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Decision support issues in automated driving systems

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Abstract

Machine learning and computational processing have advanced such that automated driving systems (ADSs) are no longer a distant reality. Many automobile manufacturers have developed prototypes; however, there exist numerous decision support issues requiring resolution to ensure mass ADS adoption. In the coming decades, it is likely that production ADSs will only be partially autonomous. Such ADSs operate within predetermined conditions and require driver intervention when they are violated. Since forecasts of their 20-year market penetration are relatively low, ADSs will likely operate in heterogeneous traffic characterized by vehicles of varying autonomy levels. Under these conditions, effective decision support must consider intangible, subjective, and emotional factors as well as influences of human cognition; otherwise, the ADS risks driver distrust and unsatisfactory performance based on an incomplete understanding of its environment. We survey the literature relevant to these issues, identify open problems, and propose research directions for their resolution.

Keywords: autonomous vehicles; decision support systems; request to intervene; trolley problems

1. Introduction

Automated driving systems (ADSs) are poised to revolutionize human transportation (Burns and Shulgan, 2019). Enabled by recent breakthroughs in artificial intelligence (AI) and computational hardware, mass public transportation via autonomous vehicles is no longer a distant reality. However, the transition to fully automated roadway transportation systems is likely to be an incremental process.

A gradual progression from manned vehicles (MVs) to autonomous vehicles is widely expected[1] and its stages are shown by the six-level taxonomy of driving automation in Table 1 (Society of

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[1]A plurality of manufacturers are pursuing level-3 automation (e.g., General Motors and Tesla), but others (e.g., Google and Ford) have elected to skip it and pursue level-4 or level-5 automation directly (Walch, 2019).

Table 1
Levels of driving automation (Society of Automobile Engineers, 2018)

Level	Name	Description
0	No automation	The driver performs all driving tasks, but vehicle features may provide some decision support (e.g., blind spot and lane-departure warnings) and limited assistance.
1	Assisted automation	Automation for specific activities to include steering or braking support (e.g., lane keeping assistance and adaptive cruise control).
2	Partial automation	Combination of two or more level-1 features that provide steering and braking/acceleration support.
3	Conditional automation	Self-driving automation with full control of all critical safety functions under certain conditions (e.g., traffic jam chauffeur). The driver is still expected to take over in some instances.
4	High automation	Vehicles are fully self-driving, without need for human intervention. The automated driving system controls within a prescribed operational domain (e.g., local driverless taxi).
5	Full automation	The automated driving system can operate the vehicle under all on-road conditions with no design-based restrictions.

Automobile Engineers, 2018). In this taxonomy, level 0 describes vehicles with no automated capacity, and levels 1 through 5 represent vehicles with increasing automated features culminating in fully automated, level-5 ADS.[2] Until recently, global roadways were populated exclusively by level-0 automobiles; however, over the last decade, manufacturers have begun to produce vehicles of higher automation levels. For example, *lane keeping assistance systems* (LKAS) and *adaptive cruise control systems* that automate select steering and acceleration inputs, respectively, are deployed by nearly all major automotive manufacturers (Consumer Reports, 2019a, 2019b). The population of level-1 and level-2 autonomous vehicles with limited self-driving features increases annually. The majority of ADSs currently available for purchase are level-1 systems, but an increasing number of level-2 systems (e.g., Tesla Autopilot, Cadillac Super Cruise, Mercedes-Benz Drive Pilot, Volvo Pilot Assist) are entering the market.

However, many crucial limitations related to ADS safety and operational robustness will likely restrict automated vehicles on roads to, at best, levels 3 and 4 over the next decade. Therefore, these are the primary focus of this paper.

These levels of ADSs require human input when operating outside of their specified operational design domain (ODD); that input is solicited via a *request -to-intervene* (RtI) operation. Although there are currently no commercially available level-3 ADSs (IEEE, 2020), some automakers have attempted to introduce them into the market. The Audi A8 was scheduled to be introduced in 2020 to European markets with its level-3 *Traffic Jam Pilot* system but, in May 2020, these plans were rescinded due to a subset of ethical and liability decision support issues discussed in Section 4.5. Moreover, aside from Google's Waymo, there exist few level-4 ADSs even in the prototype phase.

[2]Alternatives to the term ADS are utilized. Notably, in automotive-related technology environments, reference is often made to advanced driver assistance systems and autonomous driving. However, to ensure comprehension by a multidisciplinary and multinational readership, we utilize the previously defined ADS term preferred by Society of Automobile Engineers (SAE) International.

Indeed, market penetration of level-3 and level-4 ADSs will likely remain stunted until many decision support issues are successfully resolved.

The objective of this paper is to identify these issues, of interest to the operations research community at large, and propose research directions that lead to their resolution. We survey recent developments in industry and academia as they pertain to decision support systems (DSSs) in ADSs, and identify issues that must be resolved for the market penetration of higher level automated vehicles to increase. Given the nature of an ADS's operating environment, these issues are characterized by interrelated actors and interdependent factors (e.g., weather, traffic type, cybersecurity). The human factor in this setting, especially when MVs and ADSs interact, cannot be overstated. The aptitude and preferences of MV drivers, in addition to those of ADS drivers, has a major effect on the overall transportation system's performance. The need to incorporate cognition is also pressing as the ADS must consider driver attitudes in the management of driving modes and must provide effective visualizations to communicate with drivers, pedestrians, bicyclists, and other humans nearby (e.g., diners at a street-side restaurant). Moreover, the revolutionary nature of ADS technology gives rise to new ethical dilemmas, many of a subjective nature, to which the ADS must respond.

The technology challenges interact with obvious regulatory, legal, and social conditions (Taeihagh and Lim, 2019). Martin et al. (2015) sketch the wide range of certification protocols for autonomous vehicles, and Canis (2019) asserts that, at least in the United States, there is need for swifter decision making on regulatory policy by the National Highway Transportation Safety Administration. Haney (2020) describes some of the insurance and liability issues that will arise, chiefly in the context of level-5 autonomy but some issues, especially insurance pricing, generalize to lower levels. The social reaction to ADSs is unclear—in urban communities, there is already significant pressure to give up personal car ownership, and the financial, ecological, and convenience aspects of ADSs could accelerate that trend. Schoettle and Sivak (2014) survey and compare public attitudes toward automated vehicles in the United States, Great Britain, and Australia. But the focus of this paper is on technological aspects rather than societal aspects.

The remainder of this paper is structured as follows. Section 2 provides an in-depth exposition of the current state of the art and state of practice as it relates to ADSs in production and development. It also details the wide-ranging effects mass deployment of ADSs will have on society and how this relates to technical decision support problems. Section 3 systematically reviews ADS processes and components from a decision support perspective. Under this taxonomy, Section 4 reviews recent literature relating to decision support in ADSs and identifies directions of future inquiry. We discuss decision support issues arising in level-3 and level-4 ADSs concerning transitions between driving modes, operation in heterogeneous traffic, and defense against cyber threats, among others. Finally, Section 5 provides closing remarks and discusses future implications. Given the interdisciplinary nature of this manuscript, a list of acronyms is provided in Table 2 for ease of reference.

2. Operational context analysis

The ADS concept has existed almost as long as the automobile itself; in 1939, General Motors introduced a city wherein cars drove themselves across automated highways (Bimbraw, 2015).

Table 2
List of acronyms and their meaning

Acronym	Meaning	Acronym	Meaning	Acronym	Meaning	Acronym	Meaning
ACC	Adaptive cruise control system	DSM	Driver state monitoring	LKAS	Lane keeping assistance system	RtI	Request to intervene
ADS	Automated driving system	DSS	Decision support system	MV	Manned vehicle	SAE	Society of Automobile Engineers
AI	Artificial intelligence	ECU	Electronic control unit	OBD-II	On-board diagnostics II	SLAM	Simultaneous localization and mapping
AML	Adversarial machine learning	eHMI	External human–machine interface	ODD	Operational design domain	V2I	Vehicle to infrastructure
CAN	Controller area network	HMI	Human–machine interface	POMDP	Partially observable Markov decision process	V2V	Vehicle to vehicle
CNN	Convolutional neural network	LiDAR	Light detection and ranging	RADAR	Radio detection and ranging		
DIPA	Driver intervention performance assessment	LIN	Local interconnect network	RFID	Radio–frequency identification		

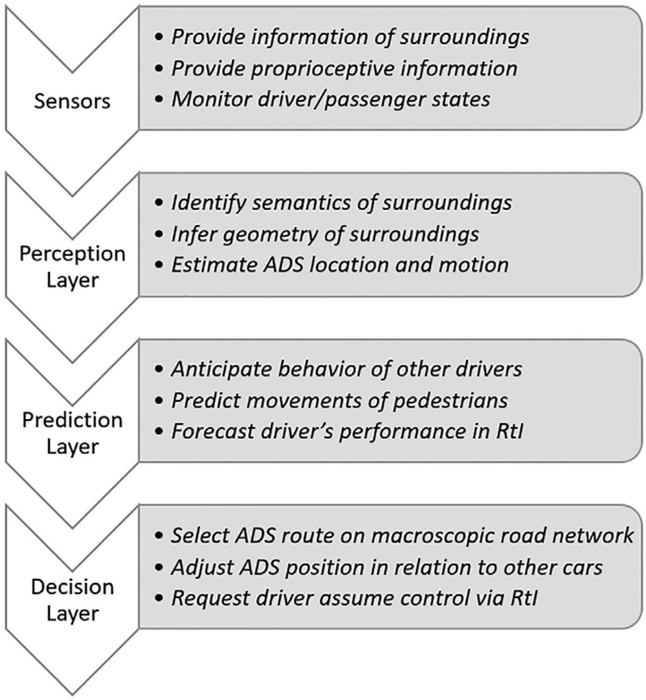

Fig. 1. Typical end-to-end, layered ADS architecture (adapted from McAllister et al., 2017).

However, it was not until the turn of the 21st century that sensors and computing technology matured to the extent that production of lower level ADSs became feasible.

Modern ADSs are built upon a pipeline of components that utilize powerful computing hardware and a variety of sensors to generate steering and acceleration outputs (McAllister et al., 2017). Information from the environment is collected via visible light cameras, near-infrared and far-infrared cameras, *light detection and ranging* (LiDAR) sensors, *radio detection and ranging* sensors, proprioceptive sensors (e.g., wheel sensors), and ultrasonic sensors, among others. Information regarding the environment may also be collected via vehicle-to-vehicle (V2V) or vehicle-to-infrastructure (V2I) communication systems. Once collected, this compendium of information is utilized in systems that perceive the environment both internal and external to the ADS (e.g., driver monitoring systems and LKAS).

The sensor inputs are utilized in a sequence of algorithms processed on powerful and compact computing platforms designed specifically for machine-learning tasks (e.g., the Nvidia Drive PX2 and MobileEye EyeQ). The algorithms utilized belong to one of three layers: the *perception*, *prediction*, and *decision layers*, frequently integrated in an end-to-end architecture, as reflected in Fig. 1.

Algorithms in the perception layer typically receive raw sensor input. They are tasked with estimating the ADS's position as well as determining the geometry and semantics (i.e., class and state of surroundings) external to the vehicle. To perform these tasks, the ADS employs algorithms such as convolutional neural networks (CNNs) for classification (Wu et al., 2017), FastSLAM for simultaneous localization and mapping (SLAM) (Durrant-Whyte and Bailey, 2006), and extended

Kalman filters for general sensor fusion (Roumeliotis and Bekey, 1997). Perception-layer outputs are used as inputs to the prediction layer that forecasts changes to the perceived environment. Modeling structures that incorporate incomplete information, such as partially observable Markov decision processes, are used in this layer (McAllister et al., 2017). Outputs from the prediction layer are inputs to the decision layer that is in charge of route and motion planning. Algorithms in the decision layer determine the ADS's macroscopic route on the road network as well as its granular movement in the traffic flow, for example, see Katrakazas et al. (2015), Gonzalez et al. (2016), and Claussmann et al. (2019).

This operationalization of ADSs has proven successful, but several important technological challenges remain prior to the mass introduction of ADSs on roadways. Proper classification of identified objects is a major issue. Misclassification errors in the perception layer are inherited by algorithms in the prediction layer, thereby increasing the likelihood of incorrect forecasts of an object's behavior and an inaccurate assessment of the environment. To minimize the risk of accidents, the system should be very sensitive and react safely when there is uncertainty about the situation. Regrettably, such systems are prone to false-positive emergency identifications that lead to unnecessary reactions. Attempts by ADS developers to balance the trade-off between system sensitivity and synthetic emergencies was a contributing factor in the 2018 accident wherein an Uber ADS killed a pedestrian in Tempe, Arizona (NTSB, 2018). The emergency braking feature of the Volvo XC90 involved was not engaged because of an anti-false-positives policy; instead, the ADS was reliant on the driver to take evasive action who, unfortunately, began braking fractions of a second before impact.

Another serious issue related to ADS performance involves sensor technology. The performance of both LiDAR and camera systems is significantly impaired during adverse weather conditions such as precipitation and fog (Heinzler et al., 2019; Goberville et al., 2020). Not only do such conditions limit visibility, but they may also induce classification errors when water droplets floating in the air are erroneously detected as objects. Classification errors such as these only constitute a small subset of the many issues that must be resolved before ADS technology can become a widespread means of transportation. Additional issues include the training of ADS's machine-learning algorithms for rare events, the development of appropriate utility functions for decision layer algorithms, and the propagation of errors from one layer to another.

Despite the technological challenges, ADSs have made dramatic gains in the last 20 years—roadways are substantially populated with level-1 and level-2 automated vehicles. However, due in part to the remaining technological limitations and regulatory dilemmas (Lee and Hess, 2020), ADSs are expected to plateau at level 3 in the near future. This will ultimately result in complex transportation systems having MVs and ADSs of heterogeneous levels occupying roadways simultaneously. Aside from global roadway composition, the incorporation of ADS en masse has the potential to revolutionize decision-making environments throughout society.

Various authors, including Brodsky (2016), Milakis et al. (2017), McAllister et al. (2017), Casualty Actuarial Society (2018), Taeihagh and Lim (2019), Burns and Shulgan (2019), and Sheehan et al. (2019), cover legal, economic, psychological, societal, and technological impacts, which we integrate and expand to showcase the richness of the decision support issues. In Fig. 2, we present an influence diagram illustrating the interconnected nature of numerous factors to ADS adoption. Dotted nodes refer to positive impacts; light gray nodes refer to negative impacts; white nodes refer to other impacts, not necessarily positive or negative, which need to be addressed. Dark grey

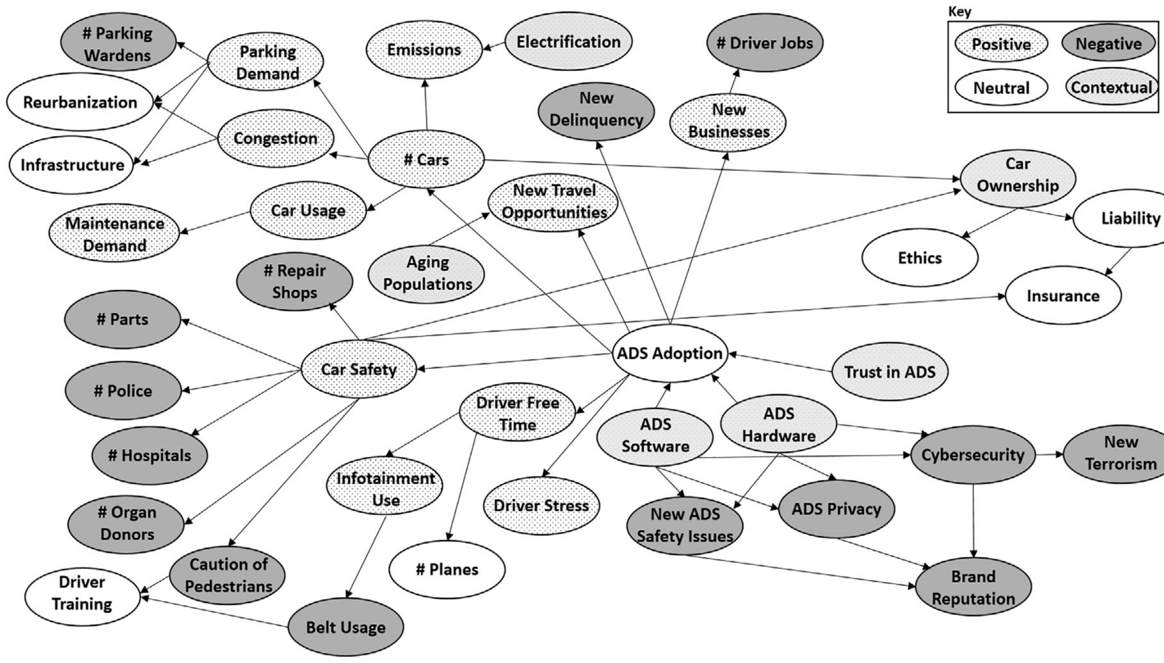

Fig. 2. Influence diagram of ADS impacts on society.

nodes refer to contextual factors (e.g., aging population, car ownership, trust in ADSs, government regulations, driver interests in ADS technologies) that might have a major influence on the massive deployment of ADS.

Our classification of nodes derives from the consolidation of the aforementioned authors findings, among others. However, the classification of nodes as positive, negative or neutral is designed to be more illustrative than authoritative. Although we provide the rationale for our classifications, the logical implications described herein correspond to a single interpretation over the potential futures; there exist many others that may be equally as valid, and a more comprehensive analysis would be required to authoritatively determine which is most accurate. However, by classifying and discussing these factors, the degree of disruption massive ADS adoption will cause on modern life becomes apparent.

The magnitude of the listed factors increases with the level of vehicle automation, the level of cooperation between vehicles, and the penetration rate of vehicle automation systems. Moreover, synergies between vehicle automation, vehicle sharing, and electrification will strengthen the potential impacts. Yet, the balance between the short and long-term impacts of vehicle automation remains an open question.

Many factors listed in Fig. 2 can be readily assumed as positive. Provided that the driving error of human operators exceeds that of ADS technology, roadway safety can be expected to increase. ADSs provide a means of personal mobility to those unable to drive MVs. New business opportunities may be created based on autonomous taxis and trucks. A change in the concept of car ownership could lead to fewer total cars as “on-demand” rental fleets and services develop. Furthermore, optimized computer-controlled driving will result in improved fuel efficiency and less emissions. Increased ADS adoption (ceteris paribus) can be expected to reduce traffic congestion due to optimized driving that will also likely improve people's perceived quality of life. ADSs will also afford drivers additional time to be used for nondriving tasks, leading to a reduction of personal stress. This free time may decrease the demand for fast-moving, high-emission vehicles because longer commutes will be compensated with more task flexibility during transit. Longer travel times will also generate further infotainment opportunities, thereby stimulating this industry. This may increase the mileage of individual cars and their usage compared to time parked. In turn, the automobile maintenance sector may experience increased demand, and there may be less demand for urban parking. Finally, companies in a variety of sectors may benefit financially by replacing MVs with ADSs.

However, other impacts exist that may be perceived negatively. Although some professions may be reenvisioned using ADS technology, others may be at risk of attenuation. Certain professions (e.g., taxi drivers) are at risk as a consequence of competitive autonomous taxis and trucks. A reduced need for parking and an increase in roadway safety may curtail the need for other professions. For example, the demand for parking wardens, traffic police, and collision repair facilities may decrease. Less collisions may also decrease demand for replacement automotive parts and affect all upstream companies in the supply chain. Furthermore, reduced accident frequency may negatively affect the private medical sector by lessening the quantity of patients. Similarly, since a large proportion of organ donations derive from automotive fatalities, increased ADS safety may reduce the supply of organ transplants. Other regulatory and legal questions arise as ADS market penetration increases. Such issues relate to privacy, safety, cybersecurity, terrorism, and delinquency more generally. Finally, the elimination of human error does not imply the elimination of machine error. As a consequence, third parties manufacturing ADS safety systems will face greater vulnerability to liability lawsuits and risk to reputation.

Other impacts associated with the massive adoption of ADSs will require a major redefinition of the current status quo, without necessarily having positive or negative connotations. Driver training will need to evolve. The car insurance industry will have to adapt, especially as it concerns liability issues. The funding of civic institutions may need to be reenvisioned due to the loss of traffic fines. Moreover, governments at all levels will need to consider the evolving requirements of roadway infrastructure, demand changes to existing public transportation, and multiple ADS ethical dilemmas.

The high degree of interconnectedness in Fig. 2 signifies that any organization concerned with a listed factor will be affected as ADS market penetration increases. The need for decision support and, perhaps novel DSSs, will increase correspondingly. Whereas having a higher percentage of ADS on global roadways is predicted to have many positive impacts, it is also accompanied by a unique set of decision support issues described in Section 4.

3. A decision support perspective on level-3 and level-4 ADSs

An effective ADS provides decision support to all relevant actors with whom it interacts (e.g., its driver, pedestrians, bicyclists, etc.). In level-5 ADS, since the driver is not required to intervene in the vehicle's operation, his/her role in decision support is of limited interest. However, in level-3 and level-4 ADS, the driver is asked to take control via an RtI when environmental conditions exceed the vehicle's ODD (Czarnecki, 2018), which establishes conditions referring to the road environment, the behavior of the vehicle, and its state, under which the ADS may operate in autonomous mode. Several estimates indicate that ADSs of these levels will occupy 25% of the global market by 2040, implying that traffic will be a heterogeneous mix of MVs and ADSs in the coming decades. Under these conditions, decision support must be provided to a wide array of actors that include the ADS's driver, pedestrians, bicyclists, and other MV or ADS drivers in the vicinity.

Perhaps the most conspicuous ADS component related to driver decision support is the vehicle's *human–machine interface* (HMI). This is the system which communicates directly with the ADS's human operator. Communication with the driver may be visual, auditory, or haptic, but is intended to help the driver maintain situational awareness of the vehicle's state, system reliability, and other environmental factors. Therefore, the HMI is connected, in one form or another, to all decision support processes and components in the ADS.

To ensure that the driver is situationally aware, the HMI must communicate to him/her relevant outputs from the perception, prediction, and decision layers. These outputs include environmental modeling from the perception and predictions layers, as well as route and path planning from the decision layer. Moreover, relevant elements of the ODD and their current status as they relate to the environmental conditions should also be conveyed to the driver. This communication allows the driver to maintain situational awareness and respond effectively to an RtI or, conversely, to determine whether a manual takeover of the vehicle is necessary and convenient. It is also the foundation for more sophisticated decision support tools in situations wherein driver intervention may be required (e.g., evasive action recommendations via a heads-up display).

The mixed-autonomous-and-manned nature of level-3 and level-4 ADSs is unique in that superior performance also requires a networked system of perception, prediction, and decision layers focused on the ADS's internal environment. RtIs involve a transition of vehicle control from the ADS to the driver when ODD conditions are violated and a transition from the driver to the ADS once the ODD conditions are restored. Therefore, the driver's current state is of particular importance. For example, if a driver is sufficiently distracted for an extended period of time, the ADS may need to request the driver regain situational awareness in case of an emergency. Much like monitoring of the external environment, a *driver state monitoring* (DSM) system is equipped with a variety of sensors to perceive the driver's state with respect to fatigue and distraction. These sensors may utilize cameras, tactile sensors, or incorporate information from other devices in the ADS (e.g., the infotainment system) or even wearables. The DSM system may also use machine-learning algorithms (e.g., CNNs for visual input) with a focused decision layer concerned with the management of driving modes. Some auto manufacturers already integrate DSM into a subset of their production vehicles (e.g., Saab, Toyota, Cadillac).

In both prototype and production ADSs, the architecture and function of DSM is in its infancy. However, it plays a crucial role in the RtI system of level-3 and level-4 ADS. Additional system inputs beyond sensors having a myopic perception time frame have been proposed. Specifically, *driver intervention performance assessment* (DIPA) systems have been proposed to record and retain historical data regarding driver interventions. This information would in turn be used to inform future RtI decisions (Bianchi, 2018). Moreover, DIPA systems can potentially allow custom decision support tailored to individual drivers. If the ADS learns that one driver has a slower reaction time than another or that he/she tends to focus on one HMI display over another, the ADS controller may decide to alter the timing or presentation of decision support to facilitate their decision making, potentially adopting a more risk-averse approach.

Finally, ADSs must also provide decision support to external actors interacting with it, such as other motorists and pedestrians. It is likely necessary to include an externally focused HMI for these individuals as well. At a minimum, safe operations demand an ADS clearly communicate its intent and, potentially, explicitly advise external actors on how to interact with the ADS.

4. Emergent ADS decision support issues

Given the transformative potential of ADS, a significant amount of research has been performed across multiple academic disciplines to improve their performance. Much of the research focuses on the ADS's control of driving operations in pursuit of level-5 autonomy. Oddly, research pertaining specifically to the decision support perspective of level-3 and level-4 ADSs is substantially less developed. Therefore, this section explores the existent body of research studying such issues and identifies promising avenues of future inquiry for decision support research in level-3 and level-4 ADS.

4.1. Managing driving modes

In level-3 and level-4 ADS, autonomous driving is limited to a specific ODD. When environmental conditions exceed the ODD or if the decision layer algorithms cannot predict a trajectory within it, the ADS will need to change modes (e.g., from automatic to manual) to ensure safety. Therefore, the ODD as well as the DSM (Rahman et al., 2015) and trajectory planning (Han et al., 2016; Wang et al., 2018) systems are critical components in the management of driving modes.

Issues pertaining to DSM have been tackled by various authors (e.g., Dong et al., 2011; Hecht et al., 2018; Akai et al., 2019). Research on the topic generally falls in one of two categories (vehicle-oriented or human-oriented) or a combination thereof (vehicle-and-human-oriented). A vehicle-oriented approach uses the vehicle's movement to infer the human's state (e.g., acceleration, speed control, driving path), whereas a human-oriented approach infers the driver's state more directly via his/her actions within the vehicle (e.g., eye closure, gaze direction, hand position, body posture). The sensors used to collect this information vary; however, human-oriented research often focuses on input from cameras (visible or infrared) that is then processed by deep learning algorithms (e.g., Brandt et al., 2004). Other sensors, such as electrocardiographs, collect biological information (e.g., Awais et al., 2017; Chowdhury et al., 2018) or infer the driver's state with a variety of wearables (e.g., Lee et al., 2017; Huang et al., 2019).

Whether human- or vehicle-oriented, probabilistic and statistical-based models have proven effective for the purpose of characterizing driver behavior. More specifically, machine-learning models have been a primary focus of DSM research recently (Akai et al., 2019; Torres et al., 2019; Yi et al., 2019), with a few notable examples adopting a Bayesian perspective (Agamennoni et al., 2011; Straub et al., 2014). A critical determination in these statistical-based models are the classification levels of a driver's state. For example, the American Automobile Association Foundation for Traffic Safety uses five categories: *attentive*, *distracted*, *looked but did not see*, *sleepy*, and *unknown*

(Stutts et al., 2001). In their DSM review, Dong et al. (2011) consider three states: *attentive*, *distracted*, and *fatigued*. Alternatively, the NTSB discusses distraction in terms of *visual*, *auditory*, *biomechanical*, and *cognitive* classifications (Ranney et al., 2001). Given that RtI decisions are based in part on the driver's state, the hyperparameters determining the driver-state classification affect ADS performance; however, there does not currently exist a widely accepted standard in academia or industry.

4.1.1. Avenues of future inquiry

As mentioned, much research has been conducted on the technology enabling the management of driving modes. But fewer studies focus on the RtI decision itself. McCall et al. (2019) provide a taxonomy of driving mode transitions (e.g., scheduled, driver- or system-initiated emergency) and discuss its relation to the SAE automation taxonomy. Although multiple authors have examined the effect of HMIs on RtIs (e.g., Walch et al., 2015; Eriksson and Stanton, 2017), the algorithmic specifics related to the management of driving modes is less developed.

The temporal nature of the RtI decision, in conjunction with the repeated sampling of the environment via the ADS's sensors, naturally lends itself to statistical decision theory (French and Insua, 2000). Therefore, an effective manner of formulating the RtI decision involves the Bayesian modeling of various perception-layer inputs as they relate to prediction layer outputs and the need for intervention. Studies of these types would provide the foundation for determining when to transfer control to the driver and help define the degree of decision support required during his/her intervention. They would also allow explicit representation of state uncertainty to reduce the effect of error propagation in ADS operations and decision support. As an alternative to statistical decision theory, reinforcement learning or approximate dynamic programming may be effective tools in determining the timing and need for RtIs.

Such dynamic aspects are crucial for safe ADS operations. Predicting departures from the ODD enable early warning for the driver. Forecasting changes in the environment facilitates anticipatory trajectory planning decisions, with the important caveat that the ADS decisions have a direct influence on the environment. Deciding the most appropriate driving mode at a given context in time could be based on the predictive expected utilities of the various driving modes. Similarly, DIPA are typically based on comparing predicted to actual performance of drivers. Thus, we should expect further incorporation of Bayesian forecasting principles in ADS research and development, as in West and Harrison (2006). In particular, we emphasize a *management by exception principle* that utilizes a group of models for learning, prediction and decision making under normal operating conditions until an exception arises for which an intervention is requested.

Regardless of the prediction method used, the degree of situational awareness a driver must maintain to effectively respond after an RtI needs to be well understood. That is, driver performance at varying degrees of distraction and fatigue should be examined in an RtI setting. Although these factors are known to degrade performance in sustained manual driving operations, Zeeb et al. (2017) showed that cognitively demanding tasks do not necessarily impair a driver's takeover performance. Research in this area must be multidisciplinary and incorporate intangible aspects of human cognition as neuroscientific, psychological, and behavioral factors. Of particular interest is the application of neuroeconomics (Glimcher and Fehr, 2013) to the problem where individual decision-making behavior is studied based on neuronal activity in the driver's brain.

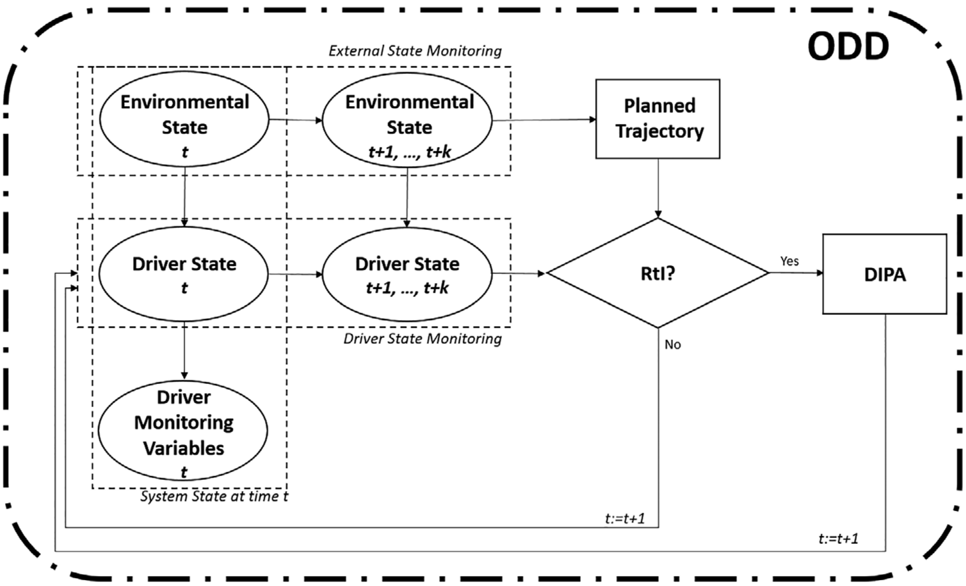

Fig. 3. Incorporation of DIPAs into the RtI decision process.

It must also be recognized that driving aptitude varies by individual. Although it is unlikely that this information can be discovered *a priori*, machine-learning algorithms can be utilized to monitor driver performance to acquire this information over time. RtIs can be executed in nonhazardous situations to perform DIPAs to determine the driver's aptitude. The utilization of DIPAs to augment DSM and trajectory planning in RtIs is an underexplored concept. Figure 3 presents a potential process to incorporate DIPAs for customized decision support based on driver aptitude. The environmental and DSM systems observe the state at time t, forecast future states through time $t + k$, update the planned trajectory, and decide whether an RtI should be executed and recorded via the DIPA. Customizable aspects of the RtI decision may correspond to timing, information content, or data visualization, possibly based on a utility function that adapts to the DIPAs undertaken.

Finally, based on recent accidents involving ADSs, the NTSB (2020) is developing DSM standards in coordination with SAE International to improve roadway safety. Once released, future research should be conducted to discern how current systems perform in comparison and, if necessary, novel DSM methodologies should be developed to comply with the new standards. Studies of this nature will help verify and certify that developed ADSs can satisfy the true operational demand. Indeed such empirical studies and statistical validation frameworks are relevant to all ADS functions referenced in this manuscript and are of utmost concern to national regulatory agencies.

4.2. Heterogeneous traffic

The fleet mix on a roadway has a nontrivial effect on an ADS's operation and the requisite decision support provided to the driver. A homogeneous fleet of ADSs can readily communicate with each other to optimize and coordinate operations while acting autonomously. For example, Hult et al. (2020) showed how level-5 ADSs can cooperate at an intersection by first solving a mixed-integer quadratic program to identify vehicle crossing order and subsequently solving a nonlinear program to determine vehicle control inputs. An extensive survey and discussion of such coordination research in higher level ADSs is provided by Mariani et al. (2020). Conversely, the anticipated gradual incorporation of ADSs worldwide presents a unique challenge: MVs and ADSs will likely cohabit roadways for a substantial period of time. Under such conditions, there exists multiple open problems relating to the efficacy of heterogeneous ADS-MV traffic systems.

A substantial amount of prior research on heterogeneous ADS-MV traffic flow pertains to its aggregate effects. Under a game-theoretic construct, Huang et al. (2020) model heterogeneous traffic as a mean field game. Their results suggest that the overall stability of traffic flow will increase with ADS market penetration. Complementary results are discussed by Bose and Ioannou (2003) and Wu et al. (2018) with regard to fuel consumption, emissions, and vehicle flow in heterogeneous ADS-MV traffic. These stability findings are reinforced by the results of multiple studies in the literature (e.g., Talebpour and Mahmassani, 2016; Xie et al., 2018). Related research examines the effect of roadway configuration and heterogeneous vehicle types on a traffic system's headway and capacity characteristics (e.g., Ramezani et al., 2017; Mohajerpoor and Ramezani, 2019). However, as discussed by Rad et al. (2020), there are many open problems in this topic.

Modeling constructs and solution methodologies for heterogeneous traffic flows vary greatly. As previously mentioned, game theory has been used to analyze aggregate behavior of the multiagent system. Control theory (e.g., Zheng et al., 2020), multiobjective optimization (e.g., Zhong, 2018), and cellular automata models (e.g., Chen et al., 2020) have also been used. However, a large body of research analyzing heterogeneous traffic flows is based on simulation models (e.g., Talebpour and Mahmassani, 2016; Yang et al., 2019; Li et al., 2020), particularly as it relates to the incorporation of empirical human behavior.

4.2.1. Avenues of future inquiry

Without a centralized coordination mechanism, the degree to which MVs and ADSs can cooperate is restricted. Such behavior is well studied in game theory via the analysis of coordination games. In these scenarios, a social welfare maximizing solution is often pursued via signaling and communication.

Similar methods can be utilized under heterogeneous traffic conditions to pursue Pareto-optimal solutions for agents in the system. As market penetration of ADSs will not dominate that of MVs in the near future, auto manufacturers will likely continue to produce and sell vehicles without autonomous capabilities as well as lower level ADSs. Cooperation between these vehicles can be facilitated if future automobiles incorporate V2V systems. For example, MVs produced with HMIs that receive input from ADSs in the driver's vicinity could provide situational awareness and decision support to the MV's driver by clearly communicating the ADS's intent, state, and knowledge. The specific design of these HMIs and the information they would provide to an MV's driver is an open research question. Furthermore, the MVs can provide decision support to the ADSs by communicating their intent and status as well. Such communication may incorporate a variety of specific technologies (e.g., RFID) but, at a minimum, these systems would need to report the vehicles identity as an ADS or MV to others nearby. Therefore, studies investigating how this communication affects the behavior of heterogeneous traffic flow is needed, from both empirical and theoretical perspectives.

Inspiration from classical game theory can also be derived from the subfield of *mechanism design* (e.g., see Caballero et al., 2020a). In it, a central authority designs a game to be played by a set of agents; their goal is to induce some desired form of agent behavior in equilibrium. Interactions between ADSs and MVs can therefore be framed as a mechanism design problem in some situations. However, as the bounded rationality of human decision makers is well established (Stahl and Wilson, 1995), research in this direction is probably best served by adapting a behavioral approach (De Clippel et al., 2019) with respect to MVs. Given the inherent stress and danger associated with some roadway decisions, empirical research should be conducted to determine how this affects a driver's depth of strategic thought.

Finally, alternative approaches to multiagent systems that adopt the perspective of a given decision maker may also be utilized (e.g., Rios Insua et al., 2009; Caballero and Lunday, 2020). Such applications would not analyze the system in aggregate but would focus on enabling the ADS's or MV's driver to make the best decision based on available information. Therefore, the information garnered by these methodologies could be directly incorporated into a vehicle's DSS. A primary concern of decision support research related to heterogeneous traffic is the degree to which MV driver behavior can be influenced to increase social welfare. Lazar et al. (2018) have taken initial steps in this regard, but there exists many avenues for future inquiry. Of note, the methodologies presented by Caballero and Lunday (2019) and Caballero et al. (2020b) are promising tools for use in single-shot decisions related to emergency evasive action in heterogeneous traffic. Moreover, in a temporal decision-making setting, methods presented by Esteban et al. (2020) and Gallego et al. (2019) are able to accommodate the nonstationary nature of the environment via the combined use of adversarial risk analysis and reinforcement learning.

4.3. Human–machine interfaces

Many authors have studied different aspects of HMIs in automotive systems. Choi et al. (2018) propose an adaptive HMI based on machine learning that alters information provided to the driver based on his/her personal characteristics as well as current aspects of the operational environment. Their structure bears a strong resemblance to the DIPA concept described in Section 4.1. Furthermore, Ohn-Bar and Trivedi (2016) provide an extensive literature review of recent HMI-related research, finding a large emphasis on computer-vision applications in DSM. The HMI also has a nontrivial impact on the feelings a driver has toward the ADS. Koo et al. (2015) show that HMIs that describe "why" an action is taken increase driving performance compared to those that only describe "how" an action is performed. The underlying implication is that a driver's trust in the ADS increases when HMIs describe their rationale. Finally, research has also focused on the design of the HMI itself, specifically as it relates to RtIs (e.g., Forster et al., 2016, 2017; Naujoks et al., 2017). It can therefore be seen that the design of internally focused HMIs is strongly related to the management of driving modes via the DSM, DIPA, and RtI constructs, reflected in Fig. 3.

Pedestrians and MVs also frequently communicate. Such communication is conducted in a variety of manners, to include eye contact and physical gestures (Rasouli et al., 2017). However, in level-3 and level-4 ADS, a driver may no longer be physically in control of the vehicle and their vigilance of environmental conditions is not assured. The study of external HMIs (eHMIs) that enable ADS and pedestrian communication has become an active field of study for these reasons. Two approaches are generally adopted for this problem via the study of explicit and implicit eHMIs.

Explicit eHMIs involve systems, which directly interact with pedestrians by (1) recommending actions, or (2) communicating the ADS's intent via visual or auditory means. These systems are designed to provide stimuli analogous to a hand wave or verbal cue. Not only have explicit eHMIs been studied in the literature (e.g., Clamann et al., 2017), but Google and Nissan have also developed prototypes (Urmson et al., 2015; Vinkhuyzen and Cefkin, 2016). A central tenet is direct communication with a specified pedestrian. However, scholars have noted that this is difficult to achieve in complex traffic situations. To avoid confusion among pedestrians regarding the individual targeted for communication, Benderius et al. (2017) advocate for *show-don't-tell* systems wherein the ADS only signals its intent; it does not recommend actions. This principle coincides with another advocated by Habibovic et al. (2018): the *autonomous vehicle interaction principle* (AVIP). Systems of this design enable an ADS to communicate to surrounding pedestrians via a light bar displaying various signals. The AVIP is akin to current technology being developed and tested by Ford (Moore et al., 2019).

Alternatively, a growing body of research suggests that implicit eHMIs are sufficient for many routine interactions between pedestrians and ADSs (Rothenbücher et al., 2016; Currano et al., 2018; Moore et al., 2019). Such systems do not preclude the use of explicit eHMIs, but they leverage the inherent communication associated with a vehicle's speed to convey intent. Moore et al. (2019) contend that implicit eHMIs are adequate for many routine ADS-pedestrian interactions. They conduct an empirical study of a cross walk to observe pedestrian behavior when interacting with a "ghost-driven" vehicle[3] and determine that many pedestrians do not appear to notice the vehicle is "autonomous." Notably, these findings are juxtaposed by others in the literature. Deb et al. (2018) investigate different types of communication in eHMIs; the authors determine that familiar images and texts (e.g., a walking silhouette) were preferred as visual stimuli and that verbal warnings were viewed positively.

As can be observed by the varying perspectives on effective eHMI systems, there is currently a lack of standardization and consensus in HMI design (e.g., differing dashboard buttons). Such ADS standardization efforts, for the HMI and otherwise, are a growing area of research and will vitally influence future ADS adoption (Verband der Automobilindustrie, 2019).

4.3.1. Avenues of future inquiry

Although fairly well studied, the design of internally focused HMIs remains an important area of research. As the ODD of autonomous driving modes increases, the underlying decision-making environment changes as well. This is particularly true with regard to the velocity of the decision-making situation. Therefore, research in the future should focus on driver information needs and its corresponding presentation in RtIs across a range of ODDs. Such research will better enable the development of context-adaptive HMIs as presented by Choi et al. (2018).

[3]A ghost-driven vehicle is an MV disguised as an ADS. A human driver operates the vehicle, but their appearance is camouflaged such that he/she looks like a seat from outside. The vehicle is also labeled with markings identifying it as an ADS.

We also note that the use of eHMIs is not limited to pedestrians. As previously mentioned, communication between ADSs and MVs is paramount in heterogeneous traffic. Therefore, the design of eHMIs focused on MV drivers is a promising area of future research. Some initial work has been conducted in this regard (e.g., Rettenmaier et al., 2020), but a more complete treatment of the psychological, human factors, and engineering elements, as well as their interactions, is necessary.

Concerning widespread acceptance of ADS, a pedestrian's perception of safety is equally important as their actual safety. It is widely known that humans do not intuitively assess probabilities in accordance with standard axioms (Tversky and Koehler, 1994); multiple descriptive decision-making models have been developed to accommodate this (Kellen et al., 2020). Therefore, an eHMI must ensure pedestrians *feel* secure. If not, it will impair adoption of ADS. Behavioral-economic studies focused on *nudging* (Sunstein, 2014) as it relates to an ADS's HMI can therefore play a prominent role in ensuring the widespread adoption of ADS.

4.4. *Protecting ADSs from attacks*

Modern vehicles are reliant on numerous, small computers (i.e., controllers) called *electronic control units* (ECUs) to ensure their proper functionality. Each ECU digitally controls a subsystem of the vehicle (e.g., the engine control and brake control modules) and communicates, as necessary, via the *controller area network* (CAN), a network bus standard designed specifically for intercontroller communication.[4] This infrastructure became the *de facto* automotive standard in the 1980s. However, design choices in that era were primarily driven by cost and network latency issues; security was an afterthought (Han et al., 2014).

As discussed by Koscher et al. (2010), increased technological functionality built upon this insecure infrastructure has created significant vulnerabilities to in-vehicle, V2I and V2V systems, potentially compromising the safe operations of all interconnected equipment. Many attacks of various forms are possible on ECUs in automotive networks (Baylon, 2018). These may be done with or without physical access to the vehicle (Rizvi et al., 2017a). Therefore, recent research has focused on how to protect against these threats. Rizvi et al. (2017b) discuss how an attacker can potentially infiltrate in-vehicle infotainment systems as a means to disrupt ECUs essential to the automobile's operation. The authors propose a distributed firewall system to combat such threats. In contrast, Yu et al. (2015) identify the *on-board diagnostics II* (OBD-II) interface as the most significant vulnerability to ECU security. The authors consider code authentication and obfuscation measures as well as on-the-fly decryption to combat the associated vulnerabilities. This is modeled in an attacker–defender framework and solved via a Markov decision process model.

Although level-3 and level-4 ADS share ECU cyber vulnerabilities with their lower level counterparts, their reliance on machine-learning algorithms implies additional security concerns. The algorithms enabling an ADS to interact autonomously with its environment are based on the assumption that the underlying data are independent and identically distributed. However, this assumption may not hold in reality. In fact, the burgeoning body of research in *adversarial machine*

[4]Other bus standards exist, such as the local interconnect network (LIN). However, these are often used to complement CAN. Alternative protocols to CAN, such as FlexRay, were also introduced with little regard to security (Han et al., 2014).

learning (AML) illustrates the havoc that can be wrecked on an AI by an intelligent opponent (Joseph et al., 2018).

An AML opponent is generally assumed to be able to influence the performance of a machine-learning algorithm in one of two ways: via *poisoning* or *evasion* attacks (Biggio and Roli, 2017). A poisoning attack consists of deliberately modifying the training data to manipulate the output of the trained predictive model. An evasion attack assumes the opponent has no control of the training data, but instead attempts to influence the algorithm's performance after the fact by modifying incoming data during operations. However, as detailed by Dasgupta and Collins (2019), AML is a nascent field of research with many open questions.

From an ADS perspective, the machine-learning applications of primary importance are likely computer vision and reinforcement learning. Algorithms of both types have been shown to be prone to AML attacks (e.g., Brown et al., 2017; Behzadan and Munir, 2017; Lin et al., 2017; Elsayed et al., 2018). Since AML is itself an emerging field, research explicitly considering the ADS setting is sparse. However, there do exist a few noteworthy exceptions. Recognizing the emergence of machine learning in future ADS technology, Tuncali et al. (2018) devise a testing framework accounting for the limited interpretability of deep learning models and illustrate its use in a virtual environment. Moreover, Boloor et al. (2019) devise a *hijacking* attack on deep neural networks utilized by ADS. Specifically, the authors were able to alter the ADS's performance, instigating it to steer erroneously, by purposefully drawing black lines on the driving surface.

4.4.1. Avenues of future inquiry

As auto manufacturers introduce new technologies into level-3 and level-4 ADSs, continued research on ECU attacks is essential. New security features to defend ECUs will defend against some threats at the expense of generating new ones. Moreover, the incorporation of additional bus systems as well as the development of alternatives to CAN (e.g., FlexRay, prototype optic cable-based systems) will alter the security setting and require additional research (Kraus et al., 2016). This is of direct importance to decision support because it alters the vehicle's operation and impedes the level of situational awareness available to the driver. These threats can be effectively managed with recent cybersecurity and cyber insurance resource allocation approaches (Rios Insua et al., 2020).

Further study of AML, in a general sense, is important to decision support in ADS. The algorithms in the ADS's perception, prediction, and decision layers are all based on machine learning; a firm understanding of AML is an essential ingredient to their protection and ensuring accurate driver decision support. However, given the extensive use of deep learning in ADSs for computer vision and reinforcement learning applications, AML research on these algorithms is most critical. Additional research analogous to that conducted by Boloor et al. (2019) studying the effects of AML on current ADS technologies is needed to ensure their safe operation. Moreover, mitigation techniques against these threats, for example, V2V-security validation protocols, need to be identified and studied.

AML research tends to adopt a game-theoretic approach, thereby adopting a common knowledge assumption (Insua et al., 2020). Extensive surveys of this approach are provided by Dasgupta and Collins (2019) and Zhou et al. (2019). However, the common knowledge assumption is often inappropriate, and this is especially true with regard to AML in an ADS setting. As an alternative, adversarial risk analysis (Banks et al., 2015) can be utilized wherein the game is a decision-theoretic problem for just one of the players. That player attempts to maximize their expected utility by taking into account their beliefs of the associated aleatory, epistemic, and solution-concept uncertainty. Naveiro et al. (2019) develop such an approach to adversarial classification and illustrate it via a Naive Bayes classifier. Additional research of this nature is important as it pertains to ADS; it provides intelligent decision rules for machine-learning algorithms that account for adversarial actions.

Finally, researchers investigating decision support issues in ADSs must remain cognizant of the far-reaching effects the technology may have. This is especially true when considering how threats against an ADS may cascade into other security settings. For example, consider an adversarial attack that leads an ADS to misclassify a railway crossing thereby triggering an accident with an automated train system. Such an attack not only affects the decision support onboard the ADS but also the DSS associated with the municipality's train scheduling. As AI and automation become increasingly pervasive in day-to-day life, it is easy to envision how attacks against an ADS's DSS may adversely affect other DSSs. Therefore, as ADS technology matures, one must identify how attacks against them can affect other interrelated systems, be they connected physically or digitally.

4.5. Ethical decisions in ADS

Ideally, one wants ADSs to adhere to Asimov's three laws of robotics; see Anderson (2008) for a discussion of the ethical implications in AI systems. But the simplicity of the laws is undercut by the complexity of implementation. It is difficult to make moral calculations about uncertain outcomes, such as the chance that pedestrian will be injured given choices made by the ADS.

As is often the case with revolutionary technologies, the increasing adoption of ADSs is associated with many subjective moral uncertainties. Lin (2016) presents a variety of vignettes illustrating the ethical dilemmas associated with ADSs that must be accommodated by their machine-learning algorithms and DSS. The author illustrates how crash-avoidance features are not adequate in many real-world scenarios; crash-optimization features must be considered. Unfortunately, such systems present the designers with unenviable ethical dilemmas. For example, in an emergency situation wherein a collision with a pedestrian is unavoidable, is it more ethical to swerve left impacting an 8-year-old girl or swerve right to collide with three 20-year-old men? Or in another emergency scenario, is it more ethical to swerve right protecting the occupants or swerve left protecting a greater number of pedestrians? Moral dilemmas such as these are collectively known as *trolley problems* and are of long-standing interest in the study of law, ethics, and psychology, among other fields (e.g., Bauman et al., 2014; Eyal, 2020).

Although the utilization of trolley problems has been criticized as lacking relevance to algorithm training (Basl and Behrends, 2020), they are widely used as an analogy in the study of ADS ethics. In fact, Awad et al. (2018) developed an online experimental platform called the *Moral Machine* wherein users are repeatedly shown trolley problems and asked to make a choice. Clustering analysis is performed on the resulting data to draw inferences regarding demographic factors affecting their decisions. In effect, machine learning and crowdsourcing are able to infer ethical behavior. However, the utility of such trolley problem applications in the evaluation of ADS ethics remains a contentious and debated topic (Johansson and Nilsson, 2016; Awad et al., 2020; Keeling, 2020).

Other authors have examined the ethics inherent in reinforcement learning structures. Gerdes and Thornton (2016) augment this discussion by exploring how the consequentialist and deontological ethical perspectives coincide with the cost function and constraints, respectively, in a control theory setting. The authors contend that, by maximizing a cost function, a controller is acting in accordance with consequentialist philosophy. In contrast, since constraints provide absolute rules of behavior regarding what is and is not acceptable, they accord with deontological philosophy. A hybrid consequentialist-deontological approach can therefore be formed via a mathematical programming framework.

Regardless of the ethical approach employed, the second- and third-order effects associated with imposing morality on ADS behavior may be undesirable. Goodall (2014) notes the following. As a somewhat forced toy example, consider an ADS that must choose between striking one of two motorcyclists, one wearing a helmet and one not. An ethical ADS may maximize survivability by striking the motorcyclist wearing a helmet, but the second-order effect of such a policy is that the use of safety equipment incurs an additional hazard. In turn, motorcycle riders may be dissuaded from wearing safety equipment to avoid being struck by out-of-control ADS. Such a result runs contrary to maximizing a society's social welfare with respect to survivability in roadway accidents.

As referenced in the motorcycle example of Goodall (2014), the examination of ethics informs the formation of law and policy. This is particularly true in the area of liability. The examination of ethics in ADSs enables decisions to be made regarding when an auto manufacturer or a driver may be held liable for damages in an accident. However, there exist many open questions in this regard. Lee and Hess (2020) provide an overview of liability laws for ADSs with respect to testing around the world. Even though their research focuses on three western nations, the authors note a significant degree of variability among them. Corroborative findings regarding regulatory structures are reflected by the work of multiple other researchers (e.g., Brodsky, 2016; Taeihagh and Lim, 2019).

4.5.1. Avenues of future inquiry

Since the study of ethics expressly considers intangible, subjective, and, potentially, emotionally evocative judgments, the achievement of universal consensus regarding an ADS's programed morality is unlikely. However, it may be possible to achieve a high level of consensus via projects such as the Moral Machine. Continued research, especially work that is cross-cultural, will advance our collective understanding of ethics in ADS, thereby informing policy and regulation. Although the Moral Machine focuses on trolley problems, extensions to liability judgments in level-3 and level-4 ADSs based on the timing of RtIs and the contextual decision support provided to the driver are particularly relevant.

Such research will inform liability regulation by providing insight into society's views on the transfer of responsibility between automobile manufacturers and operators in the management of driving modes. Within their taxonomy of driving mode transitions, McCall et al. (2019) discuss the complexity associated with liability and insurance. To a large extent, the nuanced need to assign liability arises from the degree of decision support provided to the driver by the ADS. For example, even if a successful transition of control occurs from the ADS to the driver, the driver may not have been allocated sufficient time to respond or provided sufficient information to gain situational awareness. Continued empirical research on societal perceptions is critical for the development of future regulation that has popular support.

Despite the criticism of trolley problems in the literature, their study informs consequentialist ethics programed into an ADS via its objective function. The crowdsourced nature of Moral

Machine like experiments allows for multiobjective decision weights to be inferred from aggregate choice data. This approach limits the effect of individual subjectivity; however, it will also likely overwhelm opinions of minority groups. Therefore, interdisciplinary research investigating the incorporation of psychological, sociological, and cultural factors in ADS systems and their perceived ethics is of enduring significance. An ADS's utility function can ultimately adopt a utilitarian or a self-preserving perspective. Although the utilitarian approach is more likely to maximize social welfare, it also requires that an ADS's driver operate a vehicle that may not maximize its own survival. The degree to which a populace is willing to accept such risks is likely dependent on many demographic and sociological factors that deserve study in their own right. In any case, a promising line of future inquiry relates to developing generic parametric utility models for ADS management, which take into account safety, comfort, environmental, and efficiency attributes from which designers, owners, and policymakers could choose, similar to the proposal by Couce-Vieira et al. (2020) in relation to cybersecurity.

Finally, it can be argued that the primary limitation associated with the widespread introduction of ADS on global roadways is not technological but regulatory. Audi's level-3 variant of the A8 was delayed in 2020 due to liability considerations in European laws, not technological shortcomings. Therefore, the collective study of ethics and their relationship to national-level regulation must proceed to ensure that the adoption of ADS is not delayed. This work must be interdisciplinary and empirically based.

4.6. Other DSS issues in ADS

The incorporation of level-3 and level-4 ADSs on global roadways will have far-reaching effects on DSSs beyond those associated with the routing and control of an individual ADS (e.g., Gu et al., 2021; Bogyrbayeva et al., 2021). This is particularly true in the area of ground-based logistics wherein the concept of truck platooning with ADSs has generated much research interest recently (Bhoopalam et al., 2018; Boysen et al., 2018; Scherr et al., 2019). A truck platoon is often considered wherein a manually operated semitrailer truck is followed at very close range by multiple autonomously driven cargo vehicles. Such operations are enabled by V2V technology that allows the following vehicles to cooperate with the maneuvers of the lead truck (Gao et al., 2016). The widespread use of this technology will allow for more centralized control of fleet operations, thereby increasing the demand for decision support of such operations. This concept was illustrated by Gungor and Al-Qadi (2020) who showed how centralized control of platoon routes could improve infrastructure sustainability.

ADS technology is also increasingly finding application in the defense and security settings. The study of unmanned aerial vehicles has received a substantial amount of research attention for border patrol and routing applications (e.g., Khaleghi et al., 2013; Minaeian et al., 2015; Lim et al., 2016; Rojas Viloria et al., 2021). Likewise, the U.S. Army is currently developing multiple variants of the Robotic-Combat Vehicle (U.S. Army Ground Vehicle Systems Center, 2019) and pursuing its own variant of truck platooning technology (Schaefer et al., 2019; U.S. DoD, 2020). Similar projects are being pursued by the Spanish and British ministries of defense (Cano, 2018; U.K. DSTL, 2020). Other countries, such as the United Arab Emirates, have also focused on using autonomous vehicles for policing operations (Vincent, 2017). Moreover, the U.S. and Australian air forces are increasing their interest in autonomous systems (Humphreys et al., 2016). The development of these programs follow an ever-increasing focus on autonomous systems in NATO (2015) as well as the defense and security sector more broadly (U.S. NSF and DoT, 2020). However, as described by Zacharias (2019), the desire of senior decision makers is generally to field autonomous systems concordant with level-3 and level-4 of the SAE taxonomy that require human–machine teaming. DSSs are of primary interest in the development of ADSs for these purposes.

4.6.1. Avenues of future inquiry

As the use of ADSs increases, so too will the need for DSS in a variety of applications. A roadway system populated with a substantial number of ADSs increases the actions available to a centralized controlling authority. Therefore, it is of interest to study how an air traffic control model can be adapted to the operations of national roadways.

Studies of this nature may investigate the underlying network models and algorithms, or they may address the DSS itself. For example, they may investigate the features of the HMI enabling the traffic controller's decisions or determine the best means of communication between driver and controller. Furthermore, if preliminary trends associated with the use of the Tesla Autopilot system are indicative of future ADS usage writ large (Hardman, 2020), ADS popularity may surge to such an extent that it replaces other transportation modes. DSS enabling the deliberate and sustainable design of highway infrastructure may then be needed to maximize public investment in national roadways.

ADS technology will not only affect civilian life but will also impact the nature of defense and security operations. These have a broad array of associated decision support issues. Although related, the HMI associated with a level-3 or level-4 vehicle conducting security operations has unique needs not required by its civilian counterparts. For example, the decision support needs of a border patrol agent or a soldier in an ADS do not only relate to other automobiles but also correspond to adversary behavior more generally. All of the decision support issues discussed herein can be extended to the defense and security setting, but the underlying conditions alter the decision context significantly. The use of adversarial risk analysis (Banks et al., 2015) in these conditions is appropriate and a promising area of future research.

Beyond tactical considerations, the incorporation of ADS technology also enables more nuanced and real-time command and control systems. The development of DSSs that fuse the collective information of autonomous vehicles across multiple domains (e.g., planes and cars), will be central to the development of novel networked command and control constructs (Niewood et al., 2019). Therefore, studies investigating the technical aspects of V2V and V2I technology across platforms of varying types, as well as studies informing the most appropriate HMIs for complex decision making at the strategic level, are of keen interest from a defense and security standpoint.

Finally, it must also be noted that, although described discretely in this manuscript, all ADS subsystems are interrelated. This can be observed, in part, through the proposed RtI decision process in Fig. 3. Other unlisted factors clearly have second-order effects on this system. For example, a poisoned algorithm, a poorly designed HMI, or an unethical utility function affect whether an RtI is issued and how the driver responds. This interconnectedness is magnified once one begins to reason about the effects of V2V and V2I technology wherein there exists interacting decision processes. Therefore, in the future, ADS research will greatly benefit from adopting a systems engineering perspective that considers all such interrelationships.

5. Conclusions

Although ADS technology has made tremendous strides in recent decades, there exists a number of decision support issues that must be resolved in order for ADSs to populate roadways en masse. We have attempted to lay out them systematically in this paper. Although we provided a thorough examination of the literature, given the expansive interest in ADSs from scholars across many academic disciplines, we have invariably missed some significant contributions to the field. However, through our examination, we provide operations research scholars with historical context surrounding these issues and avenues to pursue for their resolution.

Undoubtedly, the topics discussed herein cannot be viewed in isolation. Further perspectives relating to a variety of topics including the evolution of automotive insurance, the effect of ADS penetration on labor markets, and the impact of ADSs on national organ donation supplies constitute an exciting future for decision support research. Moreover, since decision support in ADSs is characterized by interrelated factors having physical, psychological, ethical, economic, legal, and sociological components, decision support scholars must pursue a holistic research agenda. Therefore, it is imperative that future ADS decision support research considers the intangible human factor, as discussed in this manuscript, to ensure the viability of large-scale ADS deployment and the certification of developed DSSs by independent accreditation institutes.

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