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Chapter 13

Connected and automated vehicles: effects on pricing

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Abstract

This chapter introduces the basic concepts of transport pricing theory applied to automated vehicles. The study covers traditional private and public transport modes, plus shared mobility systems. We briefly introduce the expected benefits and shortcomings of the automated vehicle technology, and then analyse the effect of vehicle automation on the modal attributes that are relevant to the pricing of transport services. Expected effects as discussed in the scientific literature are summarised. An optimal transport pricing model is presented considering three modes: private car, public transport, and an active mode, in order to uncover the potential effect of vehicle automation on first-best prices. We find that a cost reduction due to automation pushes towards lower optimal fares for both private cars and public transport, making both modes more accessible. Vehicle automation has the potential to make motorised transport more attractive relative to active modes, therefore, future pricing schemes should include the health and environmental benefits of active mobility.

1. Introduction

The definition of autonomous driving capabilities accounts for a spectrum of functionalities that start with basic driver support functions, all the way to the top level, which is complete driving autonomy (SAE International, 2021). The spectrum consists of six levels, where the first three (L0, L1, and L2) are denominated “Driver Support Systems” (which include currently available features such as cruise control and lane keeping), while L3, L4 and L5 are used for actual “Automated Driving Systems”. In this chapter, the terms human-driven vehicle (HDV) and automated vehicle (AV) will be used to refer to the bottom and top three levels of automation, respectively. A distinctive characteristic of the highest levels of AVs is their ability to use wireless technologies such vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications, allowing the interchange of information with other entities from their surroundings, such as other AVs, traffic signals and toll gates, among others. AVs that are equipped with this technology are called connected and automated vehicles (CAVs). This interaction capability is expected to enable better decision making by the vehicles, improving the capacity and safety of roads. At the same time, expected problems associated with the introduction of automated vehicles include the possibility of software hacking and issues on privacy and liability, among other factors that may affect the choice of automated vehicles over human-driven vehicles (Tscharaktschiew and Evangelinos, 2019).

On a broader view, the technology of vehicle automation has myriad economic, social, and environmental effects, affecting transport cost and traveller's behaviour, energy consumption, land use and urban shape, among others. The relative level of adoption of AVs for individual or shared use is crucial for the future sustainability of mobility under different scenarios of adoption of AVs. This is because the effect of AVs on energy consumption and greenhouse gas emissions crucially depends on whether future mobility is going to be mostly individual, in which we will largely replicate the current car ownership paradigm, or shared, in which people subscribe to mobility services provided by shared vehicles, either on demand or under the classic structure of fixed-route public transport. As shown by Wadud et al. (2016), the net effect of AVs on environmental outputs depends on a balance between factors that push to reduce energy consumption (such as vehicle platooning, eco-driving and car-sharing) and factors that increase energy consumption (such as new trips due to induced demand and a reduced cost of travel time). Long term decisions regarding housing location and car ownership, as well as day-to-day travel decisions on mode and destination choice will be influenced by a key variable: how future transport services will be priced, including tax and subsidy decisions.

Current developments suggest that, in early stages, AVs will be mostly deployed for shared use, given the high initial cost of the technology (Stocker & Shaheen, 2017). However, as prices decrease over time, AVs will become attractive for personal use. Anticipating this scenario, it is clear that the pricing policy for future AVs and shared transport services based on AVs will have a key role to play, just like today pricing and tax incentives shape the transport and mobility landscape. However, the transition from human-driven to automated driving may make the application of optimal road pricing more complex, instead of easier (Tscharaktschiew and Evangelinos, 2019). An updated overview of the topics related to transport pricing and automated vehicles is presented in this chapter.

In Section 2, we analyse the effect of vehicle automation on the modal attributes. Based in those effects, in Section 3 we discuss how automation will modify the transport system, and how pricing could be implemented in a scenario of automated vehicles, based on current insights gained in the academic literature. In Section 4 a transport pricing model is presented considering three modes: private car, public transport, and an active mode, incorporating the effect of vehicle automation. Finally, in Section 5 conclusions and recommendations are discussed, about the future of transport pricing with AVs.

2. Vehicle automation and modal attributes

In transport policy, pricing arises as a mechanism of behavioural change to deal with negative externalities caused by individual agents. So, to determine the role that pricing will play in an AV-based transport system it is paramount to understand the role that automation will have in all the components that influence both the cost structure of transport providers and the decisions of users. Operator costs comprise infrastructure, vehicle, fuel, and crew cost. Generalised user cost includes monetary costs (fares, tolls, running cost and/or parking in the case of cars), as well as time costs (in-vehicle, walking and waiting time) converted to money. In-vehicle time is given by the trip length and its speed, and the latter depends on traffic flow and density. Therefore, it is necessary to analyse how AVs influence each one of the aforementioned elements in order to understand the relationship between automation and pricing.

2.1 Effect on road capacity

The effect of AVs on road capacity has been extensively examined in the literature. On the one hand, AVs would have shorter reaction times, leading to both reduced gaps between vehicles (Dresner & Stone, 2008), and lower road crash rates (Fagnant & Kockelman, 2015; Keeney, 2017), thus increasing the capacity of individual roads. Also, in terms of network efficiency, V2V and V2I communications would allow to anticipate traffic conditions downstream, diminishing the likelihood of traffic breakdowns, and clearing queues faster in case of occurrence (Hoogendoorn et al., 2014). However, these predictions rely on the strong assumption of an immediate change from conventional cars to AVs, neglecting the transition phase where both technologies coexist and interact in the network. In the latter case, the capacity increase would be relevant only with a high share of AVs (Tientrakool et al., 2011). Furthermore, the introduction of AVs may even reduce the capacity if its share in the roads is low, relative to conventional vehicles (Mena-Oreja et al., 2018; Van Arem et al., 2006). Therefore, the final effect of AVs on road capacity is unclear at this stage, and likely depends on the penetration rate of AVs on the roads.

2.2 Effect on travel time and the value of travel time savings

From the user's perspective, travel time costs depend on the travel time itself and the subjective valuation that each user gives to reductions in travel time. Estimations of the effect of AVs range from slight reductions to significant increases of travel time (Chen & Kockelman, 2016; Childress et al., 2015; Gurumurthy et al., 2019; Hörl et al., 2021). Current simulation models show that schemes that promote higher occupancy of vehicles, such as shared rides or public transport, present the largest travel time reductions (Salazar et al., 2019).

In terms of the value of travel time savings (VTTS), it has been anticipated that the disutility of travel time will be reduced for former car drivers that, due to vehicle automation, would be relieved from driving tasks and therefore could experience a less distressed trip. Former drivers could also make a more productive use of their time while travelling, at least for commuting. This intuition has been assumed or estimated via stated-preference surveys in several studies (Childress et al., 2015; Kockelman et al., 2017; Kolarova et al., 2019; Van den Berg & Verhoef, 2016); results show reductions up to 50% of VTTS for car drivers.

However, it has been argued that, in actual conditions, AVs might not substantially affect VTTS (Cyganski et al., 2015; Rashidi et al., 2020), or could even increase it, relative to VTTS of driving a conventional car, for instance, if drivers experience discomfort due to not feeling in physical control of the vehicle (Singleton, 2019). Another aspect, in the case of shared rides, is that some people do not feel comfortable sharing the same vehicle with strangers, with no driver to overlook people's behaviour. Therefore, the impacts of automation in VTTS might be more modest than anticipated, especially when rides are shared (Singleton, 2019). Finally, unlike cars, it is clearer that automation in buses will not have a great impact in VTTS since the change on possible activities to perform while traveling would be little or non-existent. Even, negative attitudes towards automation could increase the subjective VTTS mainly due to a decreased perception of safety and/or security (Guo et al., 2020).

Finally, a positive effect of AVs in potentially decreasing the valuation of time is through changes in travel time reliability or predictability. Travelers are willing to pay to reduce the variability of travel time, i.e., there is a value of reliability, which has been estimated in the literature (Börjesson et al., 2012; Li et al., 2010). Therefore, if AVs provide more reliable travel times, the modal utility is increased. In the absence of human intervention, driving times should be more stable, as, for instance, V2V and V2I communication technologies will inform incidents more quickly, proposing alternative routes that would be optimised in real-time to prevent bottlenecks. In the case of automated public transport, this effect does not only apply to in-vehicle time but also to waiting time, due to the possibility of applying new strategies to stick to schedules (Cao et al., 2019) and to keep regular headways.

2.3 Effect on parking availability and price[1]

As a result of not needing a driver to operate, an expected consequence of vehicle automation is the reduction of dedicated space for parking, which would be achieved in two ways. First, the promise of a larger adoption of shared automated vehicles in replacement of personally-owned cars reduce the total fleet in the system. Narayanan et al. (2020) reviewed the literature finding replacement rates from 1.17 to 11 but emphasizing that in real conditions the actual rate would probably be in the lower bracket. Second, AVs would be able to park in compact and conveniently located facilities (Nourinejad et al., 2018), which would be a major shift from HDVs, given that vehicles cruising for parking represent a large rate of traffic in several cities (Shoup, 2006). Certainly, parking pricing would also be key for the final output of parking availability in an era of AVs.

Analysis of parking demand in an AV-based transport system shows in general a significant reduction of parking requirements, especially when shared AVs are predominant. Zhang et al. (2015) conduct an agent-based simulation to determine the parking requirement variation due to the introduction of shared AVs, obtaining reductions up to 90% . Nourinejad et al. (2018) propose a new design of parking facilities for AVs allowing multiple rows of vehicles stacked behind each other, and then develop a mixed-integer non-linear optimization model to find the optimal car-park layout with minimum relocations, decreasing parking space in 62% to 87% compared to HDV classic layouts.

3. Effects of vehicle automation on the pricing of transport modes

The central idea behind congestion pricing (CP) is that, in congested settings, individual travellers impose delays on others, therefore they cause a negative externality that can be internalized by an economic penalty (Pigou, 2013; Vickrey, 1969).[2] Though marginal cost pricing (MCP) is recognized as the first-best benchmark solution to address urban transport externalities (not only congestion, but also pollution,

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[1] The general topic of parking economics is analysed in Chapter 5 (Urban form) and Chapter 7 (Political Economy)

[2] For details on congestion pricing, see Chapter 2 (Theory of externality pricing) and Chapter 8 (Road pricing).

traffic crashes and noise, among others), it is equally agreed that practical applicability of this principle is hardly reachable in real conditions, and second-best pricing solutions must be developed to generate feasible tolling mechanisms, such as facility-based tolls, cordon-based tolls, area-based tolls, and distance-based tolls (Verhoef, 2002). But the introduction of AVs could make dynamic pricing strategies feasible in both time and space since CAVs communication channels do not require additional infrastructure (Simoni et al., 2019), and its higher computation capabilities would help to keep pricing schemes understandable and transparent, helping to increase public acceptability of CP (Gu et al., 2018). This would allow to implement pricing mechanisms that are comparable or close to first-best pricing. In what follows, we analyse how vehicle automation could influence the pricing of alternative travel modes. In the Appendix, a summary of selected studies about AV pricing strategies is presented.

3.1 Private vehicles

If a reduced VTTS, an increase in the capacity, and the ability to self-park due to automation demonstrate to be true, owning and using a private AV will be more attractive. It would offer the possibility to use a car to people unable to drive nowadays, such as people without a driving license and people with reduced mobility or cognitive problems. Also, the owners of AVs would be encouraged to use it more intensively, since some advantages of other modes such as lower cost, more convenient use of time while travelling, and avoidance of parking costs and hassles at their destinations, among others, would melt away with automation (Lutin, 2018), leading to more and longer trips by private AVs. Then, an expected consequence is a worsening of traffic conditions and energy consumption. In this point is where pricing can be used to modify the behaviour of travellers. Two approaches are identified: pricing can be applied either to vehicles or roads.

In the first approach, Van den Berg & Verhoef (2016) use a bottleneck model to investigate the effects of migration from HDV to AV in congestion for three market organizations (private monopoly, perfect competition, and public supply) and where the share of AVs is endogenous. The introduction of AVs affects congestion via three channels: the resulting increase in capacity due to AVs, the decrease in the VTTS for those who acquire an AV, and the implications of the resulting changes in the heterogeneity of VTTS. Two effects are identified; first, a 'capacity' effect, where AVs cause (as expected) a decrease of congestion. There is also a 'heterogeneity' effect, caused by the introduction of additional AVs which have lower VTTS than HDV, altering departure time behaviour of the former and therefore increasing congestion. The authors presented numerical results for the USA and the Netherlands, suggesting that a positive net externality is most likely. But, if buying an AV reduces congestion, MCP tends to lead to underconsumption of AVs, so the public supplier would need to provide a subsidy to attain the second-best optimum. In the opposite case, a corrective tax is needed to prevent over-consumption.

In the second approach, (Delle Site, 2021), analyses a link-based pricing policy only for CAVs in a mixed-traffic network with HDVs. In a conservative assumption, no increase of capacity due to the introduction of AVs is assumed. HDVs behave according to the Wardrop's user optimum, while three behavioural scenarios are considered to CAVs: 1) CAVs driven by selfish users, 2) CAVs managed as a fleet by a monopolist, where the total cost (time + tolls) of CAVs is minimized, and 3) CAVs managed by a social planner that seeks to minimize the total cost of the HDV and CAV fleet. Three pricing schemes are considered: a classical MCP, a minimum expenditure pricing, and a zero net expenditure pricing (i.e., some arcs are charged while others are subsidized) Applying these schemes in the Anaheim network, tolls collected in the minimum expenditure and the toll-and-subsidy schemes are about 10 times lower than the optimal tolls from the MCP scheme. Therefore, such pricing alternatives would facilitate the acceptability of pricing schemes among the population without compromising the benefits of the road charging schemes in terms of travel times reductions.

3.2 Automated Mobility on-Demand (AMoD)

Vehicle automation promises to significantly reduce transport operator costs due to a reduction of driving costs, therefore, the cost advantage of placing many travellers in large vehicles such as buses will be reduced. Empirical estimations of the effects of automation on reducing the costs of motorised shared mobility indicate that the effect is potentially large. In Figure 1, the ratio between driver cost and total operator cost is shown for different vehicle sizes, from cars (that could be used for shared automated vehicle services) to buses of different lengths (that are used for public transport), considering Munich data (Tirachini and Antoniou, 2020). Depending on the asset life assumed, the car-size vehicles present driver cost between 73% and 82% of the total operator cost, while in the case of buses driver costs are in the range 30-56% of the total operator cost. This is a quantification of an expected effect: the smaller the vehicles, the larger the potential cost benefits due to vehicle automation, and differences between small and large vehicles are significant. Thus, shared-mobility services with smaller vehicles are expected to play a larger role in a world of AVs.

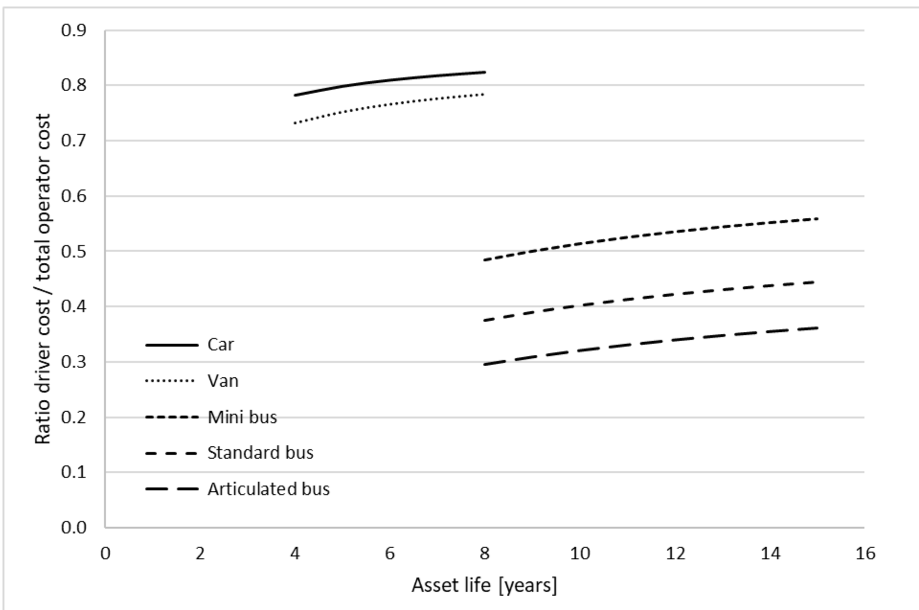

Figure 1: Driver cost as a proportion of the total cost, Munich values[3]

The anticipated large cost savings due to automation should be, at least in part, transferred to lower prices, since a strong modal competition between several travel alternatives will cause that shared AVs have to set competitive prices to attract users (Chen & Kockelman, 2016; Gurumurthy et al., 2019; Hörl et al., 2021). This trend is reinforced by an attitudinal change towards car ownership and use among young people (Zhou & Wang, 2019), so users who cannot or do not want to purchase a car, or neither want to travel by car on a regular basis, are able to access to one in case they need it. Narayanan et al. (2020) point out that SAV systems can have different booking time frames; namely, on-demand (vehicle booking

[3] Reprinted from Tirachini and Antoniou (2020), with permission from Elsevier.

in real time) and reservation-based (booked in advance) systems. To avoid confusion, we will use the term automated mobility on-demand (AMoD) to refer to the first type of operation.

As well as with private AVs, an important concern about the massification of AMoD is the worsening of traffic conditions. A lower price of AMoD (relative to a system with human-driven vehicles) coupled with improved access time and/or comfort relative to PT and active modes, suggest that AMoD will increase its modal share at the expense of other modes. Dynamic traffic assignment models show that an increase in vehicle-kilometre travelled (VKT) and travel time is seen when AMoD is introduced (Hörl et al., 2021; Kaddoura et al., 2020; Simoni et al., 2019), not only because of induced demand but also because of empty VKT (due to picking up passengers, fleet rebalancing, and charging, among other factors). So, to take advantage of AMoD possibilities while constraining the negative externalities of increased motorised traffic, centralized policies such as optimal road pricing will be crucial.

The effects of pricing on the performance of SAVs have been analysed with simulation studies. Simoni et al. (2019) study behavioural responses to different congestion pricing schemes and their effects on congestion, considering a capacity increase due to the introduction of AVs in Austin, Texas. "AV-oriented" and "AMoD-oriented" scenarios are designed, and as predicted, a rise in congestion is observed by demand shifts from PT and active modes, in addition to longer trips. VKT increases of 16% and 22% while total travel delay increases between 61% and 87% with respect to the HDV scenario (base). Then, two "traditional" congestion price (CP) schemes (distance-based and link-based) and two "advanced" schemes (MCP-based and travel time-congestion-based pricing) are evaluated. The difference between the two types of schemes is that the operationalisation of the former is fairly plausible with the existing technology, while the latter is more complex and requires new technologies (such as those of CAVs) for optimal implementation. All the CP strategies are effective in the relief of congestion by significantly reducing VKT and delays with respect to the unpriced scenarios, but advanced schemes outperform traditional ones in welfare gains. Congestion pricing schemes as a way to counteract the increase in traffic from AMoD are also studied in Kaddoura et al. (2020), who find that it is necessary to price both HDV an AMoD while the presence of AVs is not large in the market.

3.3 Public transport

For the case of public transport (PT), automation is expected to increase coverage and service frequency, as well as to significantly reduce fares, due to the reduction of operator costs if (at least a part of) vehicles are driverless (Tirachini & Antoniou, 2020; Zhang et al., 2019). The cost advantage of automation in the case of PT in large vehicles is less pronounced than for AMoD, because as shown in Figure 1, the driver cost is a smaller share of the total operator cost for larger vehicles. A potential large reduction of driving costs has been shown to reduce the degree of economies of scale in public transport (Tirachini and Antoniou, 2020). In PT, the existence of crowding externalities is known to increase optimal service frequency and vehicle capacity (Jara-Díaz & Gschwender, 2003) and to increase the optimal PT fare (Tirachini et al., 2014), therefore undermining some of the advantages of automated PT in reducing vehicle size and optimal fare as identified by Tirachini and Antoniou (2020). If there is a reduction of user cost for both private and public transport by using AVs, then this should be reflected in the optimal price of both modes, as we will formally assess in Section 4.

Previous findings, i.e., potential reductions in the optimal fare and increase of service frequency, have been found analysing PT as a single mode. In practice, if a significant cost reduction of private AV and/or AMoD materializes, the shape of PT will inevitably change, as in all the simulations where AV-related modes and PT coexist the result is the undermining of the latter (Chen & Kockelman, 2016; Gurumurthy et al., 2019; Hörl et al., 2021; Kaddoura et al., 2020; Simoni et al., 2019). The sharpest impacts in terms of travel time and accessibility are seen in low-demand areas and/or periods. Since equity issues and service standards force PT authorities to maintain the coverage even with less ridership, the natural consequence is a change on the network structure, pushing for the adoption of on-demand services in low demand markets.

Despite these concerns, it is clear that mass public transport will not disappear with automation, as it is not replaceable in high-density settings. Bösch et al. (2018) analyse the cost structure of automated buses, private AV, and AMoD (with either shared rides or not), concluding that buses will remain as the most effective transport mode in dense areas and corridors. Also, among some user groups there is still preference for fixed route lines over dynamic services since it is perceived as more readily available by users reluctant to technology (White, 2016). Finally, another interesting consequence of the savings in drivers' costs, as well as the improved platooning and precision docking of automated buses, is that a light rail transit (LRT) standard service could be offered by automated buses in a similar road width and with the same capacity at significantly lower cost (Lutin, 2018). Hence, a system with the level of service of LRT but the flexibility of bus could be offered, diminishing unnecessary interchanges and travel time.

3.4 Active modes

If PT ridership will be affected in longer trips due to the lower cost of AVs, in short trips people could be tempted to walk and cycle less due to the improved accessibility that AMoD will bring at affordable fares. In addition to increased levels of congestion, energy consumption and pollution (depending on the source of energy used to manufacture and run vehicles), this behavioural change could also represent a public health issue since for a significant fraction of the population most of their physical activity is performed while commuting (Litman, 2017; Sallis et al., 2004), either on door-to-door trips or walking/cycling as to access/egress public transport or other motorised modes. In this context, properly pricing automated motorised transport would have a double effect: on the one hand, it would reduce the attractiveness of motorised modes relative to active alternatives, and on the other hand, if at least a part of the revenues is reinvested in improving conditions for walking and cycling, demand for active modes will be induced.

3.5 Intermodal transport and Mobility-as-a-Service (MaaS)

Current estimations of the effects of AVs on quality of service and modal attributes have been made for individual modes. However, new possibilities of integration can be designed with automation by taking advantage of the best characteristics of each mode. The most effective integration envisioned is the PT – AMoD by using the latter in replacement of low-frequency feeder bus routes. Shen et al. (2018) assess the performance of this type of integration in the Tampines area, Singapore, replacing some feeder bus routes with AMoD (with either shared rides or not) to perform the first/last mile. After evaluating different ride-sharing preferences and vehicle sizes, the authors identify scenarios where that reduce waiting times and optimise the utilisation of the bus fleet, while financial sustainability for the AMoD operator is reached. Salazar et al. (2019) analyse the impact of an integrated AMoD-PT scheme in a road pricing formulation that seeks to maximise social welfare, concluding that such operation implies a reduction in congestion, operator costs, and emissions.

From the latter results, if AMoD is thought as a component of the PT system, then it could represent a path of improved quality of service in terms of waiting times, coverage, and hours of operation without neither increasing fares nor adding negative externalities. Moreover, integration could go beyond operation to include payment, booking and trip planning processes, among others, as well as to incorporate other modes as bike-sharing and car rental, for instance. This bundling of transport services has been called *Mobility-as-a-Service* (MaaS) (Kamargianni et al., 2016), and it could take advantage of vehicle automation and its subsequent drop of operating costs to become more widespread. It is to be seen if a hypothetical deployment of automated vehicles could help in one of the main struggles of MaaS today: the scalability of such services.

4. A three-mode first best pricing model

4.1 Model presentation

In this section, we synthetise the previous discussion with the analysis of a transport pricing model. We follow Tirachini & Hensher (2012) to develop a three-mode first-best pricing model (see also Chapters 2, 8 and 9 in this *Handbook*). Consider a single origin-destination pair and three modes: automobile (*a*), public transport (*b*) that could be a bus- or rail-based mode, and an active transport mode (*e*) that could be walking or cycling. The attractiveness of walking and cycling is mainly associated with trip distance and factors such as steepness and availability of safe and attractive walking and cycling facilities. Road capacity is assumed fixed, income effects and tax distortions are ignored. The joint demand for the three modes can be obtained from the benefit function $B(q_a, q_b, q_e)$, which expresses the consumers' willingness to pay for a particular combination $\{q_a, q_b, q_e\}$ of travel by automobile, public transport, and the active mode. The inverse demand function d_i for mode *i* is given by:

$$d_i(q_a, q_b, q_e) = \frac{\partial B(q_a, q_b, q_e)}{\partial q_i} \quad i \in \{a, b, e\} \tag{1}$$

Let C_i and c_i be the total and average cost functions of mode *i*, respectively (including both time and operation costs), that is:

$$C_i = q_i c_i \tag{2}$$

Let $c_a(q_a, q_b)$ and $c_b(q_a, q_b)$ be the average cost of car and public transport, respectively. We assume that the cost functions depend on demand q_a and demand q_b. The relationship between car demand q_a and car flow f_a is $f_a = \upsilon_a q_a$, where υ_a is the inverse of the average occupancy rate per car. The relationship between public transport demand q_b and frequency f_b depends on the frequency rule used in the public transport system. Cost c_b includes users' cost c_u (access, waiting and in-vehicle time costs) and operator cost c_o (which accounts for capital and operating costs):

$$c_b = c_u + c_o \tag{3}$$

We further assume that the travel time associated with the active mode is fixed and independent of demand or flow of any mode, i.e., the active mode is uncongestible. In equilibrium, the marginal benefit is equal to the generalised price, $c_a + \tau_a$ and $c_u + \tau_b$ for cars and public transport, respectively (equation 4), where τ_a is the road use charge for the automobile and τ_b is the fare for public transport.

$$\frac{\partial B}{\partial q_a} = c_a + \tau_a \qquad\qquad \frac{\partial B}{\partial q_i} = c_u + \tau_b \tag{4}$$

A social welfare function reflects the level of welfare in a society expressed as a function of economic variables. In transport economics, optimal welfare-oriented pricing decisions ensure that the external costs and benefits of travelling are internalised in the user's decisions. The social welfare (*SW)* function (5) comprises the difference between the benefit function and the total cost associated with traveling by automobile, public transport and active mode.

$$SW = B(q_a, q_b, q_e) - q_a c_a(q_a, q_b) - q_b c_b(q_a, q_b) - q_e c_e \tag{5}$$

Expression (5) is to be maximised. After applying first order conditions, we find:

$$\tau_a = q_a \frac{\partial c_a}{\partial q_a} + q_b \frac{\partial c_b}{\partial q_a} \tag{6a}$$

$$\tau_b = c_o + q_a \frac{\partial c_a}{\partial q_b} + q_b \frac{\partial c_b}{\partial q_b} \tag{6b}$$

$$\tau_e = 0 \tag{6c}$$

Solution (6a) is the well-known Pigouvian tax for cars, including in this case the marginal cost on public transport cost due to car demand (second term). Equation (6b) is the first-best fare for public transport with congestion interactions (see also Chapter 9 in this *Handbook*). If there is no congestion interaction between cars and public transport, then $\frac{\partial c_b}{\partial q_a} = \frac{\partial c_a}{\partial q_b} = 0$ in equations (6a) and (6b). Equation (6c) states that the price for walking or cycling is zero (the assumed uncongestible mode). Note that the model can be easily generalised to having four modes, including both walking and cycling as separate alternatives, in which case the solution for both would be optimal prices equal to zero, under the no-congestion assumption. For simplicity we have not included the case of a binding public transport capacity constraint in this model (see Tirachini & Hensher, 2012). A modified version of equation (6a) is presented in Tscharaktschiew and Evangelinos (2019), in a model in which travellers can choose between human-driven or automated vehicles for individual use. In this case, a new term shows up in the optimal toll function, which accounts for the feedback effect of the choice of driving mode on the road capacity.

4.2 Changes to the optimal fare of private cars due to automation

Next, let us analyse how the first best pricing rules change after introducing AVs. For simplicity we are going to assume the case of trains or buses running on segregated railways or busways. We will therefore disregard congestion interactions between cars and public transport, which is equivalent to assume $\frac{\partial c_b}{\partial q_a} = \frac{\partial c_a}{\partial q_b} = 0$. The average cost for cars can be expressed as:

$$c_a(q_a) = P_{va}(q_a)t_a(q_a) \tag{7}$$

Where P_{va} is the value of travel time savings for car users. In (7), we have assumed that P_{va} depends on the actual car demand level, following the empirical evidence that congestion increases the value of travel time savings (for a review, see Wardman & Ibáñez, 2012). Part of this increase in the value of time savings under congested conditions might be explained by a greater unreliability and unpredictability of travel time estimations. Taking the derivative of (7) with respect to q_a, we can re-write the optimal fare (6a) as follows:

$$\tau_a = q_a \left[\overbrace{P_{va}(q_a)}^{(I)} \underbrace{\overbrace{\frac{\partial\, t_a(q_a)}{\partial q_a}}^{(II)}}_{\geq 0} + \overbrace{t_a(q_a)}^{(III)} \underbrace{\overbrace{\frac{\partial P_{va}\,(q_a)}{\partial q_a}}^{(IV)}}_{\geq 0} \right] \tag{8}$$

With regard to the value of travel time savings, as analysed in Section 2.4 it can either increase or decrease due to automation, although the most likely effect for the case of car drivers switching to their own self driving car is a reduction on P_{va} because the driver is released from driving tasks. If there is no congestion, terms (II) and (IV) are zero, and the optimal car toll is zero, as expected. An extended model that includes externalities other than congestion (such as pollution and crashes) would yield a positive fare even in the case of no congestion. If there is congestion, then term (II) is positive and term (IV) might be positive (which is an empirical matter). Assuming a positive value for term (IV), i.e., that car users value travel time reductions more under congested conditions, then AVs may reduce the derivative $\frac{\partial P_{va}\,(q_a)}{\partial q_a}$, if more certain travel times are possible with AVs. For instance, the adoption of centralised route assignment strategies with AVs points to providing more certainty in travel times, therefore, we expect, reducing the effects of a demand-induced uncertainty on the value of travel time savings. With regard to term (II), automation, at least with a large penetration rate of AVs, is expected to reduce congestion, and therefore to reduce the marginal time (II).

Finally, travel time (III) may be reduced if lower congestion levels are possible with connected and AVs, however such scenario will take long to materialise, as current pilots with automated minibuses around the world show the opposite: automated minibuses are slower than their human-driven counterparts due to safety considerations in urban environments (interactions with human-driven vehicles, parked cars, pedestrians and cyclists) and the novelty of the technology. It follows that fully segregated AVs (not running in mixed traffic with human-driven vehicles, pedestrians, and cyclists) are more likely to reach travel time savings.

All-in-all, the effect of vehicle automation on the optimal (first best) car toll cannot be unambiguously determined. On the one hand, we have identified a number of elements that push to reduce the optimal toll (8), which include (i) a potential congestion relief from automation, (ii) a better use of time while travelling that pushes for a reduction in the value of travel time savings, and (iii) the provision of more certain travel times with AVs. If other externalities such as traffic crashes are included in the analysis, then the gain in traffic safety from automation increases the difference between optimal fares with AVs vs HDVs. On the other hand, an increase in the optimal toll with AVs is possible if travel time tends to increase instead, and if the VTTS also increases. Therefore, there are strong reasons to suggest a reduction on the optimal toll for private-use AVs, relative to conventional HDVs, at least under full segregation. With mixed traffic, it is not so clear if the optimal toll should be reduced.

4.3 Changes to the optimal fare of public transport due to automation

Recalling the assumption that cars and public transport do not share the right-of-way in our formulation, optimal public transport fare (6b) can be expressed as:

$$\tau_b = \overbrace{c_o}^{(I)} + q_b \overbrace{\frac{\partial[P_{ac}t_{ac}(q_b) + P_w(q_b)t_w(q_b) + P_{vb}(q_b)t_b(q_b)]}{\partial q_b}}^{(II)} + q_b \overbrace{\frac{\partial c_o}{\partial q_b}}^{(III)} \tag{9}$$

where P_{ac}, P_w and P_{vb} are the values of access, waiting and in-vehicle time savings, respectively, and t_{ac}, t_w and t_{vb} are the access, waiting and in-vehicle times, respectively. If AVs are driverless, a large unit operator cost c_o is expected, and the effect is larger for smaller vehicles (Section 3). This reduction in operator cost pushes to decrease the first-best public transport fare, as analytically shown by Tirachini & Antoniou (2020).

Next, we study the marginal effect of demand on user costs (factor II in equation 9). If both the value of waiting and in-vehicle time savings are sensitive to large passenger volumes due to crowding effects on bus stops, train stations and inside vehicles (Tirachini et al., 2013), then an operation with more reliable travel times and headways due to automation should balance station and vehicle loads in a smoother way, reducing the level of crowding in some vehicles and in some headways. Therefore, an improvement in the quality of service as perceived for the users is possible, without even increasing the fleet size, and these more comfortable travel conditions result in reductions of the value of travel time savings, therefore pushing to reduce (II). Waiting time is also reduced if driverless operation is possible and attached to this there is an increase in service frequency. In general, a waiting time reduction due in increases in demand (because of increases in service headway), translates into making term (III) negative, which is more so if access time and in-vehicle times are reduced as well as a function of demand, or at least stay equal. Changes in in-vehicle time t_b depend on how fast the operation of AVs is relative to the operation of HDVs, and therefore a change in this variable, if any, is less predictable. The same can be said about changes, if any, in access time in term (II).

Finally, term (III) is likely negative in equation (9), due to the existence of economies of scale in public transport operation (Allport, 1981). The operation of driverless vehicles reduces the level of scale economies in public transport (Tirachini & Antoniou, 2020), therefore making term (III) less negative. All-in-all, which appears to be the only study published about first-best public transport pricing shows that the decrease in operator cost (I) dominates on the other effects and the optimal fare is lower, relative to HDVs (Tirachini & Antoniou, 2020).

5. Concluding remarks

In conclusion, we have shown that cost reductions due to automation tend to push towards lower optimal fares for both private cars and public transport. Therefore, it follows that vehicle automation makes motorised transport more attractive relative to active modes. This may have serious implications for the future pricing of AVs, if not properly addressed with pricing frameworks that include, e.g., the health and environmental benefits from active mobility, which provide the basis for the promotion of walking and cycling in daily life in cities, through a range of policies that include price incentives. A comprehensive policy package aimed at making active modes more attractive might be even more relevant in a scenario of AVs for both private and public transport. These policies should be even more aggressive if reductions in VTTS as well as increasing in road capacity result to be significant (which leads to a mostly individual use of AVs). As Soteropoulos et al. (2019) concludes from a review of related studies, a large adoption of individual-use AVs leads to a more dispersed urban development and sprawling with all the negative externalities it entails. Conversely, scenarios where shared use of AVs (either AMoD or PT) is predominating implies a long-term urbanization process, fuelling a virtuous cycle of efficiency in the use of resources in the cities. Pricing will be key to the shaping of one scenario or the other.

It should be noted that most of our analysis is based on the effects of automation on optimal prices. How this should be translated into actual observed prices, that are suboptimal in most cases, is a matter of great uncertainty and a venue of further research. A numerical application of the model developed in Section 4, comparing scenarios with and without automation, is also an interesting topic for future research. The model in Section 4 was based on congestion externalities only; the formal introduction of environmental and climate change related externalities is expected to gain increased attention in the coming years and decades, if the promises of automated vehicles materialise.

Appendix

Table 1: Selected studies regarding AV pricing.

Author(s)	Objective	Available modes	Pricing/tolling scheme	Objective Function / monitoring variables	Study area	Scenarios	Main Results / Conclusions
Delle Site (2021)	Analyze arc-based pricing policies for a CAVs fleet in a mixed-traffic network with HDVs.	HDV, CAV	Arc-based tolling applied only to CAVs.	Wardrop's equilibrium in scenario 1, Min total travel time of CAV in scenario 2, Min total travel time of HDV and CAV in scenario 3 / total toll paid	Two theoretical networks (two-arc network representative of town bypass and Nguyen-Dupuis network), and Anaheim network.	0. Base (without CAVs) 1. CAVs managed as individual vehicles 2. CAV are managed as a fleet by a service provider 3. CAVs managed as a fleet by a social planner. * In all cases the proportion of CAVs is 50%. * In all cases, tolls are computed according to two schemes: one with positive tolls and minimum toll expenditure, and one with both tolls and subsidies and zero net expenditure.	Congestion prices in the min expenditure and in the toll-and-subsidy scheme are significantly lower than classic marginal cost prices (about 10% in the Anaheim network). If time+toll is desired to minimize then private monopolist is always dominant regarding the selfish agent scenario, if only toll is considered then the least costly option varies depending on the case.
Gurumurthy et al. (2019)	Determine how fleet size, pricing and fare level change under AMoD with shared rides, from private and societal goals, in presence of both HDV and AVs.	HDV, PT, Active modes, Private AV, AMoD + shared rides	AMoD is priced according Simoni et al. (2019). All mayor network links are priced in morning and afternoon peak at $0.05/min	NA / Mode share, % increase in VKT, Empty VKT, idle hours of AMoDs, average occupation, $/AMoD/day, Trips/AMoD/day	Austin, Texas	0. Base (without AVs). 1. With AMoD + DRS. 2. With DRS fare 50% discount. 3. With DRS fare 75% discount. * Scenarios 1, 2 and 3 with AMoD availability from 10 to 100.	Modal share of AMoDs is relevant only when fares are moderate to low. Operational balance and system benefits are reached with moderate fleet sizes (one AMoD vehicle for every 25 persons) and competitive prices, especially when road-pricing schemes are applied, in terms of empty VKTand revenue to the operator.

Table 1: Selected studies regarding AV pricing (continued).

Author(s)	Objective	Available modes	Pricing/tolling scheme	Objective Function / monitoring variables	Study area	Scenarios	Main Results / Conclusions
Kaddoura et al. (2020)	Investigate optimal CP strategies for AMoD and HDV users, where users are able to adjust their mode, departure time and route.	HDV, AMoD (only in inner city area), PT, Walk, Bicycle, Ride	Marginal cost pricing	Max SW / Modal share, Travel time, Traffic volume, air pollution, noise	Great Berlin	0. Base (without AMoD) 1. Base + AMoD (without CP) 2. Base + AMoD + CP 3. Case 2 + HDV CP	Implementation of AMoD increases the traffic in the city centre in all scenarios. Congestion pricing only in AMoD slightly reduces travel time and traffic. Only pricing both AMoD and HDV a significative reduction in travel times, traffic and externalities across the city is reached, with improvements in welfare.
Salazar et al. (2019)	Coordination policies for integration between AMoD and PT maximising SW under the assumption of a perfect market with selfish agents.	Only Metro in NYC; Metro, S-Bahn and Tram in Berlin, AV(AMoD) in both	PT fares equal to operational cost, road tolls equal to road congestion multipliers, road prices equal to the sum of AVs operating costs, road tolls, an the origin and destination prices (dual multipliers associated with the vehicle balance constraints)	Max welfare, with PT fare and link tolls as decision variables.	Manhattan in New York and city centre in Berlin.	- Exogenous road usage from 50% to 200%. - Two types of propulsion: Internal combustion engine (ICEV) and Battery electric (BEV) vehicles. - LW and SW vehicles.	Vehicle size is equally important than propulsion, SU BEV is app. 5 times more pollutant in CO2 emissions than LW ICEV. Integration with congestion pricing significantly reduce travel time, costs, number of vehicles and emissions.

Table 1: Selected studies regarding AV pricing (continued).

Author(s)	Objective	Available modes	Pricing/tolling scheme	Objective Function / monitoring variables	Study area	Scenarios	Main Results / Conclusions
Simoni et al. (2019)	Study behavioral responds to different congestion pricing schemes and its effects on congestion in scenarios with strong market share of AVs and AMoD	HDV - PT - walk/bike (joint) - Private AV - AMoD	- Two "traditional" pricing strategies: link-based (LB) scheme and distance-based (DB) scheme. - Two "advanced" pricing strategies: Dynamic marginal cost pricing (MCP) at link level, and Travel time congestion-based (TTC) scheme which charge users for the delay caused on everyone else.	NA / Modal share, VMT savings, delay savings, welfare change.	Austin metro area, Texas	1. AV-oriented scenario (90% of car-owners of the base-escenario have avalilability to private AV + 1 AMoD every 30 agents). 2. AMoD-oriented scenario (10% of car-owners have access to AV + 60% availability private car + 1 AMoD every 10 agents). * Both scenarios with PT network fixed. For each scenario, the 4 tolling schemes depicted before.	DB scheme seems more effective in the AMoD-oriented scenario and in Base scenario, while the LB scheme perfoms better in the AV-oriented scenario. MCP-based scheme and travel time congestion-based scheme perform better in the AMoD-oriented scenario than in the AV-oriented scenario. In all the scenarios, TTC scheme presents the largest social welfare improvements.

Table 1: Selected studies regarding AV pricing (continued).

Author(s)	Objective	Available modes	Pricing/tolling scheme	Objective Function / monitoring variables	Study area	Scenarios	Main Results / Conclusions
Tirachini and Antoniou (2020)	To assess the impact of automation for optimal vehicle size, service frequency, fare, subsidy and degree of economies of scale in public transport	PT	Optimal (first-best) pricing	Min total cost	Munich in Germany and Santiago in Chile	- HDV (Base) - Driver cost saving of 0%, 50% and 100% due to automation regarding the HDV scenario - Ratio running time of AVs/running time of human-driven buses equal to 1 and 0,5. - Demand between 100 and 4.000 [passengers/h].	Automation causes smaller vehicles and more frequent services to be optimal for PT services. There is a reduction in the degree of economies of scale in PT. Optimal fare and subsidy are also reduced. Benefit are reached if a significant fraction (larger than 50%) of driving cost are saved. Benefits are larger in Germany than in Chile due to the higher share of labour costs.
Tscharaktschiew and Evangelinos (2019)	To assess the impact of automation on optimal congestion pricing	HDV, AV	Optimal (first-best) pricing	Max SW	Highway section	- No congestion toll, manual driving only. - Congestion toll, manual driving only. - Congestion toll, manual and automated driving.	The choice between manual and automated vehicles is modelled. The marginal social trip costs are no longer strictly increasing in traffic flow. Multiple congestion pricing equilibria may lead to situations without automated vehicles, i.e., with manual vehicles only. Coexistence of manual and automated vehicles add complexity to the setting of optimal road pricing.

Table 1: Selected studies regarding AV pricing (continued).

Author(s)	Objective	Available modes	Pricing/tolling scheme	Objective Function / monitoring variables	Study area	Scenarios	Main Results / Conclusions
Van den Berg and Verhoef (2016)	To investigate the effects on congestion of using AVs for three market organizations (private monopoly, perfect competition, and public supply).	HDV, AV	Subsidies or taxes applied to (des)incentivize buying of AVs.	Equilibrium or max profit / Total Travel Cost, Total Cost (TTC+car cost), relative efficicency (gain on a policy divided by the gain from case P)	Numerical examples with USA and Netherlands data	0. Base (only HDV) 1. Socially optimal 'public' provision 2. Perfect market (marginal cost provision) 3. Profit-maximising monopolist	There is a 'capacity' effect, where getting AVs cause a positive externality due to a decreasing of congestion. On the other hand, there is a 'heterogeneity' effect, caused by the introduction of additional AVs which have lower VTTS than HDV, altering departure time behaviour of the former and therefore increasing congestion. Buying an AV reduces congestion, marginal cost pricing tends to lead to under- consumption of automated cars. To prevent this and attain the second-best optimum, the public supplier needs to provide a subsidy. However, if there is a negative externality, a corrective tax is needed to prevent over-consumption. The private monopolist is likely to lead to a large undersupply and welfare loss.

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