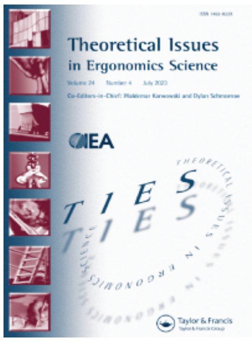


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# Human-centred design of next generation transportation infrastructure with connected and automated vehicles: a system-of-systems perspective

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REVIEW

# Human-centred design of next generation transportation infrastructure with connected and automated vehicles: a system-of-systems perspective

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**ABSTRACT**
During the transition period when connected and automated vehicles (CAVs) and human-driven vehicles (HDVs) coexist on the roadway, miscommunication and improper interactions may lead to accidents due to lack of awareness of each other's intentions. The most promising approach to this problem is to view roadway transportation as a cyber-physical-social system consisting of CAV, HDV, and infrastructure subsystems. Although adaptations of infrastructure are as critical as the technological advances of vehicles, the role of infrastructure in CAV and HDV interactions has not been fully acknowledged. We consider the roadway transportation system from the system-of-systems perspective, taking a human-centred approach that integrates the behaviours of human drivers and CAVs with the design and enhancement of transportation infrastructure. We provide an overview of prior studies regarding information-processing and communication of the subsystems. Interactions between HDVs and infrastructure are summarised by human driving behaviours and HDV crash analysis. Interactions between HDVs and CAVs focus on how they perceive and predict actions of each other. Interactions between CAVs and infrastructure are characterised by possible adaptations of infrastructure to support CAV navigation. Lastly, we propose a human-centred framework to provide guidance for research on and design of next-generation transportation infrastructure with CAVs and HDVs.

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Autonomous vehicles; driverless vehicles; mixed traffic; roadway infrastructure

## Relevance to human factors/ergonomics theory

Implementation of CAVs on the roadways with HDVs requires a system-of-systems approach that includes the CAVs, HDVs, and transportation infrastructure. Humans must be at the center of this approach because their actions are central to the success of the entire system.

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## Introduction

Calls have been made by U.S. President Joe Biden to start rebuilding the transportation infrastructure (e.g. Tankersley 2021), in part because it is essential to the growth of the American economy. Indeed, on November 15, 2021, he signed into law a $1.2 trillion infrastructure bill that includes $110 billion for roads, bridges, and major transportation infrastructure projects (Klein and Sullivan 2021). Although rebuilding may be needed, it is also vital to focus on the future to build next-generation transportation infrastructure. This infrastructure should use technological advances to serve the needs of connected and automated vehicles (CAVs) and of the human-driven vehicles (HDVs) that will share the roadway.

Statistics from the U.S. Department of Transportation show that motor vehicle traffic crashes caused an estimated 42,915 fatalities in 2021 (NHSTA. 2022). Extensive research has illustrated that CAVs have the capability to improve the safety of the transportation system significantly by reducing the number of crashes (Clements and Kockelman 2017). However, the attainment of these benefits entails close to 100% CAV penetration on the roadway (A. Sinha et al. 2020). The transition from HDVs to CAVs requires the trust and acceptance of CAVs by society. Safety during the transition period in turn necessitates understanding of the human perceptual and cognitive processes relating to such acceptance (Robertson, Meister, and Vanlaar 2016).

During the critical transition period, in which CAVs and HDVs coexist on the roadway, miscommunication and improper interactions between CAVs and HDVs can lead to accidents. For example, a report released by Waymo shows that most accidents involving their self-driving cars are caused by other drivers' 'incautious behaviors' (Schwall et al. 2020). The accidents are harmful and may produce injuries and fatalities, but they also will have the consequence of reducing the public's trust in CAVs. As of September 30, 2022, a total of 519 CAV collisions were reported to the California Division of Motor Vehicles (DMV). Although the number seems low, the crash rates of CAVs from most of the companies are still much higher than human drivers (McCarthy 2022). If the accident rate is perceived by the public as too high, this will slow the widespread adoption of the CAVs.

Human factors research concerning CAVs has focused mainly on how to facilitate the human drivers' roles of monitoring the automation and intervening when necessary (Stanton 2019). Kyriakidis et al. (2019) concluded from interviews with human factors specialists that one of six future research foci should be to investigate the interaction between CAVs, HDVs, and other road users, but to date these interactions have received much less consideration. Infrastructure was not included among the areas in need of research identified by Kyriakidis et al. (2019), but Hancock et al. (2020) did mention a need for improvements in transportation infrastructure and efficiencies for the integration of CAVs into public driving. However, they did not include infrastructure among the challenges that they identified: driver independence/mobility, driver acceptance/trust, failure management, third-party testing, and political support.

The omission of infrastructure from the lists of research foci and challenges likely reflects a tendency for the role of transportation infrastructure in the interactions of CAVs and HDVs to be downplayed by government agencies, automobile manufacturers, and researchers. Yet, adaptations of infrastructure are at least as critical as the technological advances of the vehicles themselves in maximizing safety (Gopalswamy and Rathinam 2018). Current transportation infrastructure is designed to accommodate only human drivers and is incapable of linking the interactions and communications between CAVs, much less between CAVs and HDVs. Consideration of infrastructure development has focused on the needs of communication among CAVs and not between CAVs and HDVs (Friedrich 2016). Also, it only accounts for traditional infrastructure design requirements such as pavement materials and geometry, as well as some digital communication, without incorporating CAV characteristics and how they may impact human drivers (Shi 2020).

The 'smart' infrastructure of the future needs to be able to support communication among CAVs and between CAVs, infrastructure, and HDVs for the goal of a more efficient, relatively error-free transportation system to be achieved. The most promising approach to this problem is that of *system-of-systems* (Jamshidi 2017), for which the overall roadway transportation system is comprised of CAVs, HDVs, and infrastructure subsystems (K. C. Sinha, Labi, and Agbelie 2017). This approach stresses that the entire roadway transportation system be regarded as a whole. Consideration of the subsystems should take place with the goal of satisfying the overall system requirements in the most effective way possible. Our central hypothesis in this paper is: *Transportation infrastructure optimised based on the system of CAV-HDV-Infrastructure subsystems should appreciably reduce collisions and traffic delays.* The next section reviews the system of systems approach, and the remainder of the paper develops its implications for the roadway transportation system.

## System-of-systems approach

The systems approach has been central to engineering psychology and human factors research since its emergence from World War II (Proctor and Van Zandt 2018). More recently, as systems have become increasingly complex, the terminology has shifted from referring to systems and subsystems to systems-of-systems (Iwanaga et al. 2021), but the basic point is the same. Engineers need to approach design problems from a systems perspective in which the main goals are those of the overall system, and the component systems or subsystems are considered within the structure of how to best achieve the goals of the superordinate system.

The system-of-systems view has been applied to cyber-physical systems, which involve computational and physical components (K. H. Lee, Hong, and Kim 2015). In the transportation system, CAVs are cyber-physical systems for which the automation controls the physical vehicle. Human factors engineering is based on the concept of human-machine system, involving human and nonhuman components (Millot 2014). For HDVs, the human is controlling the physical system, the vehicle. Both the cyber-physical CAVs and the human-physical HDVs must interact safely with the external physical environment, including static and dynamic roadway components and vehicles whose actions must be coordinated. The smart infrastructure can be considered as another cyber-physical system with an increasing number of cyber components that play a significant role in the control and coordination process. In totality, the transportation system can be conceived to be a cyber-physical-social (or behavioural) system (Xiong et al. 2015).

The main point of taking a system-of-systems approach to the transportation system is as follows: To advance knowledge in this field and maximise traffic safety and mobility, there is a need to integrate driving behaviours and dynamics of both CAVs and HDVs with design and enhancement of existing infrastructure. Eriksson and Stanton (2018. 6) noted, 'Consumer adoption of automated vehicles will not happen overnight. Consequently, a transition period is to be expected where automated and manually driven vehicles share the same infrastructure'. The resulting system must accommodate the needs of CAVs and HDVs in mixed traffic. Because human drivers will play a key role in the system, a human-centred design framework is needed that focuses on the perceptions and actions of HDV drivers during their interactions with CAVs.

Figure 1 illustrates the transportation system-of-systems approach, on which this paper is based. It depicts that the infrastructure plays a role in all interactions other than those that directly involve only human drivers and CAVs. In the next section, information-processing and communication of each of the subsystems of human, CAV, and infrastructure are reviewed. The section that follows focuses on the interactions between human drivers (or HDVs) and traditional infrastructure, describing existing studies on human driving behaviours and reviewing methods for analyzing crashes as evidence about what vehicle interactions are problematic for human drivers. The section after it examines how HDVs interact with CAVs, and vice versa, regarding the perception and prediction of actions. Following that, we investigate how current transportation infrastructure needs to be adapted, either physically or digitally, when CAVs are deployed on the roadway. Finally, we combine existing studies of the three subsystems and their interactions and propose a human-centred systems framework for guiding research relating to the design and implementation of next-generation transportation infrastructure with both CAVs and HDVs.

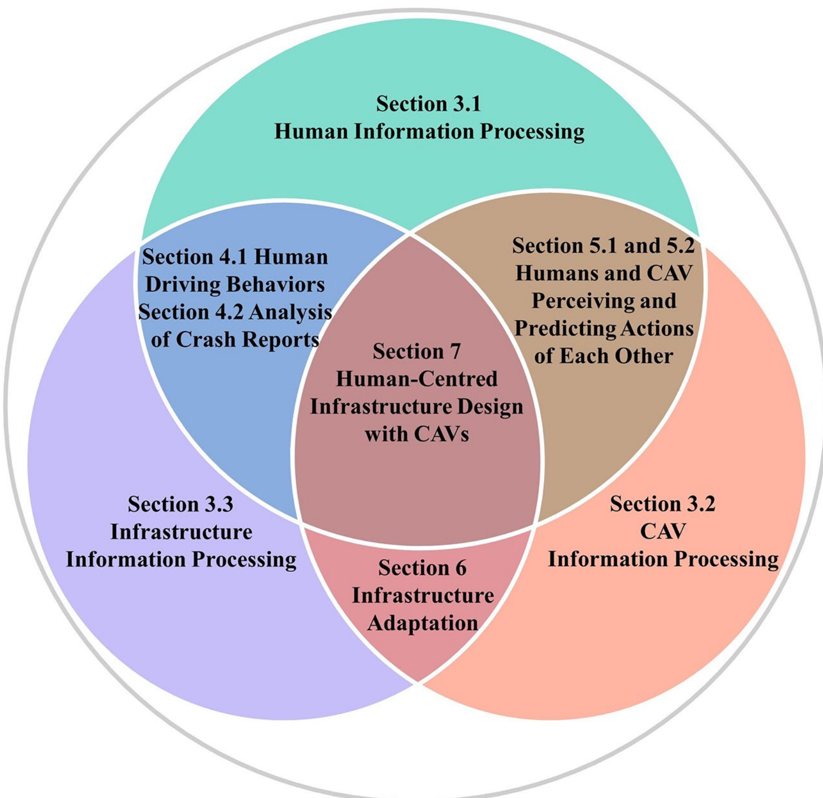


**Figure 1.** Transportation system of human, CAV, HDV, and infrastructure systems and their intersections.

## Information-processing

Information-processing is essential to human drivers, CAVs, and smart infrastructure. All three subsystems have sensors that provide input regarding environmental stimuli, memories that can be activated by the input, and output to the environment. That is, the three subsystems process and transform the activated information and take actions based on that processing (Brookshear 2011). Properties of information-processing for human drivers, CAVs, and smart infrastructure determine the nature of their interactions.

### *Human information-processing*

For humans, a simplified information-processing model distinguishes sensation, perception, cognition, and action (Proctor and Van Zandt 2018). A key concept from the human factors literature is *situation awareness* (Vu and Chiappe 2015). This awareness has three components: perception of the elements in the situation, comprehension of what the situation means, and prediction of future status (Salvendy and Karwowski 2021). Situation awareness involves contributions of almost all human information-processing up to execution of an action, which can provide feedback to update awareness. However, it should be kept in mind that some actions can be triggered without awareness and intention.

Sensory processing is a vital factor in driving, since 90% of human-caused traffic accidents are linked to visual information acquisition problems (Castro 2008). Because the region of maximal visual acuity is restricted to the fovea and the near parafovea (Tuten and Harmening 2021), fixations of a driver's eyes on the wrong regions or specific locations may result in critical stimuli not being identified or even detected. Peripheral vision, in contrast, is devoted to low-resolution processing of more global sensory information across the visual field (Binder, Hirokawa, and Windhorst 2009). These properties of retinal processing are carried through the optic nerve and visual areas of the cortex, resulting in two modes of visual processing (Schieber, Schlorholtz, and McCall 2009), *focal* and *ambient*. Ambient vision, associated with the dorsal visual stream in the cortex, is involved in guidance and control of locomotion, whereas focal vision, associated with the ventral visual stream, is involved in detailed form perception and pattern recognition. Because tasks such as driving include interplay between these two visual modes (Stewart, Valsecchi, and Schütz 2020), their roles are helpful for understanding drivers' behaviours (Horrey and Wickens 2004).

Perception is often equated with awareness of fixated objects, which can be measured using eye-tracking devices (Titz, Scholz, and Sedlmeier 2018). However, it is known that people may not perceive even salient fixated objects if their attention is directed elsewhere, a phenomenon known as inattentional blindness (Mack 2003). Thus, it should be kept in mind that the person still may not see something that seems to be the focus of their attention. It is also known that behaviour may show evidence of processing information that a person cannot verbally report (Lo 2018). One key feature attributed to attention is its limited capacity (Posner and Boies 1971). Limited capacity is also a major factor in working memory – a system in which activated mental representations, based on immediate and past events, provide a basis for thinking, learning, and action (Baddeley 1998). Oberauer (2009), for example, has developed a model that distinguishes three components: (1) an activated part of the information from long-term memory that comprises the contents of working memory;

(2) a region of direct access with a capacity of about four items from which information can be retrieved quickly; (3) a focus of attention that selects a single item as the object of the next cognitive operation. The general point is that the information of which a person is aware may be limited, but a larger amount of activated background information can influence cognition and action. This model and others emphasise the significance of activating appropriate information from long-term memory and keeping the central focus on critical events.

Cognition also includes problem-solving and decision-making, which refer to a person's thinking and choices among alternatives (Bossaerts and Murawski 2017). A prominent view is that decision-making can take place via a fast, automatic route (System 1) and a slower deliberative processing route (System 2; Kahneman 2013). System 1 thinking is based on overlearned associations and heuristics that require little cognitive effort and are applied with little awareness. System 2 thinking is a more systematic, effortful process of which a person is aware. Many decisions a person must make in a time-constrained environment need to be done quickly and automatically, without engaging more deliberative and possibly rational decision processes, which require more time and effort.

Action relates more specifically to the selection and execution of responses (Proctor and Vu 2021). Responses can be selected faster and more accurately when they are compatible with the stimuli than when they are not (Proctor and Vu 2006). A noteworthy factor in action selection is the activation of corresponding responses by irrelevant stimulus information. For example, people tend to make a spatially compatible response even if the location of the stimulus is task-irrelevant (Lu and Proctor 1995). Motor control is influenced by both perceptual and more central cognitive factors (Schmidt et al. 2018). Movements can be controlled by motor plans without feedback, though they are more accurate when sensory feedback is used to modify the actions. In both action selection and motor control, speed can be traded off with accuracy (Heitz 2014): Responses can be selected and executed quickly with a cost to accuracy, or vice versa.

### *CAV information-processing*

Depending on the level of automation (Society of Automotive Engineers 2021), lower levels of automation (L1 to L3) of CAVs require human drivers to be responsible for the driving tasks or to take over under emergency situations, whereas CAVs with higher levels of automation (L4 and L5) can navigate on the roadway without human intervention. Regardless of the automation level, onboard sensors and communication devices are installed on the CAVs to facilitate or replace the human drivers in perceiving the driving environment, communicating with other road users and infrastructure, and making control decisions and actions.

The information-processing model of CAVs is like that for humans, which includes sensing, perception, decision making (or path planning in CAV) and control. A range of sensors including camera, radar, and Lidar are essential for CAVs to sense and perceive the environment. CAVs need to identify static objects such as traffic lights, lane markings, and road barriers, as well as dynamic objects such as vehicles and pedestrians, and their relative locations and speeds (Rosique et al. 2019). After their construction of the driving environment and localization of the vehicles, CAVs plan paths in the short term (i.e. 5–10 s) with different objective functions such as safety, efficiency, and driver's (rider's) comfort (Dolgov et al. 2010). Finally, the planned path is executed to control the CAVs' maneuvers through the throttle, brake, and steering wheel. Typically, drive-by-wire control technology is applied, which replaces traditional mechanical-based control with electronic signals (Isermann, Schwarz, and Stolzl 2002). Machine Learning (ML) techniques are widely adopted in the information-processing pipeline. They can be applied in each component of the autonomy stack, or the entire system can be treated as a 'black box' to implement the End2End learning approach, in which sensed input is mapped directly to vehicle steering commands (Grigorescu et al. 2020).

Communication plays an especially crucial role in the CAVs' information-processing. Connected vehicles utilise wireless communication technology such as Dedicated Short-Range Communication (DSRC) or cellular network (C-V2X) to broadcast vehicle-to-vehicle (V2V) messages and vehicle-to-infrastructure (V2I) messages. Due to range and line-of-sight limitations of onboard perception sensors, objects that are far away or occluded cannot be detected, which may lead to fatal crashes. Communication enables cooperative sensing/perception and cooperative trajectory planning (S.-W. Kim, Qin, et al. 2015) among multiple vehicles and between CAVs and infrastructure (Yang, Feng, and Liu 2021), which can further improve the safety and efficiency of the entire transportation system.

### *Infrastructure information-processing*

Infrastructure mainly offers physical space for road users and regulates traffic. Regulation is accomplished through providing rules to vehicles by way of different types of markings (e.g. lane markings, parking lines), signages (e.g. speed limit, one-way road), and controls (e.g. traffic signals, stop signs). The shapes, colours, and fonts used in traffic signs, road surface markings, and signals in the U.S. are specified by the Manual on Uniform Traffic Control Devices for Streets and Highways (MUTCD) (Federal Highway Administration 2012). Guidelines of MUTCD can be followed in designing the content, type, location, and characteristics of the relevant information. Existing infrastructure is designed to accommodate human drivers' information-processing rather than CAVs'. A sign that attracts attention and conveys 'a clear, simple meaning' to a human may not be easily recognised by a CAV (Garcia et al. 2022). In addition, drivers' eye position is an important factor in highway geometry design, especially with vertical curves (Mannering 2020). However, the locations and angles of the CAV onboard sensors may be significantly different from drivers' line of sight. Another example involves designing traffic signal plans, where human drivers' perception and reaction time are important factors in determining transition intervals (i.e. yellow and all-red clearance) (Transportation Research Board 2015). Thus, it is critical to design signs and control traffic that are visible, interpretable, and accommodated to both human drivers and CAVs.

Existing infrastructure also collects data through infrastructure-based sensors such as loop detectors. The infrastructure-based detection system usually has high installation and maintenance costs, and the control performance can be degraded noticeably if one or more detectors are malfunctioning (Feng et al. 2015). CAVs can be considered as remote sensors that generate much richer information and have the potential to provide a complete picture of traffic conditions to the infrastructure through V2I communications. With this type of data, infrastructure is able to improve the control performance of urban traffic networks (Guo, Li, and Ban 2019).

To summarise, communication among CAVs, HDVs, and infrastructure requires transfer of information. Although all three of these subsystems process information, taking inputs and providing outputs, they do so with different strengths and weaknesses. The differences in information-processing capabilities need to be considered for interactions involving the three subsystems. An optimal system design should avoid overwhelming human's limited attention system and provide signals compatible with the human driver's intuitive interpretation, as well as decrease the difficulty of recognition for infrastructure and CAV sensors and take advantage of the information-processing efficiency of machine subsystems.

## Human actions in driving

Considerable research has been conducted specifically on human information-processing and actions in driving. In addition to studies of drivers, analyses of crash reports provide valuable information. Understanding how and why humans interact successfully and unsuccessfully with other vehicles within existing infrastructure is essential to designing the transportation system to accommodate CAVs in addition to HDVs.

### *Human information-processing in driving*

Driving engages all of the human information-processing components described previously (Foley et al. 2013): sensation, perception, cognition/decision-making, and action selection and control. Each component is critical in driving, which will be discussed in details below respectively.

Sensory processing is a vital factor in driving (Castro 2008). Especially, vision accounts for 90% of the relevant sensory information for current HDVs (Anstey et al. 2005). Other sensors are also used in driving. For example, auditory stimuli may communicate navigational directions or nearby emergency vehicles, haptic feedback and auditory signals through vibrations by rumble bars may alert drivers to slow down for potential hazards, and a smell may alert drivers of potential mechanical failure or nearby environments (Proctor and Van Zandt 2018). According to multiple-resource models of attention (Wickens 2008), which distinguish between the visual and auditory modalities, the use of visual signals that require attention may disrupt regular driving tasks (which are primarily visual) and reduce drivers' performance (Choi et al. 2020). Therefore, the use of auditory signals and displays to convey information should be considered (M. Wang et al. 2020). In addition to different information modalities, characteristics of signals can also impact human drivers' performance, such as the display location, colour and size of visual signals (Neale et al. 2007; Yared, Patterson, and All 2020), frequency and amplitude of auditory signals (Baldwin and May 2011), and frequency of vibrotactile signals (Petermeijer et al. 2015). Similarities between items should be reduced, in terms of look, sound, colour, size, continuity, format, and type to reduce the potential for information interference (Wickens et al. 2012).

Drivers need to constantly perceive road inventory information (i.e. physical elements of the road) such as speed limit, lane width, shoulder width, and curve alignment to update their awareness of road and environmental conditions (Ismail et al. 2018). Accurate perception of these conditions is essential for predicting potential driving hazards (Wetton et al. 2010). Drivers' perception is impacted by both individual and environmental factors. Individual factors include drivers' ages and driving experience, among others. Environmental factors include the distance between drivers and the perceived objects, lighting conditions, etc. In addition, because driving involves interactions with other vehicles, as well as with pedestrians and bicyclists, perception of the intentions of others is crucial to safe driving (Petersen and DeLucia 2022). A driver's intentions can be shown explicitly through signaling (e.g. left- and right-turn signals or hand gestures) or implicitly through vehicular actions (e.g. vehicular speed decrease).

Drivers' cognitive/decision-making ability is positively related to their driving performance (Ledger et al. 2019). Multiple aspects of cognition and decision-making are necessary in driving tasks. Visuospatial skill is a significant predictor of drivers' performance (Schultheis et al. 2010): Young drivers with higher visuospatial skills perform better than older drivers in route-finding tasks (Foley et al. 2013). Also, a driver's ability to focus attention on relevant driving-related information while ignoring unnecessary information is crucial (Schultheis et al. 2010). Experienced drivers are able to distribute their attention across a larger region of the visual field than inexperienced drivers, as indicated by a wider distribution of fixation allocation (Konstantopoulos, Chapman, and Crundall 2010).

Executive control functions (planning, problem-solving, and decision-making) are involved in driving (Pope, Ross, and Stavrinos 2016). Memory is a prerequisite for much of drivers' problem-solving and decision-making in that planned tasks must be remembered (Zicat et al. 2018). Executive functioning tends to decline in older adults, which implies that measures of executive function can be used to predict driving performance of older drivers (Aksan et al. 2015). Perceptual-motor skills are required for drivers to manipulate the vehicles. Older drivers with low perceptual-motor skills have a higher accident and violations rate than younger drivers (Alosco et al. 2013).

Driver actions include responses to road conditions and environment by controlling the steering wheel, gas and brake pedals, and following distance (Miyajima et al. 2007). Good drivers are those who, under road conditions with potential hazards, exhibit reduced speed, less standard deviation of lane position, and proper following distance (Doroudgar et al. 2017). Shangguan et al. (2021) proposed a method that predicted relatively accurately whether driver-risk status in a naturalistic driving study was medium or high based on several sources of information: rolling time window-based feature extraction, real-time driving risk status prediction, and driving risk influencing factors. They emphasised that their method can be applied in CAVs to reduce driver mental workload and improve driving safety. In addition to naturalistic studies, driving simulators have been widely used to measure drivers' actions under more controlled conditions that also do not put the driver at risk (Jung et al. 2019).

The main point of this section is that many factors influence drivers' decisions and actions when interacting with other HDVs, roadway conditions and contexts, pedestrians, and bicyclists. Much of the knowledge that people bring to driving with other HDVs in various situations can be leveraged to understand how human drivers might be expected to react in relation to CAVs. However, caution will be required when extrapolating data from interactions with HDVs to interactions with CAVs and to the impact of CAVs on human drivers, because the drivers' task is being altered in fundamental ways that may affect their responses to other humans and HDVs.

### *Analysis of crash reports*

If drivers' information-processing is compromised at different stages (perception, decision-making, or action) for various reasons (distraction, fatigue), traffic accidents may happen. Systematic investigation of traffic accidents would improve our understanding of root causes and help future CAV design and infrastructure adaption to improve safety. Traffic accidents are documented in crash reports, but because there are few autonomous vehicles on the roads, only a small number of crashes involving them have occurred and been reported.[1] However, for critical intersections such as roundabouts, reports for crashes involving two HDVs are numerous and can provide evidence as to the types of scenarios that are liable to be problematic for interactions that include CAVs and humans.

Each crash report records much information, including date, time, type, number of units involved, weather, road condition, and hazardous actions. These can provide sources of information concerning issues that are likely to arise when human drivers confront CAVs in the future. For example, a vital piece of information in crash reports is a narrative compiled by the filing police officer, which documents in detail what happened during the accident (Huynh, Gambi, and Fraser 2019). The narrative is the official and most useful information source for recreating a crash scene (J. Zhang, Kwigizile, and Oh 2016). Although crash reports from any local agency could be limited in terms of contexts of the crash accidents involved, accumulating reports from different agencies and across a long time-span is expected to alleviate the randomness and bias of risk factors inferred from individual reports. To analyze such large number of reports, machine learning and natural language processing techniques are typically used.

In the context of road safety research, crash databases such as Fatality Analysis Reporting System (FARS) form one of the primary data sources. They aim to reflect five 'W' (i.e. when, where, what, who, and why) for each crash with its corresponding detailed information (Imprialou and Quddus 2019). In addition, the decision-making with regard to road safety relies on the quality of the crash databases in terms of their timeliness and accuracy (Montella et al. 2013). Although manually reviewing the crash reports can be effective in some ways (e.g. crash classification), it is expensive, time consuming, and labor intensive (X. Zhang et al. 2020). Therefore, automation methods are developed to extract needed information from crash data in a more efficient and accurate manner to analyze crashes. The information that can be obtained from crash report forms such as, crash locations, crash classifications, and other sources is essential to fill the gaps in road safety management.

A variety of research has been conducted to consider road safety, especially on analyzing police reports, crash reports, and narratives. Accordingly, researchers put their efforts into advancing the state-of-the-art methodologies, techniques, and models to facilitate textual crash database-processing in the following areas: (1) leveraging and/or integrating text mining techniques with other analysis methods [e.g. structural topic modeling (STM), and network topology analysis] to discover crashes (e.g. secondary crashes and highway-rail grade crossing crashes) and identify latent themes based on crash narratives (Arteaga, Paz, and Park 2020); (2) using machine learning-based algorithms/approaches (e.g. natural language processing) to predict drivers' hazardous actions (e.g. fail to yield, and disregard traffic control) from crash reports (Kwayu et al. 2020); (3) developing various systems/platforms to automatically simulate and reconstruct car crash scenarios to convert crash narratives into 3-Dimensional scenes (Dupuy et al. 2001); (4) proposing and adopting different analysis models (e.g. statistical model and logistic regression model) to explore relationships between crash database, roadway features, and environmental parameters (Boggs, Wali, and Khattak 2020); (5) analyzing different open source data [e.g. point-of-interest data, and traffic analysis districts (TADs) by considering spatial influence for distribution analysis of traffic crash at the macroscopic level (Cai, Abdel-Aty, and Lee 2017).

As examples of such crash analysis, Zhang et al. (2020) analyzed 2015–2017 Kentucky crash reports through data mining and identified 'distracted' and 'looking' as words frequently associated with secondary crashes attributed to distraction or rubbernecking. Boggs, Wali, and Khattak (2020) analyzed narratives from the California Department of Motor Vehicles' 124 manufacturer-reported Traffic Collision Reports through text mining and found a positive correlation between travel speed of the conventional vehicle and injury crash propensity. Kwayu et al. (2021) analyzed 10 years (2009–2018) of Michigan traffic fatal crash narratives using text mining and structural topic modeling. They found that rear-end fatal crashes were mostly associated with drivers being unable to stop, performing a lane-changing maneuver, or turning left. Unable to stop was found to be more prevalent among older drivers, partially due to longer reaction time. Other related factors reported include drivers' fatigue and driving-related visual scanning mismatches (National Academies of Sciences 2013). Also, compared to other types of crashes, higher proportions of angle crashes were found to include failure to yield and turning left, both of which happened more often in older-related crashes and during the daytime. Those results are consistent with prior studies showing that older drivers more commonly make errors at intersections, such as failing to comply with signals/signs and performing improper turns (Langford and Koppel 2006). Of note, young drivers with peer passengers were found to have elevated crash risk, whereas the opposite holds for older drivers (having passengers tends to have a protective effect; Kwayu et al. 2021).

Such analysis has shown that CAVs have many potential benefits over human drivers: (1) autonomous vehicles can reduce severe injuries through automated driving mode (S. Wang and Li 2019); (2) driving mode, location, and yield to pedestrians are the main factors in determining crash collision types that involve autonomous vehicles (S. Wang and Li 2019); (3) penetration level of CAVs affects their environmental and safety impacts (Kopelias et al. 2020). With regard to the last point, a cautious car-following strategy of CAVs could improve traffic safety: the higher the CAV penetration rate is, the more improved the smooth driving and traffic safety are, with fewer environmental impacts and traffic congestions (Kopelias et al. 2020). On the negative side, there are also safety and security challenges for CAVs, including: (1) a lack of international standards for CAV development, safety, or security; (2) human-driven vehicles may make CAVs more vulnerable in traffic (Bahamonde-Birke et al. 2018); (3) CAVs are less flexible than human-driven vehicles and more likely to get stuck, stalled, or trapped on a crossing (Soleimani et al. 2019). In general, people's consciousness regarding the climate of local traffic safety could affect their attitudes to autonomous vehicles (Qu et al. 2019), and people who drive are usually less concerned about the introduction of autonomous vehicles than those who do not drive (Qu et al. 2019). In addition to safety, several factors could affect people's attitudes towards AVs such as efficiency, performance, trust, and comfort (Das et al. 2019).

In a broad sense, all the above-mentioned research areas open new doors to deal with textual crash data by considering information extraction, analysis, application, and prediction to support road safety management in a timely and accurate manner. Furthermore, CAVs have been widely used recently to help make decisions in emergency scenarios to mitigate crashes by using new techniques, methodologies, and tools (e.g. injury prediction models) (Liao et al. 2018). To be specific, crash scene analysis and reconstruction involving connected and autonomous vehicles have become a research topic of great interest in the infrastructure domain, which has attracted a lot of researchers to put their efforts into it to help improve road safety and prepare for the future. Some researchers have leveraged advanced models (e.g. machine learning models, and statistical models) to explore and understand the mechanism of crashes with autonomous vehicles in autonomous driving mode to analyze the crash severity (Ashraf et al. 2021); others have developed technical methods (e.g. model predictive control algorithm, and collision avoidance system) to plan the motion ahead for autonomous vehicles to mitigate crashes for facilitating motion planning (Lee and Kum 2019); Still, others use sensed data to analyze the determinant factors (e.g. human factors, and weather) that affect crash severity in autonomous vehicles to predict the causes and consequences of an accident (Kim and Yang 2017). There are many different techniques, methods, tools, and models available to help conduct crash analyses from computational and experimental perspectives. Also, the integration of analyzing textual (e.g. crash report) and sensing data (e.g. traffic surveillance video) is a new trend to better summarise, monitor, and predict traffic scenarios in the infrastructure domain (Ren and Zhang 2021).

## Perceiving intentions and predicting actions

Being able to predict what others will do is critical to safe driving. In the mixed traffic environment, human drivers will need to be able to perceive and predict what CAVs are likely to do, and CAVs must likewise be able to perceive and predict the HDVs' actions.

### *Humans perceiving and predicting actions of CAVs*

The implementation of CAVs can potentially have positive impacts on traffic mobility and safety (Olia et al. 2016). Automation across different levels (from none to fully automatic) complements human behaviour, but it also can change behaviour and impose new cognitive loads and psychological stress on humans (Parasuraman, Sheridan, and Wickens 2000). In mixed traffic, human drivers need to operate based on the expectations and driving styles of both other drivers and CAVs, which may impose heavy cognitive loads (Fisher et al. 2011).

Countermeasures are needed to reduce the risk of accidents involving CAVs and HDVs as autonomous vehicles become increasingly common on the roadways. In terms of driving styles, CAVs are programmed to follow rules and optimise fuel efficiency, safety, and traffic flow (Amini et al. 2020). Human drivers do not strictly follow all rules and need to drive only well enough to avoid incidents (van Loon and Martens 2015). For example, human drivers have a longer reaction time and limited perception abilities compared with CAVs (Ge and Orosz 2017), which may result in more accidents. CAVs may act in ways that are counter to drivers' expectancies (e.g. waiting longer at an intersection than a human driver would). Countermeasures must consider differences in the driving styles of CAVs and HDVs, and be able to signal their intents to other CAVs and HDVs. As described earlier, drivers can communicate with each other in ways that they cannot with CAVs (e.g. by gestures and eye contact (Schoettle and Sivak 2015).

A sign with information (e.g. to yield or to merge) can be established to convey the information to the human drivers or the CAV systems. Visual information such as texts and warning lights has been used to enable communication between human drivers and CAV systems (Eisma et al. 2019). The text information, such as the Traveler Information (TIM) message defined by SAE J2735, is applied to enable communication between vehicles and infrastructure. Human drivers can also benefit from the TIM message since the information includes traffic accidents, work zones, weather and road surface information (Aoki, Lin, and Rajkumar 2021). In addition, new vehicle lighting signals are being developed to indicate the intention of CAVs. One study used combinations of different light colours and display methods to convey five different types of information by CAVs, including slowing down, waiting, planning to go, starting to go and going (J. Zhang, Vinkhuyzen, and Cefkin 2018). The results of the study suggested that delivering three to four types of information, with various motions presented in one neutral colour, may be a more effective way for CAVs to communicate their intentions to human road users.

External human-machine interfaces are designed to communicate waiting and driving information from CAVs to human drivers (Eisma et al. 2019). Auditory signals are less used than visual signals in the communication between CAVs and human drivers since the communication is exposed in traffic flow and could be inaudible (Carmona et al. 2021). The verbal warning signaling 'safe to cross' sent from CAVs is rated the highest among various visual and auditory signals by pedestrians (Deb, Strawderman, and Carruth 2018). Lee et al. (2019) compared visual signals, auditory signals, and the modality combination of visual and auditory signals to convey information from CAVs to road users. The results show that the modality combination of visual and auditory signals was most preferred by the road users.

The number of studies on vibrotactile signals for communication between CAVs and road users is limited (Colley et al. 2019). The vibrotactile signals with different vibration patterns are developed to indicate the approaching phase, stopping and yielding phase, and re-starting phase of CAVs (Dalipi et al. 2020). In addition, many studies have shown that sending vibrotactile signals from CAVs to CAV drivers is an efficient way to improve CAVs drivers' perception of risk situations (Telpaz et al. 2015). These studies show the potential to enable the HDVs to send vibrotactile signals to human drivers, which could improve human drivers' perception of hazards from CAVs.

### *CAVs perceiving and predicting actions of humans*

Perhaps the greatest challenge to having CAVs share the roadways with HDVs is the capability of the CAVs to perceive and predict what the HDV drivers intend to do. CAVs utilise their onboard sensors to perceive the environment and predict the behaviours of other vehicles. Vision-based perception (e.g. camera) uses one or more cameras to take consecutive images in the driving environment (Ma et al. 2003). Millimeter-wave radar, which is good at detecting moving objects (e.g. distance and speed), has been widely used in adaptive cruise control applications (Mao et al. 2012).

Lidar sensors have increased in popularity in recent years due to their capabilities in obstacle detection (Levinson et al. 2011), which plays a key role in ensuring the safety of CAVs.

A CAV is usually equipped with multiple sensors, and multi-sensor fusion (MSF) algorithms are applied to improve the reliability and robustness (Wan et al. 2018). Typically, the perception and prediction process consists of three steps: vehicle detection, vehicle tracking, and driver behaviour prediction (Sivaraman and Trivedi 2013). In the first step, vehicles need to be identified and distinguished from other objects. The second step involves tracking the same vehicle through consequential sensor data (e.g. multiple frames in a video). Finally, aggregated spatiotemporal features of a tracked vehicle (e.g. trajectory) are used to characterise driving behaviours such as specific vehicle maneuvers, the aggressiveness of the driver, and short-term motion prediction.

Both cameras and Lidar are commonly used for vehicle (obstacle) detection and tracking purposes. While images from cameras provide a better appearance and semantic data (H. Wang and Zhang 2022) such as colour and plate number, Lidars have advantages in 3D modeling and are not impacted by the illumination of the environment (Han et al. 2012). Vision-based vehicle detection can utilise monocular or stereo cameras, and the approaches can be roughly divided into appearance-based and motion-based methods. Appearance-based methods (Cabani, Toulminet, and Bensrhair 2008) detect vehicles directly from individual images, whereas motion-based methods require multiple consequential frames to recognise vehicles (Jazayeri et al. 2011). Both types of cameras can be used in vehicle tracking, and Kalman filtering (Barth and Franke 2010) and particle filtering (Danescu, Oniga, and Nedevschi 2011) are the two most popular tracking methodologies. As for Lidar, grid maps are most widely used to process the point cloud Lidar data. Different types of classifiers are applied to detect vehicles from the Lidar data such as Gaussian mixture model classifier (Premebida et al. 2007), Adaboost classifier (Hsu, Ciou, and Perng 2017), and support vector machine (SVM) classifier (Cheng et al. 2014). Like camera-based vehicle tracking, Kalman or particle filter based methods are also popular in Lidar-based vehicle tracking (Miller, Campbell, and Huttenlocher 2011).

Prediction of other vehicles' behaviour or intention is essential in the CAV trajectory planning process. With detection and tracking results, trajectories of surrounding vehicles can be extracted. The trajectory data provide rich information in characterizing driving behaviours such as car following and lane changing. Over the years, researchers have been developing and calibrating different types of models to capture the human driving behaviours and predict short-term trajectories. Typical car-following models include single-regime model (Ceder and May 1976), multi-regime model (Gipps 1981), and psychophysical model (Higgs, Abbas, and Medina 2011). Among all the car-following models, the intelligent driving model (IDM) (Treiber, Hennecke, and Helbing 2000) is mostly widely used to model HDVs and their impact on CAVs in mixed traffic conditions (S. E. Li et al. 2015; Talebpour and Mahmassani 2016). As for the lane changing behaviours, many earlier works (Kesting, Treiber, and Helbing 2007) tried to predict the lane changing decision point (whether/when/where to change lanes) of HDVs without considering the detailed lane changing process, which is insufficient for CAVs trajectory planning.

Recently, with the advances in artificial intelligence, various machine learning models have been applied to predict the driving behaviours of HDVs. One popular method is the long short-term memory (LSTM) neural network (Altché and de La Fortelle 2018). Besides LSTM, imitation learning, which aims to mimic human behaviours in given tasks, is adopted to learn human driving behaviours (Ying and Feng 2022). Compared with other (deep) learning methods, imitation learning requires much fewer data points and less time for training.

If onboard sensors are expressed metaphorically as human eyes, then V2X communications are 'ears' of CAVs that receive external information. V2V communications convey other vehicles' real-time information such as position, speed, acceleration, brake system status, and vehicle size. V2I communications transmit information from the infrastructure side including traffic signal status, road map, and traveler information (SAE International 2009). V2X communications complement the onboard sensors' perception capabilities. Typical V2X communication range is longer (e.g. a few hundred meters; Kenney 2011) than the detection range of onboard sensors. Also, onboard sensors can only detect and track objects within the line-of-sight, but V2X communication can 'hear' from vehicles that are occluded by obstacles.

This section provides a high-level overview of how CAVs detect, track and predict human's actions through onboard sensors and/or V2X communications. For more details of each relevant topic, readers can refer to other review papers such as (Sivaraman and Trivedi 2013) for camera based perception, (Zamanakos et al. 2021) for Lidar based perception, (Mahmassani 2016) for traffic flow modeling, (Di and Shi 2021) for driving behaviour (policy) modeling, and (Farsimadan et al. 2021) for V2X communications.

## Infrastructure adaptation

Existing transportation infrastructure is designed for human drivers. The deployment of CAVs will gradually lead to significant changes in the infrastructure. It is essential to investigate how infrastructure should be adapted to the new CAV environment to have the intended benefits.

It is reasonable to expect that roadway design will be changed when CAVs become prevailing. If all vehicles on the road can be controlled precisely based on planned trajectories and cooperate with each other, tremendous infrastructure improvements and adaptations are possible and necessary. For example, due to closer spacing and shorter headway of platooning through cooperative adaptive cruise control (CACC), dedicated CAV lanes can greatly improve the road capacity on the highway. Ye and Yamamoto (2019) studied the impact of CAV dedicated lanes on the traffic flow throughput. Furthermore, Ghiasi et al. (2017) built an analytical lane management model using Markov chain to determine the optimal CAV lane number under different demand levels, market penetration rates, platooning intensities, and technology scenarios (i.e. time headway).

At signalised intersections, the concept of the signal-free intersection, which removes the signal head and lets CAVs coordinate their ways through the intersection, has gained attention in recent years. The majority of the signal-free intersection management strategies were proposed using reservation-based conflict avoidance algorithms (Dresner and Stone 2008) such as first-in-first-out (FIFO). However, FIFO-based reservation rules only work well under low traffic demand levels. Recent studies (Yu et al. 2019) proposed optimization-based methods to determine the serving sequence of arriving vehicles for delay minimization. However, signal-free intersections require 100% of CAV penetration and may not be implemented in the near future. To accommodate mixed traffic flow, researchers proposed new traffic signal phases called white phase (Niroumand et al. 2020) and blue phase (Rey and Levin 2019), during which CAVs lead groups of HDVs passing an intersection. It is equivalent to using CAVs as moving controllers to regulate the HDV flows to avoid conflict within the intersection area.

Besides physical adaptation, future infrastructure will also need to be equipped with advanced sensors, communication systems, and edge computing devices to enable cooperative driving automation (CDA) with CAVs, as described in the third section. Due to the extremely varied and complex driving environments of roadways across the country and the world, it is not realistic for CAVs to handle all possible driving scenarios by themselves. Under CDA, the infrastructure coordinates with vehicles to jointly perceive the environment and make decisions. Towards this goal, four classes of communication and coordination are defined by the Society of Automotive Engineers (2021) regarding CDA: status sharing, intent sharing, agreement seeking, and prescriptive.

With status sharing and intent sharing, CAVs receive real-time data such as a list of nearby vehicles and their status (e.g. relative location, turning indicators), traffic signals status and remaining time, and road geometry information. Utilizing this information, CAVs are able to better plan their trajectories to improve the situation awareness of the road (S.-W. Kim, Liu, et al. 2015). A typical application is eco-driving, in which CAVs receive traffic signals and traffic condition (e.g. queuing dynamics) information to plan trajectories that minimise fuel consumption and emissions (Barth et al. 2011). Similarly, when infrastructure receives shared status and intentions from CAVs, this information can be utilised to optimise traffic signals (Feng et al. 2015) and provide priority to emergency vehicles (Hu, Park, and Lee 2015).

With higher classes of CDA such as agreement seeking and prescriptive, CAVs and infrastructure make joint decisions in traffic control and trajectory planning, further improving efficiency of the traffic operations. Li, Elefteriadou, and Ranka (2014) were among the first researchers to propose the joint control concept at intersections, in which traffic-signal parameters and CAV accelerations are optimised simultaneously. Feng, Yu, and Liu (2018) improved the joint control framework by modeling the problem as a two-stage optimization, with signal control as the first stage and vehicle trajectory control as the second. Later, Yu et al. (2018) integrated the two-stage optimization process and built a mixed-integer linear programming (MILP) model to optimise phase sequences, green start and duration of each phase, and cycle lengths together with vehicle lane-changing behaviours and vehicle arrival times for delay minimization. This joint control framework has been extended to the corridor level with multiple intersections (Yang, Feng, and Liu 2021).

Cooperative merging at on-ramps is an example of higher classes CDA in freeway driving scenarios. On and off ramps are usually considered as bottlenecks of the freeway because of the frequent lane changing and merging behaviours. With the coordination and 'agreement seeking' between CAVs and infrastructure, an optimal merging sequence can be determined. Then CAVs can plan their trajectories accordingly to smooth the merging process, for example, creating a sufficient gap for the merging vehicles. Studies show that cooperative merging can significantly reduce the delay at merging areas, improve safety and fuel efficiency (Chou, Shladover, and Bansal 2016).

## Human-centred infrastructure design with CAVs

The prior literature review identifies many issues that need to be addressed if CAVs are to be implemented successfully in mixed traffic with HDVs. Most fundamentally, our analysis indicates the need to approach the entire roadway transportation system as composed of human, CAV, and infrastructure subsystems. The goal is to effectively manage the activities of all the vehicles. Human drivers are the most critical factor in the implementation of mixed-traffic roadways because they must coordinate their decisions and actions with those of the CAVs, and vice versa. So, a human-centred approach to infrastructure design is dictated. Hence, we propose the following procedure to study and design future infrastructure for the mixed-traffic roadways, as shown in Figure 2.

First, building and calibrating a realistic mixed traffic driving environment is critical in modeling the interactions between HDVs and CAVs, which has attracted a lot of research attention in the past few years. Increasingly, vehicle trajectory data from HDVs (collected from vehicle onboard sensors such as KAIST, from infrastructure-based sensors such as NGSIM, or from drones such as High-D) and CAV datasets (e.g. Waymo open dataset; Lyft Level 5) are becoming publicly available, which provide fine details for reasoning the human and CAV information process and constructing the mixed traffic environment.

Analyzing HDV/CAV crash typologies and their root causes is critical to understanding deficiencies in human/CAV information-processing and communication with existing transportation infrastructure. The analysis of crash reports and crash reconstructions can provide valuable insight for understanding both human and CAV information-processing. Considerable relevant knowledge exists about the general properties of human information-processing, from sensation to action. Among these are that perception of visual detail is limited to the fovea, or where the person is looking, that attention and working memory are of limited capacity, which can affect situation awareness and cause use of decision-making shortcuts. Even in specific situations, activation of information from long-term memory plays an essential role in understanding what is occurring. Besides this basic knowledge of human information-processing, much is known more specifically about how humans perform in driving contexts.

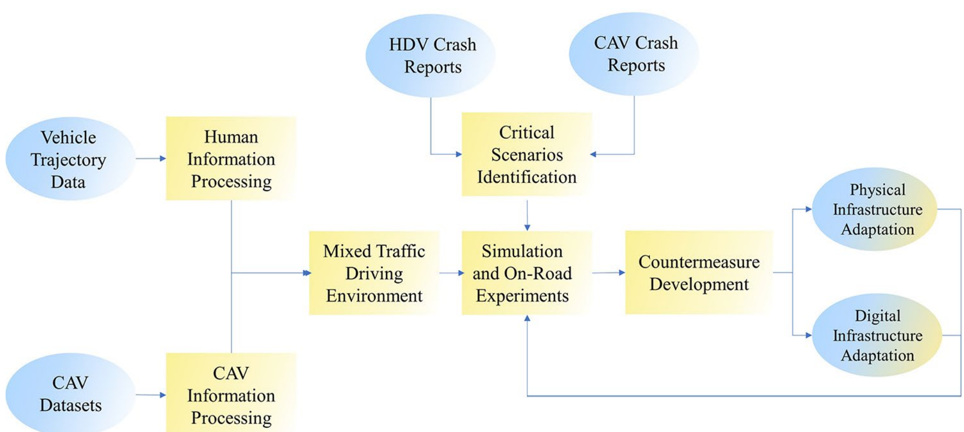


**Figure 2.** Proposed human-centred infrastructure design.

From the CAV's perspective, crash reports provide useful information in identifying errors in the CAV information-processing pipeline from perception to decision-making. The onboard sensors may fail to detect oncoming objects due to malfunction, occlusion, adverse weather conditions, or even cyber-attacks. The motion planning module may make an unsafe decision due to inaccurate input from the sensors or wrong prediction of the intentions of HDVs.

Through analysis of the accident reports, the key research question is how to identify what driving conditions are most likely to lead to traffic accidents, indicating critical driving scenarios that are likely to be problematic for CAVs and their interactions with HDVs, and what critical driving scenarios need infrastructure support to assist communication between HDVs and CAVs.

Importing critical driving scenarios into the mixed driving environment, experiments can be conducted in simulated environments or real-world environments (i.e. test facilities). For simulated environments, the widespread availability of driving simulators and equipment (e.g. eye tracker) that can be used for on-road research has enabled ecologically valid research of driving in naturalistic conditions. The control offered in driving simulator studies is particularly valuable for understanding causal relationships. Conclusions need to be verified in studies of actual driving, but generalizability tends to be good (Hussain et al. 2019). However, most simulation studies assume simplified CAV behaviours (e.g. pre-defined trajectories or driving scenarios) without modeling realistic CAV information-processing, which includes onboard sensor perception, wireless communication with other road users, and real-time decision-making. As a result, it is necessary to include the information-processing pipeline of CAVs to better model the interactions between CAVs and human drivers besides in simulators.

To this end, closed testing facilities have been built, in which real CAVs can be tested. One major benefit of closed testing facilities is that experiments can be designed and conducted in a safe and controlled environment. To address the challenge that closed test facilities do not have background traffic, emerging technologies such as augmented reality and virtual reality can be adopted to create better interactions between human subjects and CAVs. For example, one study utilised head-mounted display (HMD) to simulate a variety of virtual vehicles, driving conditions, and circumstances to conduct on-road simulation (Zou et al. 2021). Another study generated virtual background vehicles that interact with testing CAVs through microscopic simulation and wireless communication (Feng, Yu, Xu, et al. 2018).

Based on the testing results, the next step involves developing and testing countermeasures that deliver critical information through infrastructure to reduce the risk of crashes in critical driving scenarios. The following research questions should be considered in the development of countermeasures for human drivers: (1) What information needs to be communicated between human drivers and CAVs to prevent crashes and conflicts? (2) What type(s) of information including visual, auditory, and haptic signals are most effective to deliver the information content? (3) Where should the information be displayed, in vehicle, or at the infrastructure side? (4) What are the information characteristics such as colour, size, of visual signals, frequency and amplitude of auditory signals, and frequency of haptic signals? The countermeasures can be applied to either physical infrastructure and digital infrastructure. The physical infrastructure adaption includes new signage, dynamic message display, and on-pavement information, which can be easily recognised by human drivers.

As for CAVs, the additional information needs to go through the sensing and perception module, which brings uncertainties and may be vulnerable to cyberattacks. Prior study shows that perception algorithms on CAVs can be fooled to misinterpret the meanings of signs, with slight alteration (Eykholt et al. 2018). If the information is provided by digital infrastructure (i.e. through wireless communication), then the existing infrastructure must be updated with communication devices. The advantages of the digital infrastructure include: 1) the messages can be directly decoded by the CAV to obtain accurate information; 2) one message can contain multiple pieces of information ranging from safety warnings to route guidance. A disadvantage of digital infrastructure is that human drivers cannot directly interpret digital information, and some translation is required to interpret and display the information. Similar as before, how to decide the information type, format, location and features remains an open research question. All these aspects need to be considered carefully when designing future infrastructure.

Finally, the developed countermeasures should be implemented in the driving environment (simulated or real) and tested against the critical scenarios for performance evaluation. This evaluation should include multiple aspects such as safety (e.g. reduced number of crashes), mobility (e.g. reduced traffic delays), and cost-benefit analysis, in which the safety and mobility benefits can be converted into monetary values and compared with the investments in infrastructure adaptation. This process should consist of a closed loop and repeat iteratively.

## Conclusions

In the near future, the implementation of CAVs will have to be on existing roadways shared with HDVs. The degree of success in this implementation will determine in large part how readily the public accepts CAVs. Safe and effective navigation of both vehicle types requires not only that the CAVs communicate with each other but that they also communicate with the HDVs. The best perspective to address this issue is that of system of systems, which takes into account the human drivers, CAVs, and roadway infrastructure within the context of the overall roadway transportation system. Design decisions about the communication and control processes for CAV and HDV traffic within that system must be considered within that context.

Much is known about human information-processing and communication in general, CAV and infrastructure information-processing and communication, and about human information-processing and actions in driving. Along with analysis of crash reports that describe 'what went wrong', this knowledge provides a basis for designing the transportation system so that humans can perceive and predict CAVs' intentions and actions, and CAVs can perceive and predict human driver's intentions and actions. Adaptation of current traffic infrastructure to satisfy the needs of both the CAVs and human drivers will play an essential role in this process.

## Note

1. https://www.dmv.ca.gov/portal/vehicle-industry-services/autonomous-vehicles/autonomous-vehicle-collision-reports/

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