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Review

Assessing the Sustainability Implications of Autonomous Vehicles: Recommendations for Research Community Practice

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Abstract: Autonomous vehicles (AV) are poised to induce disruptive changes, with significant implications for the economy, the environment, and society. This article reviews prior research on AVs and society, and articulates future needs. Research to assess future societal change induced by AVs has grown dramatically in recent years. The critical challenge in assessing the societal implications of AVs is forecasting how consumers and businesses will use them. Researchers are predicting the future use of AVs by consumers through stated preference surveys, finding analogs in current behaviors, utility optimization models, and/or staging empirical "AV-equivalent" experiments. While progress is being made, it is important to recognize that potential behavioral change induced by AVs is massive in scope and that forecasts are difficult to validate. For example, AVs could result in many consumers abandoning private vehicles for ride-share services, vastly increased travel by minors, the elderly and other groups unable to drive, and/or increased recreation and commute miles driven due to increased utility of in-vehicle time. We argue that significantly increased efforts are needed from the AVs and society research community to ensure 1) the important behavioral changes are analyzed and 2) models are explicitly evaluated to characterize and reduce uncertainty.

Keywords: autonomous vehicles; sustainability; research practice; uncertainty; complex systems

1. Introduction

Autonomous vehicles (AVs), a staple of science fiction, are closer than ever before to entering the mass market. Since December 2018, Waymo has been providing commercial autonomous-ride hailing service in Arizona [1]. However, several fatal crashes involving Uber's self-driving cars and Tesla's autopilot systems have highlighted the importance of improving safety [2,3]. It is technically challenging to create sensors and software systems that navigate vehicles safely under myriad road conditions. Attentive human drivers actually set a high bar for the technology to match and hopefully surpass. Still, as accidents typically involve lapses of human attention, ever-vigilant AVs show promise to mitigate one of the major risks of modern life: death or injury from automobile accidents [4]. While the path from today to a future of safe AVs has yet to be resolved, successes achieved thus far and investment of significant resources for further development suggest that AVs are the future of mobility.

AVs are expected to be disruptive; that is, the changes they induce are not at the margin, but redefine the status quo. Some experts believe autonomous-electric-shared vehicles are going to bring a paradigm shift in transportation—consumers will opt for on-demand mobility services in lieu of private vehicle ownership [5]. Another reason is the potential rewriting of decisions of where and how we spend our time. Driving (and riding transit) are major parts of the day for many people.

For example, the average American worker drives 1.3 hours per day; the upper 20%, consisting of nine million people, spends 2.6 hours per day behind the wheel [6]. Choices of where to live, work, and play are influenced by having to spend time driving. By changing drivers into riders, AVs increase the utility of time spent in vehicles. Also, AVs enable mobility for elderly, young, and disabled populations currently not able to drive. There is thus a plausible future in which more people spend much more time in vehicles. Truly autonomous vehicles can also travel without a passenger, and thus could be sent out on autonomous errands, such as picking up food from restaurants or grocery stores. Driving demands a macroscopic amount of human attention, employing millions but at the same time increasing the cost of mobility. Fleets of shared AVs could deliver mobility with convenience comparable to private automobiles but at a lower cost. The future of public transit is in play as well: shared AV fleets could improve access at lower costs than many bus and train systems [7].

Changes induced by autonomous vehicles will affect economic, environmental, and social issues. Transportation costs are important in supply chains, and AVs will lower "last mile" costs (e.g., home delivery, in particular). Consumers could use AVs to travel much more, changing the face of tourism and urban form. Environmental outcomes depend on the tension between higher efficiency (e.g., smoother driving, less congestion, higher occupancy) versus higher demand due to increased access and utility of in-vehicle time. It is difficult to overstate the potential societal impacts of AVs.

In this article, we overview challenges in understanding the societal implications of AVs, review and categorize prior research results, and offer thoughts on research community practice to improve confidence in results. There are a number of prior critical reviews of AV research. Fagnant and Kockelman list AV benefits (e.g., safety, reduced congestion, and travel behavior changes), summarize prior assessments of different factors, and construct scenarios of U.S. national level economic benefits [8]. Taiebat et al. describe nested levels of interaction of AVs with the environment (vehicle, transportation, urban system, and society) and review prior research in view of this framework [9]. They also list a number of future research needs, such as more empirical analysis of Connected and Autonomous Vehicle (CAV) impacts [9]. This review is distinct from prior works in addressing how research practices need to change in order to realize more complete and robust forecasts of AV use. In Section 2, we review critical issues in AV adoption and use that will influence their societal impacts. Section 3 presents an overview of the interaction of AVs and sustainability issues (economy, environment, and social impacts). In Section 4, we review prior research on AVs and society, and in Section 5, we offer recommendations on research community practices important to realize improved forecasts of the implications of AVs on society.

2. Adoption of AVs

The larger implications of AVs, or any technology for that matter, depend on how it is used. There is a large-scale interaction of societal actors involved in a technology transition such as AVs [10]; here we focus on consumers, in particular possible patterns of how AVs will be adopted. Ensuing sustainability implications are discussed in the following section.

First and foremost, AVs will be adopted only if deemed sufficiently safe. The distinction between absolute and perceived risk is important. While automobile accidents are a major cause of death and injury, (human) driving is perceived as a controllable risk, thus more acceptable [11]. Even if AVs achieve an accident rate comparable to human drivers, people will likely demand a higher level of safety for the more uncontrollable risk. These considerations will affect the development of publicly acceptable AVs. Rapid deployment of emerging AV technologies on the road has the virtue of speeding progress, but runs the risk of more accidents, damaging public perception. A cautious approach is costlier and slower, but mitigating public concerns could smooth the path for acceptance and broader adoption. From here on, we assume that AV technology will become safer than human-driven vehicles and accepted as so by consumers.

How will people use AVs? One critical part of this question is how much more will people travel. AVs induce additional travel via three mechanisms. First, drivers being able to do more inside the vehicle presumably increases willingness to spend time traveling. Second, to the extent people are willing to share vehicles with others, AVs could reduce the cost of mobility, inducing increased travel via what is often called a rebound effect [12,13]. Third, AVs increase the population of riders by enabling access to currently underserved communities: the poor, young, elderly, and disabled. The potential for AVs to reorganize daily activities to incorporate much more travel is significant but poorly understood. That said, it is important to bear in mind that there are factors other than AVs that determine travel behavior. For example, information technology creates virtual spaces where people can work and play, regardless of location. Historically, information technology has contributed to more time at home: Americans spent eight days more at home in 2012 compared to 2003 [14]. Other social factors, such as the psychology of vehicle ownership, also influence adoption. While automobile ownership is connected with personal identity [15], there is ongoing discussion if reduced driving by millennials signals a cultural turning point [16].

A second critical part of the question of AV adoption is if people will use private, shared, or ride-share AVs. A private AV is owned and used by one household. We use the term shared AV to refer to AVs sequentially handling requests of riders from different households [17]. Finally, ride-share AVs accommodate multiple passengers with similar/different itineraries at the same time [7]. Among the three modes, ride-share AVs have the potential to address a huge inefficiency of automobile travel: low occupancy. According to most recent estimates, the average occupancy (passenger per car) is about 1.67 in the United States [18] and 1.45 in the European Union [19]. By increasing occupancy, ride-sharing could reduce travel costs and move more people longer distances with a smaller fleet of vehicles. While longer waiting times for pickup make ride-share AVs less convenient, note that waiting decreases with larger fleet size. Ride-share AVs can also be lower cost than private vehicles and many public transit systems, another factor increasing demand.

3. Sustainability and AVs

What will the age of autonomous vehicles mean for sustainability? Sustainability, like the Enlightenment, combines intellectual and social development [20] and what the word means to whom continues to evolve [21]. Here, the word sustainability denotes an attempt to understand and manage concomitant environmental, economic, and social issues.

Environmental outcomes of AVs are both direct and indirect. Taiebat et al. provide a hierarchy of effects [9]. Direct effects are impacts associated with delivering mobility (i.e., resource use and emissions associated with constructing and operating vehicles and roads). The net impact depends on the tension between efficiency improvements and demand [22]. Increased vehicle occupancy is one form of efficiency, à la the ride-share model; other efficiencies include reduced congestion, platooning, smoother driving, and better vehicle drivetrain technology. Congestion leads to wasted fuel, estimated at 3.1 billion gallons in 2014 in the U.S. [23]. AV technology can reduce congestion via improved coordination and fewer accidents [24]. Platooning is another potential efficiency gain, most effective with highway driving that has high losses from air resistance [25]. Also, as with cruise control, higher levels of automation are expected to increase fuel efficiency with smoother driving. Furthermore, Mazur et al. show that greenhouse gas (GHG) emission reduction targets cannot be achieved unless zero-emission vehicles and automated vehicles are introduced simultaneously [26]. AV technology also influences choice of vehicle technology; shared and ride-share AV models favor increased adoption of efficient drivetrains such as plug-in hybrids. Note that a full environmental assessment of AVs should go beyond fuel consumption and account for their life cycle [27]. Electric vehicles, for example, show a larger share of impacts during manufacturing [27] and lead to new recycling challenges [28]. To reduce net impacts from mobility, reductions due to efficiency improvements must exceed increases from increased demand. Indirect environmental effects of AVs link to their larger effect on society. For example, AVs increasing urban sprawl could increase impacts if more households move from urban multi-family to distant single-family homes.

The economic implications of AVs are likely dominated by systemic changes induced by their adoption. In the construction sector, AV-induced urban sprawl would result in housing and road development. In tourism, the comfort of AVs is likely to increase recreational travel. Suburban and rural populations travel more frequently to experience urban entertainments, and urban residents can more easily reach the countryside. Specialized short-term hotels could emerge for riders to freshen up after a long ride in an AV. In the retail sector, AVs can enhance service offerings (e.g., by making delivery of goods and meals more convenient). Driverless AV trucks lead to cheaper freight transport, lowering prices of goods.

AVs will disrupt labor markets by replacing drivers with technology, extending the effects of information technology on work. Many office jobs disappeared with the development of word processors and spreadsheets. E-commerce squeezes retail stores, as illustrated by abandoned malls around the U.S. A direct impact on employment of widespread AV adoption would be the elimination of most driving jobs in trucking, taxi, and public transit sectors—a significant stranding of the labor force (e.g., 2.9 million driving jobs in the U.S.) [29–31].

Congestion affects the economy through lost time and productivity. The average automobile commuter in the U.S. spends 42 hours per year, roughly an entire workweek, driving in congested traffic [23]. However, as discussed further below, it is not clear if the net effect of AVs will reduce congestion.

AVs can deliver economic benefits by increasing safety. The U.S. National Highway Transportation Safety Administration reports that in 2010, the United States incurred an economic cost of $242 billion from motor vehicle crashes, accounting for direct costs such as property damage, legal and medical expenses, congestion costs (e.g., wasted fuel in traffic), and loss of productivity [32]. If loss of life or decline in quality of life are also considered, the total cost to society becomes $836 billion [32].

Traffic safety is also a critical social issue for AVs. Automobile crashes are a major risk in modern society. In the U.S., for example, 36,750 individuals were killed in motor vehicle crashes in 2018 [4]. There are arguments from both sides on the contribution of AVs to safety. The argument in favor of AVs points to the large number of accidents caused by driver error and inattentiveness. A 2015 report found that 94% of accidents can be attributed to driver error [33], such as drowsiness, alcohol or drug use, distraction, poor reaction time, speeding, and aggression. Mechanized attention from AVs could remove human error from the equation. This said, human information processing has advantages (e.g., excellent pattern recognition). It has yet to be established that AV vehicle fleets will, on balance, be safer than human drivers.

Another social implication of AVs is improved access to mobility for elderly, young, and disabled populations. In addition, lower income populations could see mobility benefits as well from ride-share AV fleets that are cheaper and more convenient than many public transit systems [7,34]. Local governments would benefit from lower public expenditures by abandoning low-occupancy transit services.

Different AV futures are possible depending on how various drivers align. Figure 1 shows two possible scenarios. The left side of the figure depicts a future in which a combination of wealth, lower fuel prices, and/or preferences lead to consumers primarily using private AVs. The scenario also reflects consumers spending more time in vehicles (and consequently less time at home) and thus traveling more (e.g., by living further away from urban centers and/or doing more recreational travel). Outcomes from this pattern of adoption include a larger vehicle fleet than today, in order to serve populations who currently have limited access, and increased vehicle miles traveled. In this scenario, efficiency increases accorded to AV operation are not sufficient to counteract increased demand; consequently, total CO_2 emissions increase. AV-related business development centers around providing vehicle loading and parking services. Urban sprawl increases, with corresponding new construction. Drivers of congestion increase, resulting in more vehicles on the road compounded with less use of public transportation. The net outcome for congestion depends on the capacity of AV technology to manage these additional vehicles. The right side of the figure reflects a future in which a combination of higher costs and consumer preferences lead to many foregoing private vehicles (and public transit) in favor of using shared AVs. Also, the trend towards preferring virtual spaces over physical ones continues, with people spending more time accessing the virtual at home, and thus less time traveling. Societal outcomes of this scenario are fewer vehicles on the road delivering less vehicle miles traveled. CO_2 emissions are substantially lower due to lower demand and increased efficiency. Urban sprawl decreases, partly due to increased convenience and lower cost of mobility, with matching redevelopment. AV-related business centers around running shared AV-fleets for passenger transport and delivery services.

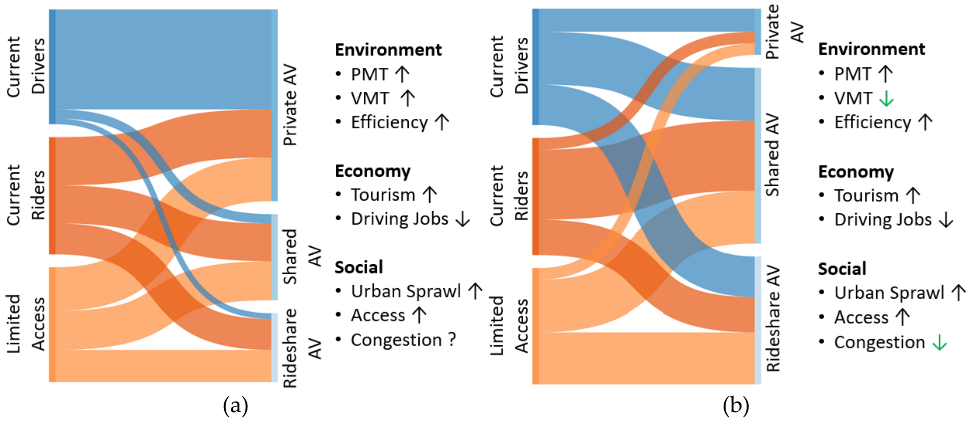

Figure 1. Qualitative visualization of two possible adoption patterns for autonomous vehicles (AVs): (**a**) Many consumers prefer and can afford owning their own AV. (**b**) For cost and other reasons, many prefer to give up owning and either ride in shared AVs or ride-share AVs. Current Drivers are people who own a private automobile; Current Riders are those relying on public transit; Limited Access refers to populations currently limited in mobility (young, elderly, disabled) (PMT = person miles travelled, VMT = vehicle miles travelled). ? refers to unknown outcome of the combination of increased vehicles on the road and capability of autonomous vehicles to reduce congestion. Green font reflects difference in scenario (**b**) versus (**a**).

4. AVs and Sustainability Research – Up to Now

In this section, we summarize prior research on the larger sustainability implications of AVs (see Table 1). Not every related work is cited, as we aim to present a review sufficient to show the lay of the research landscape. To organize, we divided the research into three groups, summarizing methodological perspectives and results for each group.

We term the first branch of AV impacts research as scenario analysis. The term scenario is used in a broad sense here, ranging from the identification of qualitative factors to quantification through the development of if/then cases informed by data. Starting with the qualitative side of this branch, a number of works aim to clarify important societal issues in the future of AVs. For example, Anderson et al. 2016 [24] and Litman 2018 [35] identify future economic, environmental, and social implications of AVs and connect these to policy questions.

Quantitative scenario analysis of AV futures involves developing base case and/or bounds for drivers and estimating ensuing effects. For example, Wadud et al. 2016 [36] developed ranges of changes in fuel consumption associated with factors, such as platooning (3–25% savings), vehicle right sizing (21–45% savings), and demand increase from reduced travel costs (4–60%). Harper et al. 2016 [37] found that if 69 million elderly, non-driving, and medically restricted people were to use AV to travel similar to current drivers, that would induce a 14% increase in light-duty vehicle miles traveled. Das et al. 2018 [6] characterized what consumers would do inside an AV by analyzing the activities heavy drivers (2.5 hours of driving/day) sacrifice compared to the rest of the population (1 hour of driving/day): 30 minutes per day of sleep, watching video, and work, respectively. Scenario analysis is useful to identify issues and bound the magnitude of their effects; however, resulting bounds are wide, and when factors are summed, that can lead to uncertainty (e.g., in the net energy impacts of AVs) [36].

A second branch of the literature investigates preferences of consumers on purchase and use of AVs. One direction of work queries stated preferences via survey or interview (i.e., asking consumers how they think they would use AVs if they had them). Surveys have addressed perception of AV risk [38], willingness to purchase [39], and expected changes in travel behavior [40].

While asking consumers how they think they would use AVs is certainly worthwhile, there are often differences between stated and revealed preferences (what people say they would do versus what they actually do). The gap between stated and revealed preferences is potentially larger for disruptive technologies. For example, in a 1995 stated preference survey on Internet use, 57% of the respondents replied that the convenience of online shopping was "Not important at all" [41]. The challenge is how to measure consumer use of a technology that does not yet exist. Harb et al. 2018 [42] developed an intriguing approach to address the difficulty, simulating AV use by providing test subjects with free chauffeur service for a period of time and measuring changes in travel and activities. A beta test of this approach for 13 subjects in San Francisco showed an 87% increase in vehicle miles traveled (VMT) [42]. While a chauffeur is not a perfect replica of AV ownership, this is a promising approach to empirically characterize future consumer reactions to the technology.

A third branch of the literature provides numerical answers to AV questions via micro simulation and agent-based models of travel and other activities. Growth in computing power and data availability have led to increasingly sophisticated modeling. Models are designed to answer combinations of the following questions: 1. What activity is demanded (e.g., shopping, socializing)? 2. Where to do this activity? 3. What mode of transport to use (e.g., car, bus, train)? 4. What route do vehicles take to satisfy demand? 5. How do multiple vehicles traveling at the same time affect one another (e.g., congestion)? Often models focus on a subset of questions (e.g., fixing travel demand as exogenous and estimating how fleets of vehicles would operate to meet it; see [7]). Transportation research is increasingly moving towards activity-based modeling of travel demand, which treats travel as derived by meeting people's needs and wants [43]. Software tools have been developed that integrate modeling of all five questions in a single framework (e.g., the open source Multi-Agent Transport Simulation Toolkit (MATSIM)) [44]. Choice models are empirically calibrated through combinations of stated and/or revealed preference data. The second research branch often thus informs the third.

Given space constraints, it is not possible to survey all prior research on AVs and society; here, we summarize a selection of results. Starting from a focused question on congestion, Lioris et al. 2017 [45] modeled throughput through road networks if AVs are platooned, finding that intersections could handle two to three times more traffic compared to human-driven vehicles. A number of modeling efforts simulate usage patterns, costs, and/or environmental attributes of drivers switching to AVs in different geographical contexts. Liu et al. 2017 [17] developed an agent-based model simulation of how conventional vehicles and shared AVs would be used in Austin, Texas. They found that vehicle owners would favor AVs for longer trips and vehicle non-owners would use AVs for trips currently done by walking, cycling, or bus. Martinez and Viegas 2017 [46] simulated ride-share AVs and ride-share minibus operation in Lisbon, Portugal, and found reductions in travel costs, vehicle miles traveled, and CO_2 emissions compared to the current system. Merlin 2017 [7] simulated the use of shared AVs or ride-share AVs to replace transit demand on city buses in Ann Arbor, U.S., finding that shared AVs reduce passenger cost relative to buses by 24%, but increase CO_2 emissions by 79%, while ride-share AVs reduce costs by 66% and reduce CO_2 emission by 21%. Bösch et al. 2018 [34] built a model to compare mobility costs of private conventional vehicles, shared AVs, and ride-share AVs of different sizes ranging from single-passenger cars to buses. One of their results is that in an urban setting, private AVs are only marginally more expensive than shared ones. Zhang and Guhathakurta 2018 [47] tackled the question of how AVs might influence urban form by modeling how travel cost savings from ride-share AVs could shift locations of home purchases in Atlanta, U.S. Electric and other advanced drivetrains become more economical when fully utilized (e.g., in a taxi fleet). Bauer et al. 2018 [48] analyzed economic cost and environmental emissions of an automated AV taxi fleet in Manhattan, finding total costs of $0.29–$0.61 per revenue mile, considerably lower than the current fleet and also lower than conventional gasoline AVs.

Table 1. Classifying prior research articles on Autonomous Vehicles (AVs) and sustainability by objectives and methods. EVs = Electric Vehicles. AV ownership refers to consumers choose purchasing conventional versus AV. AV use for mobility is how consumers ride in AVs (private, shared, and/or ride-share) to travel. Activity shifts refers to how consumers change daily schedule in response to AV availability.

		Efficiency			AV Ownership	AV Use for Mobility	AV and Mobility Access	Activity Shifts	AV Economic Costs	Urban Form	Emissions	Equity	Safety	Policy
		Platooning	Congestion	EVs										
Scenarios (Qualitative)	Anderson et al., 2014 [24]	X	X	X	X	X	X		X	X	X		X	X
	Litman, 2018 [35]	X	X	X	X	X	X		X		X		X	X
	Miller and Heard, 2016 [22]	X	X		X	X	X				X			
	Duarte and Ratti, 2018 [49]		X			X				X			X	
Scenarios (Quantitative)	Das et al., 2017 [6]						X	X						
	Fagnant & Kockelman, 2015 [8]	X	X		X	X	X		X		X		X	X
	Harper et al., 2016 [37]				X		X		X		X			X
	Wadud et al., 2016 [36]	X	X	X	X		X	X	X		X		X	X
	Terry and Bachmann, 2019 [50]					X								X
	Groshen et al., 2019 [51]											X		X
Preferences	Bansal and Kockelman, 2017 [39]				X				X					X
	Harb et al., 2018 [42]				X		X	X					X	
	Hulse et al., 2018 [38]												X	
	Zmud and Sener, 2017 [40]				X	X	X		X				X	X
	Olsen and Sweet, 2019 [52]				X					X				X
	Ashkrof et al., 2019 [53]					X								
	Tremoulet et al., 2019 [54]						X						X	
Modeling	Bauer et al., 2018 [48]		X	X		X			X		X			
	Bischoff and Maciejewski, 2016 [55]		X			X								
	Bosch et al., 2018 [34]			X		X			X					
	Chen and Kockelman, 2016 [56]			X		X			X					
	Lioris et al., 2017 [45]	X												
	Liu et al., 2017 [17]					X			X		X			
	Martinez and Viegas, 2017 [46]		X			X			X		X			
	Merlin, 2017 [7]		X			X			X		X			
	Zhang and Guhathakurta, 2018 [47]									X				
	Cohn et al., 2019 [57]					X					X	X		
	Conlon and Lin, 2019 [58]										X			
	Hwang and Song, 2019 [59]	X	X								X			
	Stern et al., 2019 [60]										X			
	Tu et al., 2019 [61]										X			

Recasting the above review to distinguish different methods to forecast future adoption of AVs, four approaches were identified: stated preference surveys, finding analogs in current behaviors, utility optimization models, and/or staging empirical "AV-equivalent" experiments. Stated preferences involve querying consumers on how they expect to use AVs through surveys and similar instruments. For example, Daziano et al. used a stated preference survey to build a preference model to estimate consumers' willingness-to-pay for autonomous vehicles [62]. The second approach, which we term "finding analogs", involves characterizing latent demand for AVs by comparing two populations, one with a specific need for an AV with another without. For example, Harper and collaborators used this approach to scope how the elderly would use the technology by assuming older people with AVs would drive the same as younger people today with conventional vehicles [37]. Das et al. compared workers with very long car commutes and shorter commute workers, postulating that the latent demand for activities lost to extra driving time is described by the activity patterns of the short commuting group [6]. In the third approach, mathematical models, generally based on utility optimization, are developed to simulate consumer choices [17]. In the fourth approach, pioneered by Harb and collaborators, empirical experiments are carried out to simulate how consumers would react to access to an AV [42].

The four forecasting approaches have their respective advantages and disadvantages. While stated preference surveys are an efficient and low-cost approach to gather empirical data, open questions remain on how actual behavior differs from reported expectations. Finding analogs has the virtue of leveraging existing data, but perfect analogs to AVs obviously do not currently exist. Choice models predict AV-related behaviors based on a widely accepted fundamental principle, utility optimization. It is not yet clear, however, how well current models forecast major behavioral changes induced by new technologies. "AV-equivalent" experiments provide a unique lens on actual behavioral change arising from a new technology. However, the "equivalent" experience differs from an actual AV and the studies are expensive ventures. Evaluating the robustness of each approach presents epistemological challenges. There is also the potential to combine them to provide more accurate forecasts.

5. Research on AVs and Sustainability– Thoughts for the Future

Understanding the interactions between AVs and society is a new interdisciplinary research challenge. Research communities are developing to address it, and it is important that there be active debates on norms needed to best respond to the challenge. Sustainability analyses in other domains have shown recurring problems. In life cycle assessment and technological progress modeling, for example, researchers often find contradictory answers to similar questions [63–65]. There is insufficient cohesive effort, at least as judged by some, to reconcile differences and move towards best practices [66,67]. Research communities decide on the validity of modeling approaches via a combination of empirical, theoretical, and social considerations. Decisions on model evaluation/validation are often left implicit, resulting in a frequent lack of emphasis on empirical approaches [64]. There are risks for AV research to fall into one or both of these traps, particularly given the breadth and difficulty of the problem. Here, we offer thoughts on how to foster robust research communities addressing AVs.

First, researchers need to acknowledge the intimidating scope of unknowns associated and develop models to address disruptive changes. Understandably, modeling thus far has focused on shifts from conventional vehicles to AVs under marginal changes in activity patterns. In the longer term, systemic changes in consumer decisions on living and workplace locations and daily activity patterns need to be accounted for. A combination of expanded modeling and empirical work is needed to reasonably forecast the scope of change. Consumer behavior models should account for shifts in expenditure patterns (due to lower cost travel and goods) and activities (what is being done in and out of vehicle). The core established with agent-based models such as MATSim can in principle accommodate such scope, but needs expansion to do so. The industry side is also important, as AVs affect logistics throughout the supply chain, from mining ores to home deliveries. In some domains, researchers emphasize tractable parts of a complex system, downplaying the more difficult interactions, and the AV modeling community must avoid this. Behavioral change, the most challenging part of the system to characterize, is likely to dominate the sustainability implications of AVs.

Models forecasting the future societal effects of autonomous vehicles face epistemological validation questions. Indeed, evaluating any prediction of a complex human-technological system requires generalization of the usual concept of model validation. Perspectives that inform model evaluation include model consistency, completeness, expert judgment, and historical validation. While forecasts cannot be formally validated (except in retrospect, when the answer is less useful), models that produce forecasts can be tested with historical data. This said, historical validation should not be the only lens used to evaluate the future of a disruptive technology. Model evaluation is difficult territory and the outside world, preferring a certain answer, does not encourage its navigation. This environment creates a risk for validation to be submerged as a largely implicit agreement between modelers on best practices. It is imperative that AV and other modeling communities not fall into this trap and engage in a rigorous debate to make explicit decisions on model evaluation.

Second, the balkanization (islands of conflicting results) seen in other research communities could be mitigated through rigorous standards of practice. At the very least, researchers need to list prior results and provide thoughts on why their findings consolidate or contradict existing knowledge. To work towards best practice, there is a need for a deeper analysis of differences, perhaps as a separate literature evaluating methods. To enable substantive comparison with prior results, more transparency is needed, the most important component of which is making model data and structure publicly available. While academic journals have enabled the inclusion of online supplemental information for many years, this capability is generally underutilized.

Third, the multidisciplinary nature of the AV problem implies a need for robust interaction between sub-disciplines. For example, the development of models to forecast behavioral changes should be informed by empirical work. Integrative studies of AV impacts rely on technical analyses of individual factors, such as the fuel savings from platooning.

Fourth, as with other disruptive technologies, AVs call for revision of government data collection systems. For example, the development of the Internet created a need for new data. Governments responded; for example, the U.S. Census developed a new program to measure growth in e-commerce [68]. Similarly, AV adoption and changes induced in other sectors should be resolved with new data collection efforts. For example, data collection efforts on transport behavior (e.g., the National Household Travel Survey) and time-use (e.g., the American Time Use Survey) should better resolve activities done within vehicles.

How to achieve the above recommendations? It is worthwhile to first mention a few obstacles. The "Publish or Perish" trend in academia conflicts with the goal of more complete documentation of research. While the Internet enables complete reporting, standards for online supplemental information are lacking, leaving the choice to individual researchers of what to submit. Detailing data and models are time consuming. Academics thus often choose to publish with partial documentation, partly due to the incentive to publish more. A second obstacle is the organization of governments into mission specific agencies (e.g., transportation, environment, energy, and so on). AVs affect multiple sectors and issues, a challenge that would be well served by integrated data collection and research support from governments.

A number of mechanisms could address the above challenges. Funders of research could play a significant role (e.g., by requiring more disclosure of data and methods) [69]. Another mechanism is the holding of forums with the explicit aim of gathering AV researchers from different fields together to exchange perspectives and debate best practices. We argue that the usual academic conference is not a suitable format because 1. Conferences tend to be organized around sub-disciplines and 2. The focus is on individual researchers presenting their most recent results, with little time devoted to critical debate. Discipline neutral agencies, such as the U.S. National Science Foundation, have more flexibility and are increasingly supporting multidisciplinary research. Such agencies should consider funding programs on the broader societal impacts of AVs, not only supporting research but also the development of research communities. Governments are learning to deal with cross-agency issues (e.g., via interagency working groups such as the U.S. group addressing social costs of carbon) [70]. These challenges and responses go far beyond the societal effects of AVs—they apply to many modeling domains being pursued to support society's navigation of sustainability (e.g., energy systems modeling and life cycle assessment, among others).

We hope that research communities and funders will consider these suggestions to ensure self-critical and inclusive research on AVs and society.

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