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Abstract

Autonomous vehicles (AVs) are expected to play an increasingly important role in future transportation systems as a promising means of improving road safety and efficiency by eventually replacing human-driven vehicles. Semi-autonomous vehicles (semi-AVs; SAE Level 2 and Level 3) feature automatic lateral and longitudinal control of the vehicle with human drivers required to supervise the system at all times (Level 2) or prepared to resume control when requested (Level 3). As these definitions reveal, semi-AVs still require human oversight and intervention to fully ensure safety. Humans are required to monitor and be ready to take over control when the vehicle fails to recognize or respond to hazardous events. Thus, it is essential to ensure effective human-automation interaction and collaboration for semi-AVs. This book chapter will discuss the critical challenges for effective human-automation interaction for semi-autonomous driving, including communicating potential risks to human drivers and maintaining proper driver trust in the semi-AV. Risks in the current context are moving or stationary objects and road environments that impose imminent threats to drivers, including overt hazards such as road obstacles, a pedestrian crossing the road, and an intruding vehicle, or covert hazards such as a pedestrian that is about to cross but is occluded by a parked truck or a roadway structure. We discuss the design of effective risk communication mechanisms to convey these risks to the human driver, which helps maintain the driver's situation awareness and facilitate the driver's actions when needed. In addition, the effectiveness of this risk communication can be influenced not only by the characteristics of the driver and the semi-AV, but also their interaction. Finally, we will discuss factors that affect drivers' trust in semi-AVs and subsequently how it affects effective risk communication in semi-AV driving.

Human-Automation Interaction for Semi-Autonomous Driving: Risk Communication and Trust

Jing Chen, Scott Mishler, Shelby Long, Sarah Yahoodik, Katherine Garcia, and Yusuke Yamani

AQ1 **Abstract** Autonomous vehicles (AVs) are expected to play an increasingly important role in future transportation systems as a promising means of improving road safety and efficiency by eventually replacing human-driven vehicles. Semi-autonomous vehicles (semi-AVs; SAE Level 2 and Level 3) feature automatic lateral and longitudinal control of the vehicle with human drivers required to supervise the system at all times (Level 2) or prepared to resume control when requested (Level 3). As these definitions reveal, semi-AVs still require human oversight and intervention to fully ensure safety. Humans are required to monitor and be ready to take over control when the vehicle fails to recognize or respond to hazardous events. Thus, it is essential to ensure effective human-automation interaction and collaboration for semi-AVs. This book chapter will discuss the critical challenges for effective human-automation interaction for semi-autonomous driving, including communicating potential risks to human drivers and maintaining proper driver trust in the semi-AV. Risks in the current context are moving or stationary objects and road environments that impose imminent threats to drivers, including overt hazards such as road obstacles, a pedestrian crossing the road, and an intruding vehicle, or covert hazards such as a pedestrian that is about to cross but is occluded by a parked truck or a roadway structure. We discuss the design of effective risk communication mechanisms to convey these risks to the human driver, which helps maintain the driver's situation awareness and facilitate the driver's actions when needed. In addition, the effectiveness of this risk communication can be influenced not only by the characteristics of the driver and the semi-AV, but also their interaction. Finally, we will discuss factors that affect drivers' trust in semi-AVs and subsequently how it affects effective risk communication in semi-AV driving. AQ2

Autonomous vehicles (AVs) are expected to be the future of surface transportation on the roadways. A multitude of assistive driving technologies have already been integrated into many new vehicles such as lane keeping systems, forward collision

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warning systems, and adaptive cruise control, just to name a few. AVs seek to integrate these assistive driving technologies into a cohesive package, which gradually relegates the human driver away from a primary operative position and into a role of a supervisor or fallback system. The eventual goal of AVs is to eliminate the need for the human driver altogether. However, full driving automation, as with most promises of complete automation for complex tasks, is a long way off. The state-of-art research and design of semi-AVs requires the human driver to remain an important aspect of the driving system.

1 Levels of Automation for AVs

AQ3

There are six different classifications of driving systems (i.e., levels of automation; LOA) ranging from Level 0—no driving automation, to Level 5—full driving automation [1]. On Level 0, the driver performs all aspects of the driving task, which is common in conventional vehicles. Many of the singular driver assistance systems such as lane-keeping or adaptive cruise control fall into the Level 1 designation where the vehicle only execute one of the subtasks of lateral or longitudinal vehicle motion control. The more advanced partial driving automation systems, such as Tesla's Autopilot, Cadillac's Super Cruise, and Volvo's Pilot assist, are categorized as Level 2. On this LOA, the vehicle has complete control of the lateral and longitudinal vehicle motion control, but the driver is still responsible for detection of objects and events and therefore avoiding any hazards as well as supervising the driving system. The definitions get a bit more complex and difficult to distinguish at Level 3, conditional driving automation. By definition, the vehicle should now be fully capable of object and event detection and response in its operational design domain, and the human driver is the fallback for the dynamic driving task. However, the human driver is required to intervene when prompted by the vehicle, which requires the driver's situation awareness of the driving environment [2]. Some of these previously mentioned systems like Tesla's Autopilot are already capable of at least minor forms of detecting objects and events and performing responsive actions to these hazards. The system might not be fully capable of managing the entire task, but it is performing some of the task and assisting the human driver at higher levels than would be strictly defined under Level 2. Additionally, much confusion from the human driver can arise where they may think the vehicle has capabilities higher than its specified automation level, or they might not fully understand the vehicle's actions. On Levels 4 and 5, the vehicle is expected to carry the entire driving task without the human driver's intervene in its operational design domain (L4) or unconditionally (L5). This chapters focuses the state-of-the-art LOAs of Levels 2 and 3 (i.e., semi-AVs), for which effective human-automation interaction and collaboration are vital.

To understand how people may engage with various levels of AVs and their conceptualization of definitions associated with AVs, it is helpful to survey the general public about their understandings. For example, Kyriakidis and colleagues

[3] examined driver opinions on automated driving and specifically what secondary, non-driving related tasks (e.g., reading or watching a movie) drivers reported they would do at various LOAs. A common trend emerged in their results showed that drivers were more willing to engage in secondary tasks as the LOA rose from manual to partially, highly, and fully automated driving systems. Note that a good portion of the respondents indicated that they would engage in secondary tasks that would prevent them from safely performing their share of the driving task at the lower LOAs. Although the respondents did not actually interact with any systems or exhibit actual driving behaviors, this result demonstrates a mismatch between the public's understanding of the AV's capabilities and their actual capabilities. Consequently, this mismatch may lead to the human driver's low awareness of the risks in the driving environment. Therefore, it is critical to communicate the capabilities of AVs and potential risks in the driving environment to provide the maximum benefits and safety.

2 Risk Communication in Semi-AVs

Risk communication is generally defined as "the exchange of information among interested parties about the nature, magnitude, significance, or control of a risk" ([4], p. 359). There are three main elements of risk communication: the message containing information from an organization or sender, the medium the message is relayed through, and the audience that the message is targeted to [5, 6]. Risk communication is associated with threat sensing and assessment [7]. The risk communication messages can be organized into four categories based on their primary objective: information and education, behavior change and protective action, disaster warnings and emergency information, and joint problem solving and conflict resolution [8]. These messages are then dispatched to the public through methods such as mass communications, community engagements, media, and even social media platforms such as Twitter [9]. Risk communication is based on the assumption that the public needs to know about possible hazards and risks and should be able to make informed decisions accordingly [7]. It is imperative for the sender to draft the risk message with the focus on the receiver, who will be receiving, interpreting, and acting on the message.

In the context of semi-AVs, risks include both overt and covert hazards in the driving environment [10, 11]. Overt hazards include moving or stationary objects on the road that pose an issue for the driver. For example, an object or a pedestrian on the road, in the driver's field of view would be overt hazards. Covert hazards include road hazards that are not immediately visible, such as a pedestrian who about to cross the road but is currently occluded by a parked car. With driver assistance systems, partial driving automation, and conditional automated driving, the human driver needs to be aware of the risks in the driving environment. The higher the LOA, the more likely the driver is to decrease their situation awareness and vigilance over time because the automation is doing more of the driving task [12–14]. In driving scenarios involving either overt or covert hazard, it is critical that the vehicle communicates existing and potential risks to the driver so that the drivers may anticipate such hazard and respond appropriately. Various risk communication mechanisms can be used to convey these risks to drivers in semi-AVs.

3 Effective Warning Design as a Risk Communication Mechanism

Designing effective warnings can help the human driver understand risks in the driving environment. The direction, content, and timing of warnings can affect the effectiveness of semi-AV warnings. Moreover, an important aspect of warnings in semi-AVs is to ensure that it is properly tailored to the LOA. In this section, we discuss research on lateral directional warnings, semantic versus non-semantic warnings, and warnings of different time to collision (TTC). These different design characteristics of warnings in semi-AVs should be considered at different LOAs given the unique human-vehicle interaction status expected at each LOA.

Lateral warnings are warnings that utilize the direction of warnings to indicate hazards that there are at the sides of the vehicle to the human drivers. These hazards can be either overt or covert, which the driver needs to be aware of and be ready take action to avoid them. An effective lateral warning needs to quickly direct the driver's attention to the potential hazard so that the driver can decide what action needs to be taken [15–17]. Because the human driver might be more disengaged and slower to react at the higher level compared to at the lower levels, warnings need to be designed differently. At lower LOAs (Levels 1 and 2), this warning would help orient the driver in the driving task and bring the hazard to their attention that they might not have noticed (e.g., a pedestrian crossing the road). Because the human driver is mostly in control of the dynamic driving task at the lower levels, the lateral warning acts as a lookout and advisor where the human can easily react because they already mostly have control. However, when it comes to the higher Level 3, a lateral warning would act as more of an alert to the human that they should pay attention to something highly critical and make a takeover decision when necessary.

Besides the direction of warnings, the warning content can also affect their effectiveness in communicating risks to drivers. Non-semantic warnings (e.g., simple auditory tones) may be adequate to orient a driver toward an object at lower LOAs, but might not provide adequate information at higher levels with reduced driver situation awareness and vigilance. They could even result in a startle effect, confusing or surprising the driver [18–20]. Even simple auditory tones may be presented differently to drivers depending on how far away the hazard is or direction the hazard is moving [17]. Instead of simple auditory tones, warnings can be semantic, in spoken words such as, "car in blind spot" to give more contextual information to the driver [21]. However, implementation of these semantic messages is dependent on the time

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to potential collision, how long the warning message takes, and even the background noise in the environment.

Furthermore, semantic warnings are expected to be especially effective for warning latent hazards. The ability to anticipate latent hazards, hazards that have not materialized yet but may materialize in any moment in the future, is a crucial skill for safe driving [22]. Although current semi-AVs at Levels 2 and 3 using local LIDAR and radar sensors and cameras are not fully capable of detecting hazards that are out of the vehicles' direct line of sight, connected vehicle (CV) technology could provide a partial solution to mitigate the risks of latent hazards and fill the gap. CVs use short-range radio signals to transmit information from vehicle-to-vehicle or from vehicle-to-infrastructure [23], which can help provide a more complete picture of the dynamic road environment and subsequently warnings to drivers about latent or developing hazards. For example, a driver would receive a warning that there was stopped traffic ahead, a latent hazard that may be visually obscured by road geometry characteristics such as a hill or curve. Semantic warnings would be more suitable than non-semantic warnings to communicate this kind of information. With effective semantic warnings, drivers will be able to allocate their attention effectively to the objects that are "cued" to them and likely better anticipate them. In a simulated driving study, for example, participants were shown a visual head-up display warning that alerted participants to a possible, upcoming pedestrian and vehicle latent hazards [24]. The warnings were effective at increasing the number of drivers who fixated on the hazard. In another driving simulator study examining different hidden hazard warning schemes, participants were better able to avoid crashes when the warnings contained specific information regarding the placement of the hazard (distance or direction) than when they received general warnings [25]. In fact, human drivers' latent hazard anticipation was found to be worse when driving a simulated Level 3 vehicle than when driving a simulated Level 0 vehicle [26]. Thus, drivers of higher LOAs are more likely to possess an incomplete picture of the immediate, dynamically changing road environment, thereby limiting their latent hazard anticipation abilities. As a result, semantic warnings can be more helpful indicating latent hazards to drivers at higher LOAs.

The timing of the warning is crucial for the warning to be effective so that the human driver has sufficient time to perceive a hazard and take action [6, 24]. Intuitively, it is beneficial to warn the human driver of a potential hazard as early as possible. However, the semi-AV may not always be able to do so due to limitations of sensors, and early warnings might be compromised in terms of its accuracy. The timing of a warning is typically defined in terms of time to collision (TTC), which is the time from the onset of the warning to the time of potential collision [15]. Lodinger and Delucia [27] examined whether automation affected drivers' braking response to a hazard as well as their visual perception measured by TTC judgment. They found that, compared to manual driving, automaton freed up participant's resources and facilitated their process of visual information to use for more accurate TTC judgment. Research on manual driving showed that TTC modulated the effect of the direction of lateral warnings on their effectiveness. For example, Straughn et al. [15] found that with a shorter TTC of 2 s, warnings signaling the avoidance direction are

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more effective than warnings signaling the collision direction, but this effect reversed with a longer TTC of 4 s. However, there has been mixed results found for automated driving. Cohen-Lazry et al. [28] found the avoidance-direction warnings are more effective than the collision-direction warnings with a 4-s TTC, whereas Petermeijer et al. [29] found no difference between these two types of warnings with a longer TTC of 7 s. Chen et al. [17] found that for a pedestrian starting from one side of the road and walking towards the center, collision-direction warnings are more effective than the avoidance-direction warnings, and the advantage of the former increases with greater TTCs. It is clear, though, faster responses were yielded when the TTC was shorter, possibly due to shorter TTCs reflecting higher urgency of the situation to respond to the hazard.

4 Human Trust in Semi-AVs

Proper human trust in semi-AV is one of the most important aspects of ensuring proper cooperation and efficiency between the semi-AV and the human driver. Trust is a multifaceted and complex concept that many may be nominally familiar with but applying trust to automation adds more complexity. Lee and See [30] have defined human trust in automation as “the attitude that an agent will help achieve an individual’s goals in a situation characterized by uncertainty and vulnerability” (p. 51). Researchers built upon theories of interpersonal trust to establish theories of human-automation trust [31–33]. Specifically, Muir and colleagues [32, 33] adopted a triadic model of trust from theories of interpersonal trust (e.g., [34, 35]) to describe trust development. She asserted that automation trust develops from predictability, dependability, and faith progressively. *Predictability* is defined as the perceived consistency and desirability of behaviors of the machine, *dependability* is defined as the extent to which the stability of machine behaviors is based on accumulation of behavioral evidence, and *faith* is defined as the expectation that the machine performs beyond the current situation that operators gathered behavioral evidence that can generalize to future situations. Lee and colleagues [30, 31] further developed this triadic model, asserting that performance, process, and purpose are the three dimensions responsible for automation trust development. *Performance* is defined as what the automation does according to past and present operation, *process* is defined as how the automation operates in terms of its programmed algorithm, and *purpose* is defined as why the automation was developed, representing the automation designer’s goal.

As trust is considered a critical factor for successful human-automation interaction, researchers have begun to explore trust in the context of semi-AVs. For example, Choi and Ji [36] examined the role of trust in initial adoption of AVs through a survey. They identified that trust is one of the major determinants for automation use. System transparency, technical competence, and situational management positively impacted trust, whereas perceived risk negatively impacted trust [36]. In another survey-based study, Zhang and colleagues [37] explored constructs of the Technology Acceptance

Model, including trust, of a Level 3 AV. Regarding trust, the authors found that initial trust was the most critical factor for positive system attitudes. Additionally, they assert that trust can be improved by reducing perceived safety risk and improving perceived usefulness. More recently, Lee and Kolodge [38] conducted a study exploring qualitative ratings for level of trust in semi-AVs using structural topic modelling. They found topics that align with the three proposed dimensions of trust (e.g., "safer than a human" relating to the performance dimension of trust, "technology improving" relating to the process dimension of trust, "hacking and glitching" relating to the purpose dimension of trust).

In terms of trust development, we consider the following three main categories or phases: dispositional, situational, and learned trust [39]. Dispositional trust is an individual's likelihood or propensity to trust anything based on their age, culture, or personality. It can change over time but is slow to adapt and is usually relatively static throughout one's life. Situational trust considers the factors that may influence a persons' trust in a system both internally (e.g., self-confidence, expertise, mood, attention) or externally (e.g., system type, complexity, task difficulty). Learned trust is split into initial and dynamically learned trust, referring to the timing of your interaction with the system. In the context of semi-AVs, if a driver has yet to interact with an semi-AV system, they still have an initial learned trust in that system, even if they have never used it. Perhaps a driver has never driven a Tesla or used their Autopilot feature, but they have heard of the company's brand and their reputation or they have experienced a similar technology and might understand some of the basic concepts. All of these factors can influence the initial learned trust in the system before the driver even experiencing it. Once the driver begins to interact with the system, they continue the trust learning and development process in what is referred to as dynamically learned trust. The system's performance and design features can influence the trust of the driver while using the system. Dynamically learned trust is the section where trust is actively calibrated according to this specific system and can greatly vary as experience mounts. Over time, operators can learn the system capabilities (e.g., system reliability, types of errors) and properly calibrate their trust. With a reliable automation system, the level of trust should increase to match an equivalent level of reliability [40, 41].

Established trust can be impaired by automation errors, one of the most influential factors affecting trust, depending on the severity of the error. For minor errors, trust decrement might be small and inconsequential. However, major errors like a vehicle crash could be much more potent [42, 43]. These results are expected and indicate proper calibration of trust [30, 44–46]. However, the decline of trust could hurt the performance of the human-automation system if the level of trust does not rebound from the decrease. If the human driver does not understand why an error occurred, they could lose trust in the automation because they do not know the conditions under which automation was unable to perform or what caused the error. Increased transparency of the semi-AV can provide the driver a better understanding of limitations of the driving system and causes of errors. Trust can recover after an error with no intervention if no more errors occur and performance continues to be good [39, 47, 48]. However, it may take a long time to reach previous levels of trust and may cause confusion about the systems capabilities if no repair strategy or transparency is employed [43].

There are different strategies for repairing human trust in automation after a system error [48], similarly to the best human-human teams trying to intentionally build rapport and fix trust if any problems occur. There is limited work in the area of trust repair for human-automation systems; however, de Visser et al. appraised studies about trust repair and provide a list of several active trust repair strategies (e.g., apologize, deny, empathize, explain). These strategies seem to be promising, but many are new or require more testing. Some of the most obvious methods like apologize and explain can be seen as transparency measures that demonstrate that the vehicle is trying to work as a team and communicate the issue so that the human driver can understand and react appropriately. Solutions like deny could be less obvious to implement in a vehicle, but are often commonly employed by other humans such as denying that an error occurred or assuring someone else that it was not as big of a deal as it seems. However, in the interest of promoting transparency and teamwork, the negative approach towards repair could further damage trust in the automated system and impact safety later.

5 Risk Communication and Trust in Semi-AVs

The importance of risk communication is also underscored by the relationship between perceived risk and trust. Innate within Lee and See's [30] definition of trust is the necessity of uncertainty and vulnerability for trust to develop, both of which are characteristics of risk. Mayer and colleagues [49] outline that trusting behavior without risk is best represented by other constructs, such as cooperation, confidence, or predictability. Recently, researchers have explored risk as a variable in studies on trust in automation. For example, Sato and colleagues [50] found that, in a multitasking scenario with varied task load and risk, participants with higher levels of perceived risk reported more trust than those with lower levels of perceived risk, suggesting that risk is a critical factor that influences trust development.

Proper risk communication from the semi-AV to the human driver is closely related to the driver's trust in semi-AV. Effective risk communication can improve system transparency, which in turn increases driver's trust in semi-AVs. In addition, the more helpful the human driver finds the risk messages, the more they would trust the semi-AV as a whole. Repeated false alarms or unhelpful warnings may be seen as annoying and could decrease trust and response time to hazards [40, 51, 52]. Specifically for higher LOAs, a takeover request (TOR) may be required when the system can no longer perform the driving task due to some limitation or condition change. This TOR can be viewed as means of communicating risks to the driver. For example, some roadways or weather conditions might not be conducive or suitable for the semi-AV and it may be able to let the human driver know well in advance about the upcoming issue and tell them about the need for a takeover [53, 54]. However, other times takeover may occur in an emergency situation due to unforeseen road events or system issues [55, 56]. TORs are usually not considered as system errors because they are intended actions of the semi-AV [1]. However, research has shown mixed effects of TORs on driver's trust. On the one hand, TORs can affect the human driver's trust negatively possibly due to driver seeing a TOR as incapability of the semi-AV [43, 57]; on the other hand, TORs are found not to affect trust, likely because of the specific situation and timing of TOR implementation or when trust is measured [55, 58].

6 Conclusion and Future Considerations

Human-automation interaction is essential for systems that require collaboration between the human and the automation. Semi-AV is such a system that requires close collaboration between the human driver and the vehicle. The challenges for successful collaboration include how to effectively communicate risks and enhance proper trust between the parties. We have discussed risk communication mechanisms from the vehicle to the driver and human trust in automation in semi-AVs. Apparently, both concepts can be bidirectional. A further consideration is to investigate mutual risk communication and trust between the human and the automation system in semi-AVs. We have also only focused on driver-vehicle communication. Another future consideration is to incorporate the interactions between the semi-AV and pedestrians, other vehicles, and the infrastructure from a system-of-systems perspective. The ultimate goal of consideration the interactions surrounding semi-AVs is to ensure system safety and security before AVs become fully autonomous.

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Chapter 17

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