a possible massive reduction in car ownership levels might have a critical negative impact on the automotive industry. New business models in this industry are likely to emerge, reflecting the convergence of different technologies in automated vehicles, while car-related industries might experience losses (e.g. motor vehicle parts, primary and fabricated metal, and plastics and rubber products). Also, jobs in professional and technical services, administration, wholesale and retail trade, warehousing, finance and insurance, and management of automotive companies could be negatively affected by the reduction of turnover in the automotive industry. Full vehicle automation could also directly lead to job losses for various professions such as taxi, delivery, and truck drivers. On the other hand, new jobs in hardware and software technology for automated vehicles might be generated. It is likely that such job related changes will vary between countries and regions. Finally, overall household expenditures can change because of automated vehicles (either increase or decrease). This could subsequently influence expenditures on other goods or services (assuming constant saving rates). Such changes in households' expenditures could create or reduce jobs in various sectors.

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Literature results

A first systematic attempt to provide an order-of-magnitude estimate about both the social and private economic impacts of automated vehicles in the US context was made by Fagnant and Kockelman (2015). Their estimation took into account the safety, congestion, parking, travel demand and vehicle ownership impacts and was based on several assumptions about market share, the number of automated vehicles, fuel saving, delay reduction, crash reduction, and VMT, among other things. Their results showed that social benefits per automated vehicle per year could reach $2960 (10% market share) and increase up to $3900 (90% market share) if the comprehensive costs of crashes, in the context of pain, suffering and the full value of a statistical life, are taken into account. These estimations were based on the assumption that crash and injury rates would be reduced by 50% and 90% for 10% and 90% market penetration rate of automated vehicles, respectively. The main reason behind such significant reductions in crash rates is assumed to be the near-elimination of crashes caused by human error because of the vehicle automation technology. These researchers also showed that benefits for individuals are likely to be small, assuming current technology costs at $100,000. Yet, an investment in this technology when purchase price drops to $10,000 seems to generate a positive return rate for many individuals, even with quite low values of time. Another study examined the susceptibility of 702 occupations to technological developments (Frey & Osborne, 2017). This study concluded that about 47% of total US employment across all sectors of the economy, including occupations in the transportation and logistics sector (e.g. taxi, ambulance, transit, delivery services, heavy truck drivers, chauffeurs, parking lot attendants, and traffic technicians) has a very high risk (probability of 0.7 or higher) of being replaced by computer automation within next two decades. This study assumed that not only routine, but also non-routine cognitive and manual tasks would be increasingly susceptible to automation because of the expansion of computation capabilities (i.e. machine learning and mobile robotics) and the decrease of the market price of computing in the future. Yet, it was also assumed that non-routine tasks involving perception and manipulation, creative, and social intelligence would still be extremely difficult to automate in the near future.

Public health

Assumptions

Public health benefits might result from reduced congestion, lower traffic noise, increased traffic safety, and lower emissions from automated vehicles. Literature has shown a clear positive association between morbidity outcomes, premature mortality rates, stress, and traffic congestion (see Hennessy & Wiesenthal, 1997; Levy, Buonocore, & von Stackelberg, 2010; Miedema, 2007). Furthermore, the enhancement of road capacity, along with the reduction of on-street parking demand, might allow conversion of redundant road space into bicycle and pedestrian infrastructures. Several studies have indicated that the provision of such infrastructures is associated with higher levels of use of active modes (Dill & Carr, 2003; Buehler & Pucher, 2012) and subsequently with important public health benefits (e.g. obesity and diabetes; see Pucher, Buehler, Bassett, & Dannenberg, 2010; Oja et al., 2011). However, an increase in vehicle use because of automated vehicles (either more or longer vehicle trips) could also have a negative impact on public health, since levels of physical activity is likely to decrease.

Literature results

No systematic studies were found about the implications of automated vehicles for public health.

Conclusions and directions for future research

So far, current literature has mainly explored the technological aspects of vehicle automation and its impacts on driver and traffic flow characteristics. However, interest in the wider implications of automated vehicles is constantly growing as this technology evolves. In this paper, the effects of automated driving that are relevant to policy and society were explored, literature results about these effects were reviewed and areas for future research were identified. This review is structured, based on the ripple effect concept, which represents the implications of automated vehicles at three stages: first-order (traffic, travel cost, and travel choices), second-order (vehicle ownership and sharing, location choices and land use, and transport infrastructure), and third-order (energy consumption, air pollution, safety, social equity, economy, and public health). General conclusions are presented below and more specific ones for first, second and third order impacts, along with suggestions for the future research are presented in subsequent sections.

Literature about the policy and society related implications of automated driving is rapidly evolving. Most studies in this review are dated after 2010. This does not mean that research on development of automated vehicle systems and their implications has only been done in the last 7 years. Bender (1991) offers a comprehensive overview of the historic development of automated highway systems from the late 1950's up to about 1990 (e.g. the General Motors' systems). Moreover, several explorative or in-depth modeling studies examined a wide arrange of the impacts of automated highway systems several decades earlier (see e.g. congestion, travel speed, vehicle hours

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of delay, Benjamin, 1973; Miller, Bresnock, Shladover, & Lechner, 1997; emission rates, Barth, 1997) or initiated discussions about the implications of these systems for safety and driver convenience (Ward, 1994), infrastructure and urban form, (see Miller, 1997) and social equity (see Stevens, 1997). These studies can offer valuable information about the historical evolution of automated systems and the initial estimations of their impacts.

The majority of the studies in our literature review have explored impacts on capacity, fuel efficiency, and emissions. Research on wider impacts and travel demand in particular has started to pick up during the last 3 years. The implications of automated vehicles for the economy, public health, and social equity are still heavily under-researched (see Table 2).

The policy and societal implications of automated vehicles involve multiple complex dynamic interactions. The magnitude of these implications is expected to increase with the level of vehicle automation (especially for level 3 or higher), the level of cooperation (vehicle-to-vehicle and vehicle-to-infrastructure), and the penetration rate of vehicle automation systems. The synergistic effects between vehicle automation, sharing, and electrification can strengthen the potential impacts of vehicle automation. Yet, the balance between the short-term benefits and the long-term impacts of vehicle automation remains an open question.

Further research in a number of areas, as indicated in following sections, could reduce this uncertainty. A holistic evaluation of the costs and benefits of automated vehicles could help with urban and transport policies, ensuring a smooth and sustainable integration of this new transport technology into our transportation systems.

First-order implications of automated driving

Conclusions

First-order implications of automated vehicles comprised travel cost, road capacity, and travel choices. The fixed cost of automated vehicles is likely to reduce over time. GTC will possibly be lower while both road capacity and travel demand will probably increase in the short term.

Vehicle automation can result in travel time savings. Simulations have explored this assumption on highways, intersections and contexts involving shared automated vehicles. Intersections appear to have more room for travel time optimization compared to highways, while a higher penetration rate of vehicle automation systems seems to result in more travel time savings. Literature results also suggest that vehicle automation systems could result in lower fuel consumption and subsequently reduced travel cost in the short term. Research on various aspects of the third component of GTC (travel effort) is rather limited. Moreover, there is still very little to read in existing literature about the impact of vehicle automation on the values of time, leaving a striking gap in the literature on this subject. Most, studies have focused on incorporating comfort (in terms of acceleration and jerk) as the optimizing metric in path-planning algorithms. Yet, human comfort is influenced by many other factors (e.g. time headway), some of which remain unexplored (e.g. motion sickness, apparent safety, and natural paths). Therefore, there is no conclusion about the balance of all comfort related effects. Also, studies about vehicle automation impacts on travel time reliability and on utilization of travel time while on the move are scarce.

Research results show that automated vehicles could have a clear positive impact on road capacity in the short term. The magnitude of this impact is related to the level of automation, cooperation between vehicles and the respective penetration rates. A 40% penetration rate of CACC appears to be a critical threshold for realizing significant benefits on capacity (>10%), while a 100% penetration rate of CACC could theoretically double capacity. Capacity impacts at level 3 or higher levels of vehicle automation and more advanced levels of cooperation among vehicles but also between vehicles and infrastructure (e.g. multi-platooning leaders, intersection control systems, and variable speed limits) could well exceed this theoretical threshold.

Most studies show that automated vehicles could induce an increase of travel demand between 3% and 27%, due to changes in destination choice (i.e. longer trips), mode choice (i.e. modal shift from public transport and walking to car), and mobility (i.e. more trips). Additional increases in VMT are possible for shared automated vehicles because of empty vehicles traveling to the next customer or repositioning. However, one study (Childress et al., 2015) indicated that if user costs per mile are very high in a shared automated vehicle based transportation system, VMT may actually be reduced. The same study attained mixed, non-conclusive results about the trade-off between increased travel demand, capacity increases and congestion delays. No study took into account the potential changes in land use patterns, which may also influence future travel demand.

Directions for future research

There is still a critical knowledge gap about the impact of vehicle automation on individual components of travel effort (i.e. comfort, travel time reliability and utilization of travel time while on the move). For example, how can factors such as motion sickness and perceived safety affect the travel comfort of automated vehicles? To what extent can vehicle automation systems reduce travel time variability? How will people utilize available time in

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automated vehicles? Also, what is the collective impact of the different components of travel effort on values of time for different socioeconomic groups and trip purposes? Evidence about these individual factors—and subsequently GTC—can offer valuable input to a multitude of other related areas of research, such as the impacts on travel choices, accessibility and land uses, energy consumption, and air pollution.

Additional research on travel demand impacts is critical as well. Possible travel demand changes will to a large extent determine the magnitude of several of the other impacts of automated vehicles. Future studies should further explore travel demand implications not only because of changes in destination choice, mode choice and relocation of (shared) automated vehicles but also because of possible changes in land uses, parking demand and latent demand from social groups with travel-restrictive conditions.

Furthermore, although first-order impacts of vehicle automation on capacity are well-researched, potential trade-offs between additional capacity and GTC associated factors such as travel comfort, safety, and travel time reliability remain relatively unexplored.

Second-order implications of automated driving

Conclusions

Second-order implications of automated vehicles comprised vehicle ownership and sharing, location choices, land use and transport infrastructure. Literature results suggest that shared automated vehicles could replace a significant number of conventional vehicles (from about 67% up to over 90%) delivering equal mobility levels. The overall reduction of the conventional vehicle fleet could vary according to the automated mode (vehicle-sharing, ridesharing, shared electric vehicle), the penetration rate of shared automated vehicles and the presence or absence of public transport. For example, a wide penetration of shared automated vehicles supported by a high capacity public transport system would be expected to result in the highest reduction of conventional vehicle fleet. Few studies have explored the impact of automated vehicles on location choices and land use. According to their results automated vehicles could enhance accessibility citywide, especially in remote rural areas, triggering further urban expansion. Automated vehicles could also have a positive impact on the density of economic activity at the center of the cities. Parking demand for automated vehicles could be shifted to peripheral zones, but could also remain high in city centers, if empty cruising of shared automated vehicles is not allowed. Moreover, several studies showed that shared automated vehicles can significantly reduce parking space requirements up to over 90%. Finally, less wheel wander and increased capacity because of automated vehicles could accelerate pavement-rutting damage. Yet, increase in speed of automated vehicles could compensate for such negative effect by decreasing rut depth.

Directions for future research

A critical research priority is the exploration of the implications that automated vehicles have for accessibility and, subsequently, for land uses. Results from this kind of research will give some input into the assessment of many other longer-term impacts of automated vehicles, including energy consumption, air pollution, and social equity. A comprehensive assessment of accessibility changes should focus on all components of accessibility (transportation, land use, individual, and temporal).

The impacts of automation on vehicle ownership could be further explored. Thus far, research has discovered how many shared automated vehicles can substitute conventional vehicles to serve (part of) current mobility demand. Yet, a more important question is: what will the size of vehicle fleet reduction be if possible changes in travel demand and the willingness of people to own or use shared automated vehicles are taken into account?

Possible changes in urban streetscape and building landscape because of vehicle automation also offer an area for design research and experimentation. To what extent will vehicle automation affect the level and geographical distribution of parking demand? What will be the potential changes in the geometrical characteristics of roads and intersections because of capacity enhancement, motion stability of automated vehicles and automated intersection management? How will potential new urban space be redistributed among different land uses (e.g. between open space and new buildings) and users (e.g. vehicles, cyclists, and pedestrians)?

Third-order implications of automated driving

Conclusions

Third-order implications of automated vehicles comprised energy consumption and air pollution, safety, social equity, the economy, and public health. First-order impacts on fuel efficiency, emissions and accident risk were also included in this section of our analysis for consistency reasons. Literature results suggest that the use of automated vehicles can result in fuel savings and lower emissions in the short term. The net effect of vehicle automation on energy consumption and GHG emissions in the long term remains uncertain. Traffic safety can improve in the short term but behavioral adaptation and low penetration rates of vehicle automation might compromise these benefits. Few studies on the economic and social equity impacts exist, while no systematic studies were found for public health implications of automated vehicles.

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Various longitudinal, lateral and intersection control algorithms and optimization systems can offer significant fuel savings and lower emissions of NOx, CO, and CO_2. Studies reviewed in this paper reported fuel savings up to 31% for longitudinal and lateral movement controllers and up to 45% for intersection controllers. Both fuel economy and emission reductions are reported higher as the penetration rate of vehicle automation systems increases. Furthermore, shared use of automated vehicles is associated with reduced emissions (VOC and CO in particular) because of the lower number of times a vehicles starts. One study (Greenblatt & Saxena, 2015) associated the long-term impacts of battery electric shared automated vehicles with up to 94% less GHG and nearly 100% less oil consumption per mile, compared to conventional internal combustion vehicles. Yet, several factors could lead to increased energy use (e.g. longer travel distances and increased travel by underserved populations such as youth, disabled, and elderly). Thus, the net effect of vehicle automation on energy consumption and GHG emissions remains uncertain.

As for traffic safety, literature results suggest that advanced driver assistance systems can reduce exposure to accidents. Level 3 or higher levels of automation can further enhance traffic safety. However, as long as the human driver remains in-the-loop, behavioral adaptation—namely the adoption of riskier behavior because of over-reliance on the system—can compromise safety benefits. Moreover, fully automated vehicles might not deliver high safety benefits until high penetration rates of these vehicles are realized. Cyberattacks, such as message falsification and radio jamming, can compromise traffic safety as well.

Finally, research on the impacts of vehicle automation on the economy, social equity and public health is almost non-existent. Automated vehicles could have significant impacts on all three areas. Results from one study (Fagnant & Kockelman, 2015) indicate that social benefits per automated vehicle per year could reach $3900 where there is a 90% market share of automated vehicles, while a positive return rate for individuals should not be expected before the additional cost for vehicle automation drops to $10,000. Another study (Frey & Osborne, 2017) concluded that occupations in the transportation and logistics sectors (e.g. taxi, ambulance, transit, delivery services, heavy truck drivers, chauffeurs, parking lot attendants, and traffic technicians) have a high probability (>0.7) of being replaced by computer automation within the next two decades. In-vehicle technologies can have positive effects (i.e. avoiding crashes, enhancing easiness and comfort of driving, increasing place, and temporal accessibility) for elderly. Such improvements could extend driving life expectancy for older adults. One study estimated that automated vehicles could induce up to 14% additional travel demand from the non-driving, elderly, and people with travel-restrictive medical conditions.

Directions for future research

The emission and fuel efficiency effects of vehicle automation are well researched. However, the magnitude of the effect at different levels of automation and penetration rates could be further tested. A clear research priority is the exploration of the long-term effects of automated vehicles on energy consumption and emissions, taking into account potential travel demand changes but also the additional synergistic effects between vehicle automation, sharing, and electrification and possible changes in vehicle size. Results from this kind of research will allow us to better assess the balance between the short-term benefits and the long-term impacts of automated vehicles on energy consumption and emissions.

Another critical research priority concerns safety implications in the transitional contexts of fully automated and conventional vehicles. To what extent will vehicle automation and human drivers of conventional vehicles compromise the performance of each other in mixed traffic situations? A better understanding of the types of cyberattacks and their potential impacts on traffic safety is critical too.

A comprehensive assessment of economic, public health and social impacts is also missing from current literature. For example, what could be the scale of job losses (or gains) due to full vehicle automation? Which sectors and which countries and/or regions would be most affected? And what could be the strategies to mitigate the economic impacts of expected job losses? The impact of vehicle automation on public health is also an important area for further research. To what extent will vehicle automation induce lower levels of physical activity and what will the possible impacts be on activity-related public health issues, such as obesity and diabetes? The exploration of social impacts and distribution effects through the analysis of potential accessibility changes would also contribute to a better understanding of the social implications of automated vehicles. To what extent could (shared) automated vehicles influence the ability of vulnerable social groups (e.g. people with physical, sensory and mental disabilities, younger or older people, and single parents) to access economic and social opportunities? How benefits stemming from vehicle automation will be distributed among different social groups?

Methodological challenges in exploring the implications of automated vehicles

To further explore the implications of automated vehicles, we will have to face several methodological challenges.

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One critical issue is that this technology (especially at level 3 or higher levels of automation) is still in its infancy. Thus, no adequate empirical data about the use of automated vehicles exist yet. Therefore, studies have mainly made use of micro and macro traffic simulation, driving simulators, field experiments and analytical methods to explore first-order implications of automated vehicles on travel time, capacity, fuel efficiency, emissions, and safety. More empirical studies about first-order implications of vehicle automation are a clear priority as this technology evolves. For second and third-order implications, the armory of methods needs to expand to capture the behavioral aspects, underlying potential changes due to vehicle automation. Thus, for example, qualitative methods, such as focus groups or in-depth interviews, in combination with quantitative methods, like stated choice experiments, could be used for exploring questions about the impacts of vehicle automation on travel comfort, utilization of travel time while on the move, value of time, travel, and location choices. Yet, people may have difficulties in envisioning automated vehicles, so stated choice experiments could suffer from hypothetical bias (see Fifer, Rose, & Greaves, 2014). More creative techniques such as virtual reality or serious gaming would be useful in behavioral experiments about the impacts of automated vehicles. Another approach may be to investigate similar systems that are essentially automated. For example, investigate the value of time for train commuters who both live and work near stations, as for them a train trip is essentially automated. Travel behavior changes because of ICT (e.g. telecommuting) could offer insights into possible behavioral changes because of vehicle automation. Expert opinion research (e.g. Delphi technique) could also be an alternative method.

Agent-based and activity-based models could then be used to simulate possible changes in travel demand, vehicle ownership and other environmental indicators, such as energy consumption and emissions. The connection of travel models with land use models (in so-called Land Use—Transport Interaction, or LUTI models) would also allow potential long-term land use impacts on travel demand to be captured. Alternative approaches could involve empirical models for the analysis of comparable systems and their potential impacts on land use (e.g. valet parking, car-free neighborhoods, and high speed train). Finally, accessibility metrics and measures of inequality could be used in the analysis of the social equity impacts of automated vehicles.

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