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Literature Review of Behavioral Adaptations to Advanced Driver Assistance Systems

March 2016



Title

Literature Review of Behavioral Adaptation to Advanced Driver Assistance Systems.
(March 2016)

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Abstract

In this literature review, theories of driver behavioral adaptation (BA) are examined for the insight they can provide into how drivers will use advanced driver assistance systems (ADAS). Such systems are designed to support driving tasks formerly managed exclusively by the drivers themselves. How drivers react to this assistance will depend on the accuracy of their understanding (or mental model) of the functions and capabilities of a particular ADAS. Negative BA effects can arise when a driver's mental model of an ADAS is incomplete or inaccurate. This may happen when an ADAS has functional limits that are reached only infrequently, and that are therefore difficult for a driver to notice and understand. Various ways to address this issue are described in the conclusions.

Acronyms and Definitions

AAA - American Automobile Association
AAAFTS—AAA Foundation for Traffic Safety
ABS—anti-lock braking system
ACC—adaptive cruise control
ADAS—advanced driver assistance system
AS—active steering
BA—behavioral adaptation
BRT—brake reaction time
CIB—crash imminent braking
CSW—curve speed warning
ESC—electronic stability control
FCW—forward collision warning
GSR—galvanic skin response
HAD—highly automated driving
HMI—human machine interface
ISA—intelligent speed adaptation
IVBSS—integrated vehicle-based safety system
JCTF—Joint Conceptual Theoretical Framework
LCA—lane centering assist
LCM—lane change merge
LDP—lane departure prevention
LDW—lane departure warning
LKA(S)—lane keeping assist (system)
NASA-TLX—National Aeronautics and Space Administration-Task Load Index
OECD—Organisation for Economic Co-operation and Development
RDCW—road departure crash warning
RHT—risk homeostasis theory
RSME—rating scale of mental effort
SA—situation awareness
SAGAT—Situation Awareness Global Assessment Technique
TJA—traffic jam assist

The Problem of Behavioral Adaptation

Advanced driver assistance systems (ADAS) hold the promise of benefiting drivers and other road users by providing relief from tedious control tasks, alerting drivers about dangerous conditions, and intervening on drivers' behalf when physical limitations preclude an effective driver response. It has long been recognized that, in practice, safety impacts of these technologies often fall short of expected benefits because drivers change their behavior as they integrate these new support systems into their driving routine. This change in behavior is called behavioral adaptation (BA). It represents a significant point of uncertainty about the efficacy of many of these systems and undermines efforts to address many safety issues using technology. Some factors that trigger BA have been variously identified as a driver's reduced perception of risk, over trust in the capability of ADAS, faulty understanding about the competence of ADAS, and potential loss of engagement in the driving task particularly with the introduction of partial automation, or what are known as "self-driving" vehicles.

Previous AAA Foundation for Traffic Safety (AAAFTS) research efforts to evaluate the ability of technology to enhance driver safety have identified BA as an important component in the evaluation of potential safety benefit ([Mehler, Reimer, Lavalliere, Dobres, & Coughlin, 2014](#)). How BA affects net safety benefit is difficult to predict and often results in the benefit of ADAS falling short of expectations. This outcome is referred to as negative BA and is generally the focus of research (although positive BA is sometimes reported in which safety benefit is enhanced more than expected). This fact is directly acknowledged in [Mehler et al. \(2014\)](#) by scaling benefits based on theoretical evidence differently from directly observed evidence. Greater weight is given to empirical observations. This is because theoretical and engineering-based forecasts of safety benefits often overestimate benefits and, in the absence of good predictive models of how a driver's behavior changes when faced with ADAS technologies in the real world, empirical evidence is considered the best evidence.

For the driving public, it is important to ensure that the excitement and enthusiasm with which these new assistance technologies are received do not reflect unrealistic expectations. Especially with the growing amount of task automation in the vehicle, drivers must understand that ADAS technologies do not release the driver from responsibility for the safe conduct of the vehicle. Drivers should also be aware of the kinds of changes that could occur either consciously or unconsciously in their driving behavior as their role as driver alternates between controller and supervisor. Likewise, as automation becomes more commonplace, driver awareness of the particular limitations of these technologies will become important so that drivers are adequately prepared to intervene when automation falters. Indeed, in prior surveys of early adopters of adaptive cruise control, the AAAFTS observed clear evidence of substantial overestimation of the reliability and safety benefit of the technology (AAAFTS, 2008; [Jenness, Lerner, Mazor, Osberg, & Tefft, 2008](#)). As technology becomes more and more a collaborative partner with the driver, it will be increasingly important to find ways to address these issues.

Overview of Behavioral Adaptation

That drivers change their driving behavior in response to ADAS has become a growing concern as efforts are made to improve driver safety through use of technologies that advise and warn drivers about unsafe conditions (e.g., forward collision warning, lane departure), relieve drivers of the tedium of vehicle control tasks (e.g., adaptive cruise control, lane keeping assistance, lane departure prevention), and/or support drivers with additional information about their vehicle's immediate environment (e.g., backing cameras, night vision systems, adaptive frontlighting, pedestrian detection). Such concerns are not new. An early mention of a driver's BA in response to an improvement in safety technology was given in a footnote of a paper by [Gibson and Crooks \(1938\)](#):

“Except for emergencies, more efficient brakes on an automobile will not in themselves make driving any safer. Better brakes will reduce the absolute size of the minimum stopping zone, it is true, but the driver soon learns this new zone and, since it is his field-zone ratio which remains constant, he allows only the same relative margin between field and zone as before.”

Since then, mounting empirical evidence suggests that modifications of the driving task environment (which can include the driver, vehicle, and road) will result in changes to a driver's behavior that can complicate the net effect of any intended safety improvement. There are many examples of this phenomenon. Road improvements such as wider lanes, delimiters, and more accommodating shoulders were expected to improve safety, but it was also noted that drivers increased their travel speeds (e.g. Kallberg, 1993; OECD, 1990) suggesting that some of the potential improvement may have been offset by increased risky behavior. Likewise, vehicle improvements like studded tires and anti-lock braking systems (ABS) permitted shorter braking distances, but drivers so equipped appeared to increase their travel speed (OECD, 1990; [Rumar, Berggrund, Jernberg, & Ytterbom, 1976](#)). The OECD (1990) recognized this problem, characterizing BA as “...behaviors which may occur following the introduction of changes to the road-vehicle-user system which were not intended by the initiators of the change.” The OECD also suggests that the effects of behavioral adaptations may range from a net increase in safety to a net decrease.

In some respects, the increased introduction of ADAS technologies into vehicles may have further complicated the picture of BA because ADAS technologies change driving in many different, and sometimes complicated, ways. Some ADAS systems intervene autonomously, taking full control of a vehicle function (e.g., crash imminent braking (CIB), electronic stability control (ESC)); others provide discrete warnings when a safety bound is exceeded to call a driver's attention to an issue (e.g., forward collision warning (FCW), lane departure warning (LDW)); others continuously assist with longitudinal and lateral control tasks, temporarily relieving drivers of this responsibility (e.g., adaptive cruise control (ACC), lane keeping assist (LKA)); and, others provide routing and navigation guidance, suggesting less congested or more eco-friendly routes to a destination. Many of these systems address crash risk directly and are conceived as “safety systems” (e.g., CIB, ESC, FCW, LDW). Other systems are intended to relieve drivers of the tedium of continuous control, which requires continuous monitoring of the roadway and control of lateral and longitudinal position. While reduced crash risk might be an indirect byproduct of such systems, they are largely conceived of as a comfort option (e.g., ACC, LKA). Those that provide route guidance and

other information may not be considered specifically safety-related to drivers, but may nevertheless reduce confusion, uncertainty, and stress among drivers.

How each system makes its presence known to the driver is likely to influence the amount of adaptation, the rate of adaptation, the basis for the adaptation, and the kind of BA observed. For example, the triggering of a crash imminent braking system is likely to be a rare event—indeed, some drivers may never observe this form of ADAS in operation. What kind of BA might be expected for such a system? For some drivers, an adaptation may occur based on second-hand knowledge about the system, and not from direct experience of the device (i.e., a brochure, advertising, or owner’s manual materials versus direct observation). Interestingly, opportunities to directly observe the system in action could encourage a driver to abandon (or forget) the second-hand knowledge. Indeed, such direct communication and interaction has been shown to correct incorrect initial knowledge about ACC, promote trust in such a system (Beggiato & Krems, 2013; Lee & See, 2004), and avoid human-automation interaction issues (Abbink, Boer, & Mulder, 2008; Seppelt & Lee, 2007).

The characteristics of a driver’s BA will then depend on the driver’s mental model of the ADAS function and how confident the driver is about this knowledge. Adaptation to an LDW might be quite different from adaptation to an FCW. LDWs trigger frequently and can permit drivers to directly test the system’s competence without placing the driver at risk. Moreover, both driver and LDW can see the same lane markings on the roadway, so the driver has an opportunity to directly observe how it succeeds and how it fails. Because of the obvious relationship between lane position and warning, it is probable that a driver will be able to quickly infer the basic LDW ADAS operation, and even some of its limitations. Of course, drivers may not be fully aware of “corner-cases” where the system may fail the driver in a particular set of conditions. A negative BA might arise if the driver’s mental model of the LDW suggests that the LDW consistently detects lane exceedances such that the driver comes to believe that careful monitoring of the roadway is no longer necessary.

There is growing concern regarding BA to various levels of automation introduced into the driving task. For the most part, automation of lateral (steering) and longitudinal (headway management) control appears to be an immediate focus of concern, although triggered warnings may also be regarded as a form of automation of the driver’s lookout task. The key adaptation concern with automation is that by reducing the need for the driver to monitor the vehicle and roadway, drivers will adapt by redirecting their attention to other more interesting non-driving activities. This could then result in declines in situation awareness, promote engagement in secondary non-driving tasks, and, as a consequence, introduce delays in taking full control of the vehicle when the ADAS falters or becomes inactive.

Modeling of Behavioral Adaptation

Simple models of BA suggest that after a change is introduced into the driving task environment, drivers will develop an idea of how the change alters their level of risk and then modify their driving behavior with this knowledge in mind. In this review, our focus will be specifically on how drivers adapt to ADAS technologies that automate control (like ACC or LKA) or provide advisory support by monitoring the roadway and alert the driver to developing conflicts (like forward collision warning or lane departure warning). Restated, we would say that BA occurs in response to the introduction of ADAS technology after the driver develops an idea of how the ADAS operates and integrates this knowledge into their driving. Of course, this statement is somewhat facile—the situation is actually more complicated and requires addressing several related questions. For example, how do drivers develop this “idea,” or mental model, of ADAS operation? At what point is the driver sufficiently confident (or trusting) in this knowledge that it is relied on during driving? How can HMI design (visual, auditory, or haptic) aid in developing this trust? How is this confidence influenced by exposure, culture, personality, and other driver-related factors? How long does it take to achieve such a trustworthy mental model? Does trust in a mental model necessarily mean that the model accurately reflects the complete ADAS functionality? What should be done about trust in a flawed mental model? How do flawed mental models arise and how can they be prevented? When a mental model is adopted, how is it integrated into the driver’s behavioral repertoire—i.e., what sorts of adaptations do drivers make when they trust in the operation of an ADAS? At what level in the driving task hierarchy are we most likely to see adaptations? And ultimately, when all of these questions are answered, how do we use this knowledge to mitigate negative BA?

In the next section, we will discuss some models of BA that have been suggested in the past. In general, most of the early models specifically attempted to explain a driver’s motivation to alter his or her behavior, casting the problem in terms of managing or balancing various assessments of risk. While many of these models cite specific driving behaviors as evidence of risky behavior, their focus is primarily on behavioral change that results from maintaining a target risk level ([Wilde, 1982](#)), crossing a risk threshold ([Näätänen & Summala, 1974](#)), or as a non-specific driver of behavioral change. With such a focus on risky behavior alone, these theories provide little guidance about what particular kinds of change in driver behavior are likely to result from adaptations to specific ADAS functionalities. These may include factors like driver complacency, human error, loss of situation awareness (SA), and driver overload/underload ([Martens & Jenssen, 2012](#)). Moreover, these early motivational models of BA do not explicitly address detailed mechanisms of BA that relate directly to how experience using an ADAS in the real world builds knowledge representations that are generalized and applied to the driving task. Instead, they simply appeal to mechanisms whereby risk is adjusted by driver action.

Behavioral Adaptation Models in Historical Context

Most early discussions of BA were focused on risk compensation and were influenced by a study by [Taylor \(1964\)](#) on galvanic skin response (GSR) changes during driving. Taylor found that variation in road segments and driving conditions produced little effect on GSR, although large differences were observed across individuals and between periods of driving

and rest for individuals. His interpretation was that GSR rate could be considered an index of subjective risk or anxiety and appeared to be independent of variation in road conditions. This happened, he argued, because drivers voluntarily influence their risk level by choosing “to engage in more risk on one part of the road than another.” This initial result proved influential in shaping theories of driver BA that followed, directing the initial theoretical focus on subjective risk ([Carsten, 2013](#)). [Näätänen and Summala \(1974\)](#) described an internal subjective risk monitor that continuously evaluates risk and either allows an action when no subjective risk is detected or inhibits behavior when subjective risk reaches a critical threshold. The theory was later described as the “Zero-Risk” theory by [Summala \(1988\)](#). Use of the risk construct was again used when [Wilde \(1982\)](#) suggested that drivers each have a target level of risk that they will accept. If the perceived level of risk falls below this target, drivers will act to increase it; if perceived risk falls above this target, drivers will act to reduce it. Thus BA occurs to maintain this target risk level, achieving a kind of equilibrium between perceived risk and target risk. [Wilde](#) called this the risk homeostasis theory (RHT). It proved controversial because it suggested that, no matter what measure is taken to increase traffic safety, it would be countered by a behavioral change in drivers that would completely offset the increase and result in no net improvement in safety. Increased safety could only be achieved if a driver’s target risk could be altered.

The development of models of BA are more completely described by [Carsten \(2013\)](#) and [Lewis-Evans, de Waard, and Brookhuis \(2013\)](#). The focus of later BA models generally shifted away from characterizations of behavioral change as a byproduct of crossing risk thresholds or maintaining target risk levels and moved toward more subjective ideas related to feelings of risk or underlying subconscious processes ([Fuller, 2000, 2005, 2008](#); [Kinnear, Stradling, & McVey, 2008](#); [Lewis-Evans & Rothengatter, 2009](#); [Summala, 2007](#); [Vaa, 2007](#)). Both [Carsten \(2013\)](#) and [Lewis-Evans et al. \(2013\)](#) have raised concerns that these and other models of BA are often descriptive, and may provide little basis on which to form testable hypotheses or guidance in anticipating whether or not BA might occur. For example, validation of a model might hinge on determining if a response (e.g., feeling of risk, subjective difficulty) to a gradual increase in objective risk is manifest as a discrete step change or a continuous change in the response (e.g. [Lewis-Evans, de Waard, & Brookhuis, 2011](#)). While this work might help describe the point at which one might expect to observe a driver’s behavior to change, it provides less insight into what kind of adaptation might be expected from a particular ADAS.

[Michon \(1985\)](#) was directly critical of these motivational models, suggesting that they were actually discussing “...the products of cognitive functions (beliefs, emotions, intentions) rather than such functions themselves.” Instead, [Michon \(and Janssen, 1979\)](#) offered a framework that sought to fit several of the existing behavioral approaches, into a “cognitive” framework. Such a cognitive framework looked to production system architectures and human information processing approaches (e.g., [Anderson, 1993](#); [Anderson & Lebiere, 1998](#); [Lindsay & Norman, 1977](#); [Newell, 1990](#); [Newell & Simon, 1972](#)) to describe “cognitive” procedures to account for driver behavior. These models sought to identify explicit inputs, processes, and outputs that accounted for driver behavior, but differed from more traditional control-theoretic models (e.g. [Reid, 1983](#)) in their use of processes that included pattern matching, propositional logic, learning mechanisms, and goal-directed behavioral hierarchies. One of [Michon’s](#) key contributions was to cast the task of driving into a hierarchical behavioral framework whereby the driving task was divided into strategic, tactical (or maneuvering), and control (or operational) levels ([Janssen, 1979](#);

Michon, 1979). The strategic level governs overall travel goals and planning, the tactical level governs deliberate maneuvers (like passing), and the control level involves automatic actions like lane tracking and speed control (see Figure 1). Rasmussen (1983) suggested a similar hierarchy in describing the performance levels of skilled operators, dividing the levels into knowledge-, rule-, and skill-based behavior, similar to the aforementioned strategic, tactical, and control levels, respectively. In his assessment of models of driving behavior, Ranney (1994) endorses this hierarchical approach, binding it to cognitive theories of automatic and controlled processes (Schneider & Shiffrin, 1977; Shiffrin & Schnieder, 1977), attention, and error—adopting an information-processing approach—suggesting that it might lead to more fruitful and testable theories of driver behavior. Risk compensation theories were also critiqued by Hedlund (2000) who observed that four factors were necessary for compensation to safety measures. These included visibility—*“If I don’t know it’s there, I won’t compensate for a safety measure”*; effect—*“If it doesn’t affect me, I won’t compensate for a safety measure”*; motivation—*“If I have no reason to change my behavior, I won’t compensate for a safety measure”*; and control: *“If my behavior is tightly controlled, I won’t compensate for a safety measure.”* Thus, Hedlund indirectly endorses a view in which the specific characteristics of the safety system are expected to govern a driver’s response to it. Smiley (2000) makes similar observations in her characterization of BA, suggesting that a driver’s mental model of the safety system (or ADAS) influences the character of adaptation effects.

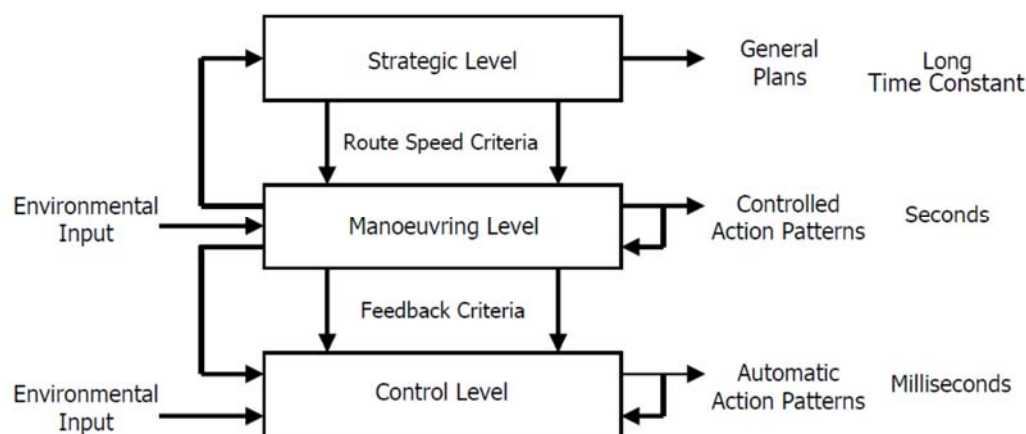


Figure 1. A hierarchical model of the task of driving (from Michon, 1985).

One clear implication of these theoretical views is that the kind of BA observed will likely be particular to a particular ADAS. (The same view is echoed in the Workshop Notes on Behavioral Adaptation, Appendix A.)

In the context of a study of BA to ACC, Rudin-Brown and Noy (2002) were the first to offer a qualitative model of BA that specifically focuses on adaptation involving ADAS technologies. The model recasts the problem into a more cognitive/information-processing framework by identifying the flow of information between discrete processes. The model features a driver component that models internal operations that drive behavior; a behavioral component that categorizes overt action using Michon’s (1985) hierarchy; and an external world (Object) that reflects the combined influence of the environment, roadway, and vehicle. On the driver side, components such as trust, the driver’s mental model (of the ADAS and vehicle), as well as some personality factors such as locus-of-control and

sensation-seeking are seen as contributors to the development of BA (see Figure 2). While qualitative in nature, the model has led to some testable hypotheses and results (e.g., Rudin-Brown & Noy, 2002; Rudin-Brown & Parker, 2004) related to the link between BA and those personality factors included in the model. The model was later revised to include other driver factors such as gender, driver state, and age, as well as a role for adaptive design to influence the driver's mental model (Rudin-Brown, 2010).

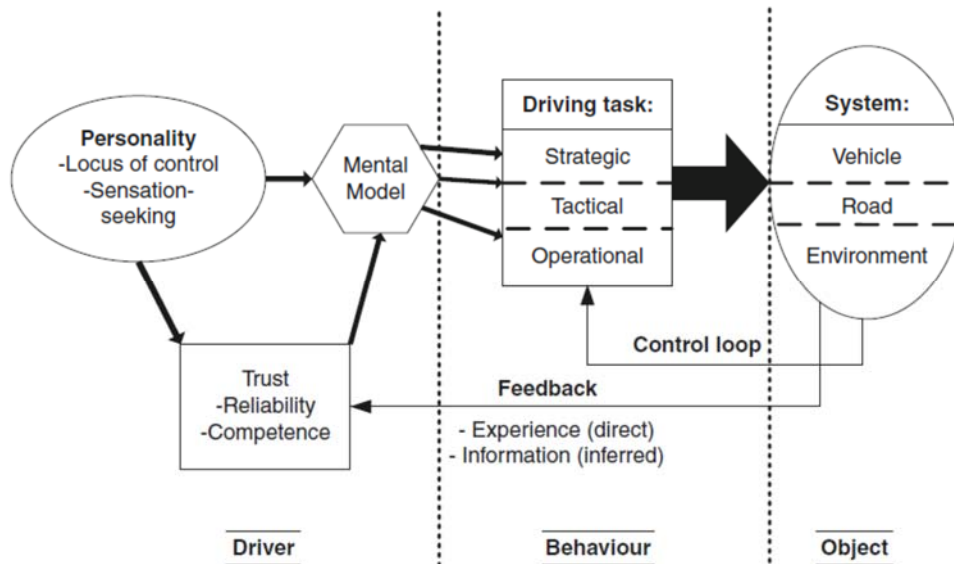


Figure 2. An early version of the Qualitative model of Behavioral Adaptation (Rudin-Brown & Noy, 2002).

A similar conceptual model of “*driver appropriation*” was developed in conjunction with the European Commission’s 6th Framework Programme (Cotter & Mogilka, 2007). This is shown in Figure 3. It extends the model of Rudin-Brown & Noy (2002) by incorporating additional constructs such as situation awareness (SA) (Endsley, 1995a), level of automation (Parasuraman, Sheridan, & Wickens, 2000), and workload (Endsley & Kaber, 1999). Like Rudin-Brown’s model, it also seeks to describe the internals of the driver mental operations, similarly combining personality factors, mental representation (i.e., mental model of the ADAS), trust, decision making, attention control, situation awareness, and driver state. A few arguably minor differences are the inclusion of behavior within the driver component, and the distinction drawn between the System (i.e., ADAS characteristics) and the Environment (i.e., all sensed consequences of an action from the physical world). There is also a component labeled Situation, which might be best conceptualized as representing a driver’s understanding of the key goals of the trip (e.g., arrive on time) and the external demands of the environment.

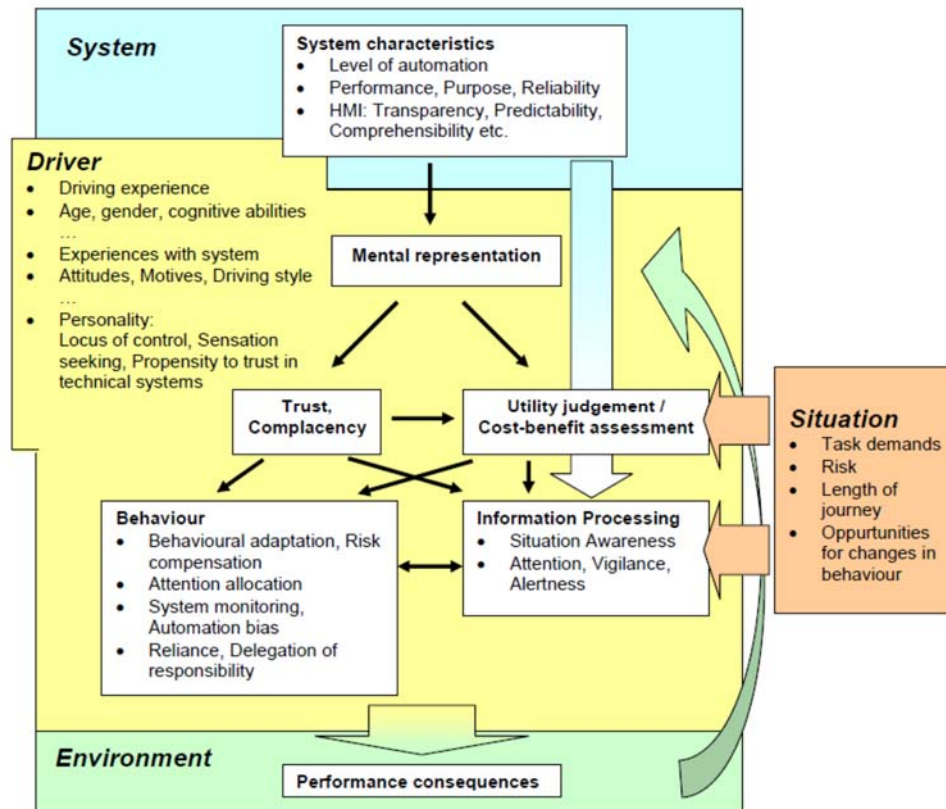


Figure 3. Model of driver appropriation (from Cotter & Mogilka, 1997)

A more recent and elaborate framework has been offered that includes many of the same elements of the Qualitative Model and the Driver Appropriation Model, called the Joint Conceptual Theoretical Framework (JCTF) of Behavioral Adaptation by Wege et al.(2013)—see Figure 4. The framework is quite inclusive, in that it identifies and groups many pieces of the BA puzzle, although it is not specific regarding how the elements actually interact. That is, it is not so much a model as it is an attempt to show a “...wide view regarding the nature of adaptation processes (Wega, Pereria, et al., 2013).” For researchers in the area of BA, it is something of a laundry list of potential factors that can and do play some role in BA. A greater effort is needed to more rigorously define these named constructs and describe how they relate to each other. For example, most information processing theories include perception, attention, decision making and problem solving as components ([Lindsay & Norman, 1977](#)); trust is often seen as a byproduct of the observed accuracy of a mental model (e.g. [Beggiato, Pereira, Petzoldt, & Krems, 2015](#)); reduced mental workload is sometimes associated with greater situation awareness (e.g., [Endsley & Kaber 1999](#); [Ma & Kaber, 2005](#)), however in some contexts automation may reduce workload and situation awareness at the same time. For example, Stanton and Young (2005) point out that workload reduction that removes the driver’s task of longitudinal control might also remove the requirement for the driver to attend to the feedback formerly needed to control the vehicle, resulting in a loss of SA for longitudinal position. It is fair to say that the theoretical landscape is replete with concepts and ideas, but tying so many pieces together into a coherent picture has become a considerable challenge.

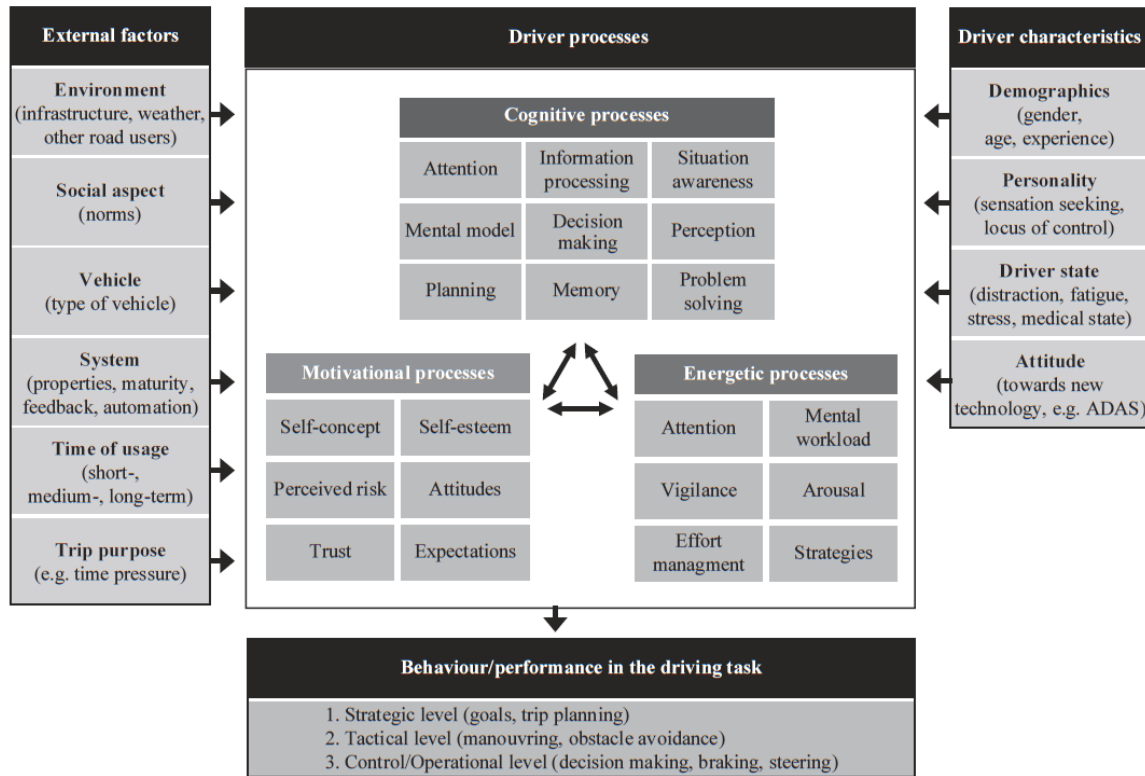


Figure 4. The Joint Conceptual Theoretical Framework (JCTF) of Behavioral Adaptation (Wege, Pereira, et al., 2013)

Behavioral Adaptation to Advanced Driving Assistance Technologies

Earlier vehicle technology improvements that inspired thinking about BA could be characterized as performance improvements to existing vehicle functions that are directly managed by the driver (e.g., power assisted braking and steering, improvements in forward lighting) or improvements that offer better protection of the driver (e.g., safety belts, air bags). With the introduction of sophisticated electronic interventions, it also became possible to address problems like brake lock-up and loss of traction that presented significant challenges to the average driver. Collectively, these changes provided the driver with general vehicle performance improvements without substantially altering the driving task. Reported BAs in response to these changes were largely focused on broadly defined behavioral markers for increased risky driving. This included measures of a driver's increased crash involvement, greater travel speeds, reduced gap acceptance, closer following distances, and more aggressive roadway maneuvers.

This early characterization of driving risk did not always note that behavioral changes seemed to differ among different safety improvements. For example, drivers demonstrated virtually no adaptation response to airbags, but travelled at higher speeds and shorter following headways with antilock brakes ([Sagberg, Fosser, & Sætermo, 1997](#)). While a specific effect of seatbelt use on driver behavior was debated (based on crash data) ([Adams, 1982](#); [Mackay, 1985](#)), no behavioral changes were initially observed ([Evans, Wasielewski, & Vonbuseck, 1982](#); [Lund & Zador, 1984](#)) although modest increases in speed and reduction in headway were reported ([Janssen, 1994](#); [Streff & Geller, 1988](#)). When driving a vehicle equipped with studded tires that improved traction on icy roads, drivers were found to drive somewhat faster, although they drove well below the maximum speed traction limits, compared to drivers of vehicles not so equipped ([Rumar, et al., 1976](#)). Although described in terms of risk compensation, one might argue that the observed changes in driver behavior may have been differently influenced by different safety modifications. That is, behavioral changes were related to the effects drivers believed those improvements had on different components of their driving, rather than to broad changes in risky driving.

Unlike many of these earlier technologies, the new classes of ADAS are more precisely targeted. They change more than aspects of vehicle performance. They can extend a driver's sensorimotor capabilities by revealing objects hidden in darkness (e.g., night vision pedestrian detection systems; [Serfling & Löhlein, 2013](#)); they can warn about potential conflicts with extreme vigilance and precision (e.g., blind spot detection, lane departure warning); and they can detect and respond to an imminent forward collision faster than humanly possible (e.g., pre-crash braking; [Kusano & Gabler, 2012](#)). These vehicle technologies can be characterized as supplementing the driver's lookout task, bringing potential threats to the driver's immediate attention. Other technologies relieve drivers of the tedium of repetitive control tasks, such as headway maintenance (e.g., ACC), lateral control of lane position (e.g., lane keeping assist—LKA; lane departure prevention—LDP), and management of stop and go traffic (e.g., traffic jam assist—TJA). This class of vehicle technology automates part of the vehicle control task. Thus, we see technologies that expand a driver's sensory capacity, supplement the lookout task, and manage the control task. Arguably, these technologies are more active participants in the task of driving than those that came earlier.

In this review, we will first discuss research on ADAS that automate longitudinal and lateral control—adaptive cruise control and various forms of steering support. Interest in these systems is important because they are considered stepping stones to full vehicle automation. Following this, we will focus on warning and alerting ADAS, where drivers are advised about potential conflict conditions without any direct intervention from the ADAS.

Driver Response to Automation of Longitudinal and Lateral Control

Longitudinal Control

By far the largest body of research on BA to ADAS has been focused on automation of the management of longitudinal (i.e., speed and headway), and lateral (i.e., steering) control. Longitudinal control was first introduced as cruise control, a means of maintaining a selected speed over a long travel distance, relieving the driver of having to monitor speed while holding a foot in position on the accelerator pedal over a long period of time. Over long trips involving constant speeds, this control support allowed the driver to move his or her foot off the accelerator while ensuring that speed would not drift far from an established target. This original form of longitudinal control has come to be known as conventional cruise control (CCC) to distinguish it from the later enhancement, called adaptive cruise control (ACC) that added forward-looking sensors to allow the system to detect and manage headway to a lead vehicle.

Thus, ACC allows a driver to select both a target speed and a headway time that the vehicle will maintain for longitudinal control in car-following situations. Headway to a lead vehicle is managed using forward sensors that detect the distance and closing speed to a lead vehicle. Vehicle speed is regulated to maintain the selected headway. Headway selection is a time-based parameter, selected by the driver to maintain a minimum distance to a forward vehicle based on travel speed—normally the headway time is between 1 and 2 seconds. When not preceded by a lead vehicle, ACC operates like CCC, regulating speed alone.

There are some limitations with most ACC systems that may be worrisome for drivers. In particular, the sensor systems used for forward detection may not detect small forward objects such as pedestrians, bicycles, animals, or motorcycles. On highly curved road segments, forward objects may not be well aligned with the radar such that the radar may detect an object in an adjacent lane as a forward object, or fail to detect a forward object outside of the radar's field of view. Most high-speed ACC systems do not detect forward objects that are moving slowly or stopped in the forward travel lane. There are also limits on the stopping authority of most ACC systems—many are incapable of any form of braking exceeding 0.3 g and will thus fail to avert a forward collision in such circumstances. Finally, ACC sensor performance can deteriorate in snowy, rainy, or foggy weather, rendering the system's forward detection capability unreliable. These limitations are a concern since drivers may not be fully acquainted with these performance limitations, but must nevertheless be prepared to intervene if the ACC encounters such conditions.

Lateral Control of Lane Position

Active control of lane position is a more recent outgrowth of lane departure warning technologies which detect when a vehicle is crossing a lane or road boundary. However, instead of simply warning the driver that a boundary is being crossed, many systems are capable of steering the vehicle back into the center of the lane. This capability is seen as a step toward autonomous vehicle control, particularly when paired with ACC. Current versions of this steering control capability have been variously named Lane Keeping Assist (LKA), Lane Departure Prevention (LDP), and Lane Centering Assist (LCA). Most of these systems provide limited steering authority and cannot fully maintain a vehicle's lateral position at speed on high curvature roads. Nevertheless, this capability in combination with ACC constitutes a Level 2 autonomous system (Trimble, Bishop, Morgan, & Blanco, 2014)—at least 2 controls are automated at the same time.

Like ACC, lateral control capability is limited by the degree to which the system sensors are able to detect lane boundaries. Currently, this is accomplished using video, laser, or infrared sensors that detect lane boundary markings on the road. The system works to maintain the vehicle position between the two lane boundary lines. When lane markings are obscured by snow, road wear, or other debris, the lateral control system fails. In most cases, it will return lateral control to the driver. Lateral control systems are currently not sufficiently sophisticated to detect obstacles in the center of the roadway to effectively steer around them. They are entirely focused on keeping the vehicle within the lane boundaries, and will do so even if a large boulder lies in the center of the lane. Likewise, when lane boundaries are distorted by extreme roadway geometry (e.g., high curvature) or when complicated line patterns are drawn in the road, the system's understanding of lane position may deteriorate.

Research involving lateral control is primarily relegated to simulator studies because there are few lateral control systems available in the marketplace, and those that are available have very limited steering authority. We include discussion of lateral control systems along with ACC because the two systems are frequently paired together in simulator studies that investigate progressively greater levels of automation. In this context, lateral control is commonly referred to as active steering (AS) (e.g., [Carsten, Lai, Barnard, Jamson, & Merat, 2012](#); [Jamson, Merat, Carsten, & Lai, 2001](#); [Jamson, Merat, Carsten, & Lai, 2013](#); [Merat, Jamson, Lai, & Carsten, 2012](#); [Merat, Jamson, Lai, Daly, & Carsten, 2014](#); [Stanton & Young, 1998](#); [Young & Stanton, 2002, 2007a, 2007b](#)).

Control Automation and Changes in Driver Behavior—Critical Event Detection

The first studies of control automation began in the late 1990's with early versions of ACC. ACC continues to be one of the most actively researched ADAS topics today. This early work was directly concerned with the effects of ACC use on a drivers' management of headway and travel speed as well as its effect on the driver's preparedness to step in and take control of the vehicle when roadway conditions exceeded ACC capabilities. In simulator studies, drivers with ACC were found to be generally slower than drivers with manual control in reacting to critical traffic situations such as abrupt lead vehicle braking, cut-ins, the sudden appearance of stationary vehicles on the roadway, or other system failures (Bianchi Piccinini, Rodrigues, Leitão, & Simões, 2015; de Winter, Happee, Martens,

& Stanton, 2014; Hoedemaeker & Brookhuis, 1998; Larsson, Kircher, & Andersson Hultgren, 2014; Nilsson, 1995; Stanton, Young, & McCaulder, 1997; Stanton, Young, Walker, Turner, & Randle, 2001; Vollrath, Schleicher, & Gelau, 2011; Young & Stanton, 2007a). For example, Nilsson (1995) observed later braking among ACC-equipped drivers approaching a stationary queue compared to manual driving. Stanton, Young, and McCaulder (1997) observed 4 of 12 drivers fail to regain control of their vehicle when the ACC system accelerated into a forward vehicle. Hoedemaeker and Brookhuis (1998) observed larger brake force maximums and smaller minimum headway times for drivers of vehicles equipped with ACC. Larsson, Kircher, & Andersson Hultgren (2014) observed longer brake reaction times in response to cut-ins with ACC, compared to manual driving. A similar pattern was also observed in a test-track study of Rudin-Brown and Parker (2004) where drivers with ACC took about 0.6 to 0.8 s longer to react to a lead vehicle's brake lights than the average 2.0 s when driving without ACC.

Similar results have been observed in studies involving active steering (AS) paired with ACC. The combination is often collectively referred to as highly automated driving (HAD) (e.g., de Winter et al., Merat et al., 2014). For example, Strand, Nilsson, Karlsson, and Nilsson (2014) found more hard braking and collisions among HAD drivers than ACC drivers under conditions of automation failure. Merat and Jamson (2009) also found that drivers braked about 1.5 s later in response to a forward vehicle braking when using HAD compared to manual driving. Summarizing many of these findings in a meta-analysis, de Winter et al. (2014) report that most of the evidence suggests that HAD and ACC evoke "...long response times and an elevated rate of (near-) collisions in critical events as compared to manual driving."

In some respects, it is worth asking whether these effects are a consequence of BA or relative ignorance about the functional characteristics of an unfamiliar ADAS. Whereas adaptations might be thought of as behavioral changes that develop over time, many of the above results are generated shortly after the driver is introduced to the system for the first time. In many studies, drivers are relatively new to ACC and AS capability and the critical event had been preceded by only a brief period of exposure to these systems. For example, in the driving simulator studies of Stanton and Young, trials with different levels of ACC lasted between 10 and 20 minutes and were preceded by about 5 min of practice (Stanton et al., 1997; Stanton et al., 2001; Young & Stanton, 2007a) the simulator trials in Hoedemaeker and Brookhuis (1998) each lasted about 15 minutes. Many of the later simulator studies use longer periods of ACC and AS exposure. For example, simulator studies conducted by the researchers at Leeds typically employed about 45-mins of simulator practice, followed by experimental trials also lasting 45 min each (Carsten et al., 2012; Jamson et al., 2001; Jameson et al., 2013; Merat et al., 2012; Merat et al. 2014). Judging by track length and travel speed, other simulator experimental trials seem to exceed 30 min (Beggiato & Krems, 2013; Bianchi Piccinini, Rodrigues, Leitão, & Simões, 2014; Bianchi Piccinini et al., 2015; Vollrath et al. 2011). Similar levels of exposure were also used in the test track study (Rudin-Brown & Parker, 2004), where exposure to the ACC system involved a briefing on ACC operation and a 30-minute warm-up session on the track. There were 2, 30-min experimental trials with the ACC active.

Thus, most of the studies of ACC and HAD involve drivers who are relatively unfamiliar with these systems, apart from an initial briefing and test drive. Is it surprising that drivers are less prepared to respond to critical events that involve what could be

characterized as different forms of ADAS failures? The point here is that many participants in these studies had very limited exposure to the ADAS such that driver responses in these circumstances suggest that they had not so much *adapted* to ADAS, but may have *misunderstood* its limitations.

One diagnosis of this effect might suggest that drivers have not yet internalized an accurate representation of how the (simulator-based) ADAS actually functions. That is, these drivers are relatively novice users of these ADAS control systems and are unlikely to have a sufficiently refined mental model of how these systems work to enable them to predict the level of assistance that they provide. It is one thing to be told that an ACC has limited braking authority, but is it realistic to expect a driver to understand what this actually means when it comes to relying on the ACC's stopping power? In the earlier theoretical discussion of BA mechanisms, the driver's mental model was identified as one of several components that influence BA. While it is important to first have a mental model of an ADAS, it is also important to understand that both the objective accuracy of the model and the driver's level of confidence or trust in his or her model also play a role in adaptation.

A closer look at the role of mental models

The issue of the driver's familiarity with the functioning of ADAS has been recently explored by selecting drivers who are experienced users of ACC systems (e.g., Bianchi Piccinini et al., 2015; Larsson et al., 2014). Comparing both experienced and novice ACC users, Larsson, Kircher, and Andersson Hultgren (2014) found both groups of users had slower brake reaction times (BRT) under automation, compared to manual control; however the effect was smaller for those experienced with ACC. A comparison of experienced ACC users and ACC novices also found that those experienced with ACC were faster to respond than were novices. These results suggest that some level of experience with ACC can influence the degree to which drivers appear able to respond to unpredictable events. Two recent studies directly examine drivers' trust, acceptance, and mental models of ACC. Beggiato and Krems (2013) conducted a simulator study involving 3 separate drive sessions over a 6-week period in which drivers were given different briefings about the ACC's functional capabilities. The *correct* group of drivers were given an accurate briefing about the ACC that included details related to the system's difficulty detecting small vehicles, functioning in adverse weather conditions, and its management around narrow road bends. The *incomplete* group was provided a basic functional overview of ACC, but were not advised of the ACC problem areas. Finally, the *incorrect* group were given the same information as the *correct* group, but were also given erroneous information that the system had problems with large vehicles and with white/silver cars. Mental models were probed using questionnaires immediately after the ACC description was read, and after each experimental trial. Over time, the three groups' mental models converged. Notably, non-occurring non-experienced failures originally called out in the descriptions (e.g., white/silver cars, large vehicles) seemed to be forgotten, while unexpected experienced failures (*incomplete* group) led to quick shifts in the mental model toward the correct group. A follow-up on-road study (Beggiato et al., 2015) was conducted that involved drivers with no ACC experience, driving an ACC-equipped test vehicle in 10 drives over 2-month period. Drivers were initially given a complete description about the ACC function, which likely included specific details about ACC problem areas (i.e., detection of small vehicles, operation in adverse weather, detection of stationary objects, performance on curved roads).

The driver's mental model of the ACC was probed after drives 1, 2, 3, 5, and 10. Among the most interesting results is that driver's awareness of ACC limitations drifted over time. For example, initially strong disagreement with the statement "ACC detects stationary objects" drifted toward agreement by the 3rd session and began to decline toward disagreement by the 10th session. This rise and fall effect is attributed to the driver's evolving experience with ACC—it might take time to directly encounter the ACC limitations called out in the owner's manual, before drivers adjust their mental model to include this. In the meantime, drivers mentally generalize rules of ADAS functionality much like children regularize rules of grammar until they are explicitly confronted with exceptions. Thus, an ACC is expected to detect stationary and small forward objects until confronted with such objects, much like the plural of *mouse* is *mouses*, until the exception is learned.

This lack of awareness about ADAS exceptions has also been noted in several survey studies of users of ACC. Jenness et al. (2008) and AAAFTS (2008) report that drivers of ACC-equipped vehicles are generally unaware of the ACC's limitations and overestimate its ability to prevent collisions. There are some suggestions that driver awareness improves over time—for example, with prolonged use, drivers are less likely to be identified as unaware about their ACC function (Dickie & Boyle, 2009); prolonged use appears to be associated with greater awareness of system limitations (Larsson, 2012). It is also notable that when special measures are taken to apprise drivers that an automation control has exceeded a bound, drivers can more effectively take control (Lee, McGehee, Brown, & Marshall, 2007).

One interpretation of these results is that drivers are not so much slow to intervene because of BA to the ADAS system, as they are mistaken about the ADAS's capabilities. Complete understanding of ADAS functionality may be particularly difficult for drivers because ADAS exceptions in functionality do not follow human cognitive/behavioral rules. For example, a human has no more difficulty seeing a large stationary object as a large moving object. However, some ACCs are, by design, blind to stationary objects because they cannot easily distinguish whether the object is on the roadside or in the driver's forward lane. It assumes the stationary object is on the roadside and ignores it—if it did not, it would constantly trigger on stationary roadside objects on non-straight roadways. With limited information about how such systems "see," drivers use their own intuitions about how the ACC functions, no doubt modeled after fellow humans and not machines. Indeed, Manser et al. (2013) suggest that adaptation should be considered in three temporal stages: immediate, when a driver initially experiences the ADAS; short term, which plays out over days or weeks; and long term, which plays out over months or years. Most simulator-based studies are principally looking at immediate adaptation effects. Until drivers have an opportunity to observe deviations from their initial mental model of the ADAS, there is little opportunity for the model to be amended. Getting to know a system both depends on where and when it is experienced as well as the length of time it is used (Pereira, Beggiano, & Petzoldt, 2015). Longer term evaluations will likely be required to better understand BA that is not a consequence of an immediate, and potentially immature, mental model of ADAS function.

Drivers will act based principally on their mental model of ADAS operation, their confidence that their understanding is accurate, and their trust that the system will behave reliably. A faulty model, overconfidence in the model, or misplaced trust in the ADAS can

result in a delayed response to assume control when the ADAS malfunctions or reaches a performance limit.

Measures of trust

Most studies of trust in automation have examined longitudinal control with ACC. They suggest that both experienced and novice users are likely to over-trust automation. Trust increases with exposure to ACC and seems insensitive to failure (Itoh, 2012; Rudin-Brown & Parker, 2004). Similar trends have also been reported for inaccurate lane departure warning systems (Rudin-Brown & Noy). If drivers are initially provided with a large number of details about ACC exception cases, some of which are incorrect, rated trust is initially low but increases over successive exposures to ACC (Beggiato & Krems, 2013). When drivers are given incomplete information about ACC function, trust starts high and declines with exposure to unanticipated boundary conditions. Trust increases over sessions according to a power law (Beggiato et al., 2015) leveling out by about the fifth exposure session. This suggests that trust in an ADAS will quickly grow with exposure alone and may become inappropriately high if the driver has limited or no experience with boundary conditions, allowing gaps or inconsistencies to develop in the driver's mental model.

Control Automation and Changes in Driving Behavior—Control Management

A commonly reported BA to automated control relates to how drivers change their management of speed and headway in the presence of ACC. Early reports suggested that drivers increased their travel speed and adopted shorter time headways to lead vehicles. For example, in a simulation study Hoedemaeker and Brookhuis (1998) observed driving speed and headway with and without ACC in two sessions of three 15-min drives on separate days. On the first day of driving, they also drove a condition in which ACC was inactive at the very beginning of the session. Average speed in the no-ACC condition was 107 km/h and with ACC it increased to 115 km/h; a smaller minimum time headway was also reported in the ACC condition. A similar result was also reported in a test track study by Ward, Fairclough, and Humphreys (1995). Reduced minimum time headway was also observed in a simulator study of highly automated driving by Merat and Jamson (2009). In contrast, Bianchi Piccinini et al. (2014) report longer headways and lower speeds, especially for experienced ACC drivers. Stanton et al. (1997) report no effect on speed or headway. Hoedemaeker and Kopf (2001) report lower speeds with ACC and no effects on headway in an ACC-enabled test vehicle. In a field test, Ervin et al. (2005) report systematic reductions in the incidence of short headways (less than 1 s) with ACC use. Finally, in another field test, Viti et al. (2008) report increases in average headway, smaller headway variability, lower speeds, and smaller speed variability. Other than Stanton et al. (1997), the studies that did not find safety-compromising changes in speed or headway involved field tests (Ervin et al., 2005; Viti et al., 2008), experienced users of ACC (Bianchi Piccinini et al., 2014), or drives on public roads (Hoedemaeker & Kopf, 2001). Perhaps the relatively brief exposure times in the early studies underpin the results, and the effect is greatly diminished with increased exposure. It is also possible that the experimental procedure in the Hoedemaeker and Brookhuis (1998) study may have also contributed to the result. The non-ACC condition was confounded with trial order—it was the first trial for all subjects. It is possible that as subjects made successive drives in the simulator, they became more familiar with the driving environment and perhaps picked up some speed to complete the

session sooner, leading to faster speeds and shorter headways. In the Merat and Jamson (2009) study, all highly automated car-following defaulted to a 2-s time headway. It would seem that, by design, automated driving could not achieve a minimum greater than 2-s. In contrast, the minimum headways observed in manual driving were well above 2-s. It is possible that the result is more a constraint of the automation condition than a driver BA.

There have also been some suggestions that control automation may affect a driver's tactical decisions; however, few such reports exist. [Ervin et al. \(2005\)](#) report that, with ACC, drivers linger behind forward vehicles twice as often as they do when ACC is not active. Consistent with this, [Jamson et al. \(2001; 2013\)](#) report that in highly-automated conditions, drivers refrain from behaviors that require temporarily retaking manual control of the vehicle (e.g., overtaking). Perhaps this occurs because drivers perceive a disincentive in turning automation off once it is activated. This could be a direct consequence of workload reduction in the driving task. Such a reduction might create an incentive for the driver to keep automation active. In the next section, we discuss reduction in workload as a kind of precondition that could enable other forms of BA that may lead to diminished situation awareness (SA) in drivers.

Control Automation and Driver Workload

Driver workload is principally measured two ways: directly, using questionnaires which elicit subjective reports, and indirectly using secondary task performance which is somewhat more objective. Subjective workload is most commonly measured using questionnaires such as the NASA-Task Load Index (NASA-TLX) ([Hart & Staveland, 1988](#)) or the Rating Scale of Mental Effort (RSME) (e.g., [Hoedemaeker & Brookhuis, 1998](#)), although other custom scales have been used as well (e.g., [Ma & Kaber, 2005](#)). Secondary task performance is used as an index of workload following the rationale that as workload lightens, the driver has increased mental capacity to devote to a secondary task. Consequently, secondary task performance is inversely related to workload. In making this kind of assessment of workload, self-paced visual and non-visual tasks have been used as secondary tasks.

In a comprehensive review of studies of ACC and HAD systems on driver workload and situation awareness, [de Winter et al. \(2014\)](#) reported that subjective workload measured using surveys showed a small workload reduction between manual driving and ACC-equipped driving, while workload with HAD was nearly halved.

Secondary task performance measures show similar effects. In self-paced visual tasks (e.g., [Rudin-Brown & Parker, 2004](#); [Stanton et al., 1997](#); [Young & Stanton, 2007, 2007a](#)) performance of the secondary task improved when automation was introduced. In the meta-analysis of [de Winter et al. \(2014\)](#), self-paced secondary task performance was marginally improved with ACC (increased by 12%), and substantially improved with HAD systems (+152%). However, it also appears that control automation has less effect on non-visual tasks. Little difference was found between automation conditions and manual driving when drivers performed more cognitively loaded tasks such as a twenty-questions task ([Merat et al., 2012](#)) or an auditory/verbal task ([Seppelt & Lee, 2007](#)).

It is worth noting that the results of workload questionnaires do not always agree with secondary task performance. For example, Stanton et al. (1997) noted that while [Nilsson \(1995\)](#) found that drivers reported no difference in workload using ACC assessed using the NASA-TLX questionnaire, he found significantly more correctly identified secondary task items in the ACC condition, suggesting a workload reduction. One difference, Stanton pointed out ([Stanton & Young, 1998](#)), was that when roads are straight and longitudinal control is the driver's predominant control task, ACC provides significant assistance; when roads are curved, and the lateral control task predominates, ACC provides comparatively less reduction in workload compared to manual driving. In a later study comparing manual, ACC, AS, and ACC+AS, Young and Stanton (2004) observed a subjective workload reduction between manual and ACC-assisted driving using NASA-TLX measures in Experiment 1, while finding no difference in secondary task performance. They suggested that the subjective measure reflects sensitivity to the presence of automation, while the secondary task performance was related to automatic performance. That is, the constant speed longitudinal control task of Experiment 1 did not impose any additional demands because drivers were able to handle the task with some degree of automaticity. Experiment 2 introduced variable-speed longitudinal control, requiring manual-control drivers to regularly monitor their headway to a lead vehicle that changed speed by braking and accelerating at random intervals. In this case, both subjective (NASA-TLX) and objective measures (secondary task performance) of workload showed a reduction.

Returning once again to the result that non-visual secondary tasks exhibit little difference in performance under manual vs. automated driving conditions, it might be suggested that this happens because these tasks do not rely on the redirection of the driver's visual attention off the roadway to perform the task. Thus, the reduction in necessary road monitoring may be responsible for the declines in workload measures. Consistent with this possibility is the observation of differences between longitudinal and lateral control that was noted by [Carsten et al. \(2012\)](#) where drivers redirected glances away from the roadway much more when under lateral control compared to when under longitudinal control. That is, lateral control automation seems to produce dramatically greater workload reductions than longitudinal control alone ([Carsten et al., 2012](#); [Jamson et al., 2013](#); [Stanton & Young, 2005](#); [Young & Stanton, 2007a, 2007b](#)) possibly because lateral control requires more regular roadway monitoring. When this is no longer the case, as during automated LKAS, the driver is free to reallocate visual attention to other matters. Thus, drivers appear to look away more from the roadway and engage in more secondary tasks when visual monitoring workload is reduced with automation ([Carsten et al., 2012](#); [Llaneras, Salinger, & Green, 2013](#); [Rudin-Brown & Parker, 2004](#)). Interestingly, this redirection of visual attention can lead to changes in a driver's situation awareness. This will be discussed in the next section. For a recent comprehensive review of the state of the science of workload, see Young, Brookhuis, Wickens, & Hancock (2015).

Control Automation and Situation Awareness

Gugerty (2011) concisely defines situation awareness (SA) in the context of driving as: "The updated, meaningful knowledge of an unpredictably-changing, multifaceted situation that operators use to guide choice and action when engaged in real-time multitasking." Endsley (1995b) distinguished three levels of SA: Level 1—Perception of Elements in the Environment; Level 2—Comprehension of the Current Situation; and Level 3—Projection of

Future Status. Simply put, situation awareness means “knowing what is going on around you.”

SA has been measured using the Situation Awareness Global Assessment Technique (SAGAT) whereby a freeze of a simulation scenario occurs in order to pose queries to the operator about the state of the simulation scenario (Endsley, 1995a, 2015). Other, more indirect methods infer driver awareness using behavioral measures—for example, time to detect an unpredictable event, overt eye movements, or time to perform an avoidance response (Gugerty, 2011).

While driving, there are many “situations” for which a driver needs to maintain a good level of awareness: drivers must monitor potential traffic conflicts from many directions, pedestrians, cyclists, traffic signs, traffic signals, other vehicle turn indicators, their own vehicle’s speed, lane position, headway, and vehicle states relayed by the instrument cluster. When automation is introduced that, for example, supports headway or lane position management, a driver may well redistribute attention differently within/across the scene. If the measure of SA happens to target one of the areas that the driver has added some focus, automation will appear to enhance SA. For example, pedestrian hazards may be better detected (Funke, Matthews, Warm, & Emo, 2007) and performance on SAGAT queries improve when driving is supported by ACC. In Funke et al. (2007), drivers were aware that they would be asked about pedestrians. In the Ma and Kaber (2005) study, they were given 15 min of instruction on the SAGAT questionnaire which was administered 3 times in each of two ACC conditions (inactive, active). It seems likely that drivers would know they would be asked questions about the roadway environment, questions about tactics to address various drive issues, and questions about predicting upcoming events. Thus, there may have been an incentive to redistribute attention in a manner that would improve performance in answering these questions.

In other studies cited earlier, where drivers are given less direction about how to redistribute their freed attentional resources, the results are less positive. For example, in the presence of both lateral and longitudinal control, drivers will take up non-driving-related secondary tasks, if available (Carsten et al., 2012; Llaneras et al., 2013). The choice in how to redistribute their freed capacity could easily lead to drivers losing awareness of what is going on around the roadway, and being slow to intervene when an unexpected situation arises.

Behavioral Adaptation to ADAS Warning Systems

There has been substantially less work on adaptation to ADAS-type warning systems than control support systems. Most warning systems present a visual, audible, or haptic display that is triggered when a specific condition arises or limit is reached. For example, curve speed warnings (CSW) trigger an audible alert when a driver approaches a curved road segment at a high rate of speed; lane departure warnings (LDW) are triggered when a lane boundary is crossed, often producing a haptic pulse or a rumble-strip sound; forward collision warnings (FCW) trigger audible alerts when headway or time-to-collision reaches an established limit; and intelligent speed adaptation (ISA) systems can either warn the driver or directly intervene to help the vehicle conform to posted speed limits.

Adaptation to Intelligent Speed Adaptation (ISA)

Different versions of ISA were developed in Europe in the late 1990's to address the problem of speeding (Brookhuis & de Waard, 1999). Some ISA systems simply provide advice to drivers about the speed limit for the current roadway; other systems can be optionally engaged to restrict exceedance of a speed limit; other systems automatically engage and do not allow drivers to disengage; finally, some systems incorporate information about weather and current road conditions and dynamically adjust speed to suit both posted speed and real time conditions. Comte (2000) reports a simulator study on driver BA in three variations of ISA: one that allowed a driver to engage or ignore an ISA system; another *Mandatory* system that engaged automatically; and a third, *Variable*, system that resembled the *Mandatory* system, but also adjusted speed to accommodate hazardous conditions. Gap acceptance in turns and headway was generally reduced among the *Mandatory* and *Variable* ISA users, suggesting that growing impatience/frustration encouraged a tactical decrease in gap acceptance and increased risk. No effect was observed on overtaking behavior, traffic violations, or responses to surprise events.

In a field test of an ISA variant that provided speed regulation advice in the form of accelerator pedal counterforce against the driver's pedal application, speed reductions were observed without compensatory speed boosts around intersections (Varhelyi, Hjalmdahl, Hyden, & Draskoczy, 2004). Similar speed reductions have been observed in other field studies as well in which ISA override is permitted (Lai & Carsten, 2012; Lai, Hjalmdahl, Chorlton, & Wiklund, 2010), although ISA overriding appeared to increase with exposure. This was particularly true of the drivers who were likely to intentionally exceed the speed limit.

Lane Departure Warning

BA to lane departure warnings was examined in both simulator and track studies by Rudin-Brown and Noy (2002). Their studies were specifically interested in whether trust develops differently among drivers who differed in measures of locus-of-control and sensation seeking. Drivers used an accurate LDW or an inaccurate LDW (that generated false occasional positive warnings and detection failures one-third of the time) while performing a secondary destination entry task on a navigation system. In a baseline session, all drivers drove without the LDW activated—a control condition. In a post-test session both groups drove while using the inaccurate LDW system. Drivers were asked to rate the level of workload and trust in each of the LDW systems after each session. Trust increased with exposure for all groups, regardless of accuracy. In the simulator study, drivers who completely departed the roadway when the LDW failed to report a lane departure exhibited stronger trust in the LDW than those who did not depart the roadway.

Forward Collision Warning

Relatively few studies have examined BA in the context of FCW. This is possibly because FCW is often bundled with ACC, and the adaptation effects of ACC seem to overshadow those of FCW alone. Moreover, there seems to be a general consensus that FCW provides a net benefit to drivers, and that FCW events are relatively rare and consequently difficult to experience and adapt to. In any case, engagement in secondary tasks (measured using eye gaze behavior) seems to be the most commonly used method to assess warning-based BAs.

One study ([Muhrer, Reinprecht, & Vollrath, 2012](#)) examined an enhanced form of FCW that included emergency braking. There were concerns that autonomous braking would lead to increased involvement in secondary tasks among drivers who experienced FCW. Though, based on eye gaze behavior, no evidence of this was found. On the other hand, a post-FCW negative adaptation has been reported by [Wege, Will, and Victor \(2013\)](#) using a B-FCW system. A B-FCW system warns the driver of an impending collision if the situation exceeds the braking capacity of an ACC system. It lets the driver know that footbrake intervention will be necessary to avoid a forward collision. In scenarios involving distracted drivers, [Wege et al. \(2013\)](#) discovered that in the post-threat-recovery-period, after a B-FCW event, distracted drivers look away from the roadway toward the instrument cluster area where the warning was initiated, perhaps in an effort to comprehend the reason for the warning, or confirm that the threat is over. This could be undesirable if drivers need to continue monitoring the roadway in the aftermath of the event.

Combination Discrete Warning Systems

Adaptation effects have also been investigated in field studies of combination systems, including LDW systems in combination with other warning systems. In many cases, LDW is combined with forward collision warning (FCW), curve speed warning (CSW), and some form of side-collision warning such as a blind spot detection system. A field test of the road departure crash warning system (RDCW) specifically examined an LDW system in combination with CSW ([LeBlanc, Sayer, Winkler, Bogard, & Devonshire, 2007](#); [Le Blanc et al., 2006](#); [Wilson, Stearns, Koopman, & Yang, 2007](#)). Drivers were given vehicles to drive in their daily routines with the RDCW system initially disabled during the first week. This was followed by three additional weeks with the RDCW system unconditionally enabled. Behavioral changes observed with the system active included increased lane change signaling, reduced occurrences of the vehicle coming close to the lane edge. Reduced lateral acceleration along ramps was observed, although no effects were observed along other curved road segments. No change was observed in secondary task activity.

The integrated vehicle based safety system (IVBSS) field test examined a combination of discrete warning systems that included forward crash warning (FCW), lateral drift warning (LDW), lane change/merge warning (LCM), and curve speed warning (CSW) ([Sayer et al., 2011](#)). A total of 117 drivers were given instrumented vehicles to drive in their daily routine, first with the system turned off (a baseline period) for 12 days, followed by a treatment period with the system enabled for another 28 days. With the system active, fewer lane departures, shorter lane departure durations, increased turn signal use, marginal reduction in lane offset, and increased lane changes were observed. No changes were observed in drivers' engagement in secondary activities (e.g., eating, drinking, and cell phone use). Thus, in both field tests, generally positive BAs were observed.

A more recent field test of a similar integrated warning system, called the Continuous Support system ([Várhelyi, Kaufmann, & Persson, 2015](#)), advised drivers about speed limit exceedance, curve speed warning, forward collision, and warnings about vehicles in the blind zones. The on-road study involved two 45-minute drives along a prescribed route: once with the system turned on, and once with the system off. There were limited observed changes in driver behavior. For example, no change in speed or headway management was observed, although driver speed on curves appeared to be lower with the system active. Some negative outcomes were also observed—turn speeds through intersections were

higher, and drivers appeared to come dangerously close to the sides of the road more frequently with the system active.

Behavioral Adaptation Research Methods

Field Tests of ADAS Systems

Research methods using field tests to investigate BA phenomena follow a simple baseline-treatment paradigm to assess the effect of an ADAS that remains present in the vehicle, or baseline-treatment-baseline paradigm to evaluate behavioral effects that might continue after an ADAS is no longer present. The skeleton procedure is:

1. Baseline 1: Measure driving behavior likely to be affected by an ADAS before the ADAS is introduced. This is called a baseline and reflects driving before adaptation.
2. Treatment: Activate the ADAS in the vehicle; continue driving.
3. Measure: Compare baseline driving behavior to treatment behavior after a suitable delay to allow for behavior changes to stabilize. If there are differences, they are likely associated with ADAS adaptation.
4. Baseline 2: Deactivate the ADAS.
5. Measure: Compare the baseline 2 behavior to treatment behavior, after behavior has stabilized, to determine the amount of behavioral rebound. Compare baseline 2 to baseline 1 to determine more enduring effects.

Hidden below the surface in this simple portrayal of the research methodology are two key challenges. First, behavior likely to be influenced by an ADAS must be identified. To do this, researchers must consider which, out of myriad driver behaviors, are likely to be affected by the ADAS. Appropriate ways to measure this behavior must also be determined. For example, ACC studies have looked at measures of headway management quality, travel speed, or responsiveness to system failure (e.g., [Hoedemaeker & Brookhuis, 1998](#); Rudin-Brown & Parker, 2004). Other measures may relate to tactical behaviors (e.g., passing maneuver execution) and even strategic planning (e.g., route selection).

The second challenge is to determine what exactly is “*a suitable delay to allow for behavioral changes to stabilize*.” It is important that drivers receive sufficient exposure to the ADAS in operation, and this may vary from driver-to-driver and system-to-system. For example, because the base rate of an FCW trigger condition is lower than an LDW trigger condition (i.e., unsignaled lane crossings occur more frequently than near rear-end collisions)—drivers are likely to become more quickly acquainted with the operation of an LDW. ADASs designed to operate under particular conditions may vary from driver-to-driver in their frequency of use. For example, ACC is most often engaged on limited access roadways, since many require a minimum travel speed. Drivers who travel along local surface streets will likely be less familiar with ACC than drivers who commute daily on limited-access roadways. The targeted adaptive behavior of interest may also develop at varying rates. For example, control-related BAs (e.g., headway maintenance, lane position) are likely to develop sooner than strategic or tactical adaptations. It should also be noted

that practical limits of study time and cost often influence this choice. A comprehensive discussion of these and other challenges can be found in Manser, Creaser, and Boyle (2013).

Simulator Studies and Instrumented Vehicles

We also note that two main platforms have been used to investigate BA: driving simulators and instrumented vehicles (see Dotzauer, Berthon-Donk, Beggiato, Haupt, & Piccinini, 2013 for a comprehensive review). Each method has advantages and disadvantages. Simulator advantages include substantial control over the driving scenario, a safe environment for the driver, and time and money savings. Their disadvantages include occasionally questioned external validity, diminished real-world fidelity, simulator sickness, and perhaps alteration in driver motivation (i.e., they are aware they are safe). Instrumented vehicle studies fall into three basic categories: test-track studies, naturalistic driving studies (NDS), and field operational tests (FOT). In general, studies involving instrumented vehicles enjoy a greater degree of face validity (i.e., it's a real car on a real road) but are usually substantially more expensive undertakings than relatively short duration laboratory studies. Carsten, Kircher, and Jamson (2013) describe advantages and disadvantages of these “real world” methods. For example, they note that NDS studies lack baseline driving periods which may render them unsuitable for the study of BA. FOTs, on the other hand, usually involve an initial baseline period, before the technology is introduced, allowing for clearer comparisons between normal driving and ADAS-supported driving.

Automation and the Driver's Responsiveness

As discussed earlier, there is concern that when some of the driver's tasks become supported by partial automation, drivers may adapt in ways that could jeopardize their safety. A simple example is the automation of lateral control. When lateral control is automated, drivers show a greater inclination to engage in secondary tasks compared to when longitudinal control is automated such as with ACC (Carsten et al., 2012). This is worrisome since it suggests an eventual loss of SA. As multiple control tasks are automated, there is a growing concern that the driver will be significantly delayed in retaking control of the vehicle, should the need arise. To address this concern, new driver interface concepts have been suggested to help remediate this problem. One method, haptic shared control, never fully removes control of the vehicle from the driver. Instead, the driver continues to participate in the control activity along with the automation in a manner that maintains mutual awareness and interaction between the driver and the automation. Another method of maintaining driver engagement allows full control to transition to the vehicle, with the expectation that the driver assumes an engaged supervisory role. This is enforced by driver monitoring—primarily using gaze tracking measures. If the driver does not appear to be fully engaged in driving (i.e., looking toward the forward roadway), an alert is issued or an attempt is made to return control to the driver by withdrawing the automation support.

Haptic Shared Control

Haptic shared control is based on the *H-metaphor* idea in which the shared control between a horse and rider serves as a model of the driver's role in operating a highly automated vehicle (Flemisch et al. 2003). From this concept, the idea of haptic shared control between driver and vehicle was explored with respect to longitudinal control to determine its viability for car following through use of a haptic gas pedal (Hjalmdahl & Varhelyi, 2004; Kuge, Boer, Yamamura, Ward, & Manser, 2006; Mulder, Abbink, van Passen, & Mulder, 2011) and for lateral control through a haptic steering wheel (Abbink, Mulder, & Boer, 2012; Griffiths & Gillespie, 2004, 2005; Mulder, Abbink, & Boer, 2008, 2012). The idea of haptic shared control is that the driver 1) always remains in the direct manual control loop, 2) receives continuous haptic feedback about the automation functionality that can be easily overridden, and 3) allows the driver to respond to the road and road users through fast spinal reflexes (Abbink, Mulder, van der Helm, Mulder, & Boer, 2011).

Haptic shared control can be accomplished by force feedback alone or by manipulating both force feedback and stiffness feedback (Abbink & Mulder, 2009), thereby allowing smooth shifts in control authority between driver and automation (Abbink et al., 2011). By manipulating several design parameters (e.g., Petermeijer, Abbink, & de Winter, 2015), designers can balance benefits of automation (e.g., reduced effort, increased performance) to its drawbacks (e.g., driver-automation interaction issues like overreliance). Haptic shared control might allow for decreased negative BA—an initial study showed no evidence of BA in steering with shared control (Mars, Deroo, & Charron, 2014).

Haptic shared control inherently requires the driver's continued and active steering inputs, a key (and perhaps controversial) feature of this concept. Under certain circumstances, one might expect that highly automated driving could be possible, where hands could be taken

of the wheel until warned to resume control. The H-metaphor concept can be extended to include this as well, as Flemisch argued in later work ([Flemisch et al., 2012](#)), where he compared this to ‘securing the reins’ of the horse, leaving the rider only to observe. The smooth authority transitions offered by haptic shared control might be especially beneficial for automation handovers and driving with the variable reliability of automation.

Driver Monitoring

With advanced head pose and facial recognition, and remote detection of driver physiological state becoming more and more available, it is now becoming feasible to implement in-vehicle technologies that directly monitor the driver to distinguish when the driver is not fully engaged in driving. Continental Automotive has been piloting a system that analyses a driver’s head and eye movements for fatigue or distraction, flashing panels of LED arrays around the driver if he or she is not satisfactorily engaged (automotortechneik, 2013; Coxworth, 2013). Similarly, Volvo is also developing a driver-monitoring system called the Driver State Estimation system. Its intended use is to report to autonomous systems whether the driver is capable (or incapable) of taking over driver duties (Weiner, 2014), although it is unclear what the system does if the answer is no. If used as a prod to maintain driver engagement, issues will arise about the kind of action the automation will take to address perceived driver disengagement, the accuracy of this perception, and the frequency of the monitoring. For example, disengagement may be addressed by temporarily denying the driver access to entertainment or automation features. However, if detection of driver disengagement is flawed, these actions may be regarded with annoyance.

Behavioral Adaptation to ADAS: Summary

Overall, it seems clear that theories of BA are transitioning to a more cognitive-attentional theoretical perspective in which it is important to recognize that drivers apply some form of attentional control policy/process to allocate and reallocate visual/cognitive resources to activities that are important to the driver. Constructs such as mental workload are useful in identifying when the driver's resources are not overloaded and available to be redistributed to other tasks. This redistribution is, no doubt, driven by what the driver believes the level of ADAS capability actually is—that is, the driver's mental model of the ADAS functionality. Especially with short simulator-based or test-track exposures, drivers have relatively little experience with ADAS and they are generally poor at recognizing when an ADAS reaches a limit or malfunctions in an unanticipated way.

Drivers appear to either misperceive or oversimplify ADAS capabilities and do not appear to remember operational exceptions (even if told) unless they are given more direct experience of the exception ([Beggiato et al., 2015](#)). This suggests that drivers will require substantially more time to develop an accurate understanding, or mental model, of an ADAS function, especially when the conditions where ADAS limitations become apparent are also very uncommon. Drivers are then left to discover these limitations by happenstance, and may never acquire a full understanding of what an ADAS is capable of doing as these system's complexity increases. Longer-term studies of driver interaction with ADAS technologies seem warranted. Initially, this might help insure that the driver develops a reasonably accurate mental model of the ADAS capability. After stabilization of this mental model, continued observations may be warranted to investigate how driving behavior changes on the tactical and strategic levels. Recent work has begun to focus on longer observation periods to examine the evolution of trust and mental models ([Beggiato & Krems, 2013](#)) as well as the involvement of experienced users of the technology ([Bianchi Piccinini et al., 2015](#)). The need for longer periods of time over which to examine BA is similarly echoed in the recommendations from the AAAFTS Workshop on Behavioral Adaptation (Appendices A & B).

Owner's manual accounts of ADAS exceptions do not appear to be adequate sources of information about the performance of these complex assistance systems—drivers often do not read the owner's manual. Such exceptions are unlikely to become easily integrated into the driver's mental model of the ADAS. There is evidence that drivers often do not accurately remember this information even after receiving some direct training (AAAFTS, 2008; [Beggiato & Krems, 2013](#); [Dickie & Boyle, 2009](#); [Jenness et al., 2008](#)). If a driver's mental model is flawed, it will likely be reflected in a drivers' use of an ADAS. Different flaws are likely to be manifest in different kinds of BA. Thus, a BA to ACC may result in a delay in braking because the driver's mental model of ACC braking authority is based on the driver's knowledge of their own braking abilities. Similarly, a BA to active steering may result in lane departures on tightly curved roads, because the driver's mental model of steering control is based on what the driver already knows about his or her own steering ability. The need to recognize that BA is likely to differ across ADAS technologies is also echoed in the AAAFTS Workshop outcomes.

A driver's development of a flawed mental model can happen in many ways. In some cases, the driver has no information about the performance envelope of the system. For example,

braking and steering authority may be unknown. In other cases, the ADAS behaves in an unexpected fashion that differs from what might be considered a more natural model. For example, drivers may be surprised by a lane keeping system's blindness to objects in the middle of the road, especially when the system seems to be able to "see" lane markings so well. Encouraging the development of more accurate mental models might be accomplished in several ways:

1. ADAS technologies might be designed to operate in a manner that better matches a driver's likely mental model of the system. This may require making ADAS technologies function more like people would in the same situation. Alternatively, it may help to reduce the number of 'exception' conditions where the ADAS function is altered, making the system more predictable (Goodrich & Boer, 2003). Unless the exceptions conditions are minimized (or eliminated) it seems likely that drivers' mental models will deviate from the ADAS function.
2. Provide more explicit information to the driver about the ADAS limitations. A visual interface example of this is described in Seppelt and Lee (2007) where drivers were given continuous information about the state of an ACC system with respect to brake exceedances and sensor failures. The success of this approach may be limited if the amount of information required to understand system function becomes too large. A viable alternative to providing information about ADAS limitation and functionality is through the haptic channel (Mulder et al., 2012).
3. Provide explicit training about ADAS exception conditions, perhaps providing drivers with periodic refresher training about ADAS function or specific on-road test experience (Bianchi Piccinini et al., 2015). Specialized training might also target drivers who exhibit traits that make them more susceptible to BA in response to ADAS (Rudin-Brown & Parker, 2004).

The first two approaches are most appropriate during ADAS development, before a product is released to the marketplace. The third approach attempts to address the situation through training after an ADAS is released to the consumer. It also represents another research priority suggested in the AAAFTS Workshop.

Besides mental model, the issue of driver trust is also an important factor related to BA. A driver's trust in a particular ADAS technology is actually trust in what the driver believes the ADAS does—namely, the driver's own mental model. That drivers will quickly develop some trust in their mental models seems likely, once the ADAS is used a few times successfully and without incident, although there may be significant personality factors that influence the degree of this trust. Because drivers are generally aware that automobile manufacturers have no interest in providing technology that is faulty or dangerous to customers, it seems likely that most will be initially inclined to trust the technology. If the ADAS initially seems to work, it is likely that drivers may quickly become confident that it *does* work. Even if an individual driver is an *internal* on the locus-of-control scale (Montag & Comrey, 1987; Rudin-Brown & Parker, 2004), initial successful operation of an ADAS is likely to create sufficient confidence or trust in the ADAS that the driver will rely on it to some degree. How that trust is maintained, particularly when confronted by evidence of malfunction, seems to be related to individual personality factors (Rudin-Brown & Noy, 2002).

How a driver distributes mental resources to the driving task is also likely influenced by the driver's mental model. If the driver believes that the ADAS has competently taken on tasks he or she normally performs, it seems natural to expect that the driver also considers responsibility to be delegated (as it would to another person). However, most ADAS automation support requires the driver to actually assume a supervisory role. Dr. John D. Lee characterized this condition as *on-the-loop*—an intermediate state that requires an indeterminate amount of monitoring or intervention. Regardless of the expectation that driver supervision of the automation is mandatory, drivers will likely experience a reduction in workload with automation. This frees perceptual/cognitive resources for reallocation. As discussed earlier, the driver's reallocation strategy may be influenced by what he or she thinks the next task priority should be. If advised that pedestrians may need to be detected or that SA queries may follow, the result will be an apparently elevated level of SA. If offered crossword puzzles, access to DVDs, or other non-driving activities, SA will be diminished as attention is reallocated to these non-driving tasks. Change in SA is a consequence of reduced mental workload triggered by a driver's confidence in their understanding, or mental model, of the ADAS.

It seems the best way to ensure that drivers are not “caught” over-trusting a mental model in this manner is to provide supplemental real-world experience of ADAS limitation conditions on a real roadway in a real car. If a driver is expected to remember that an ACC system is blind to stationary objects, the driver should be given an opportunity to approach one in a real car with ACC active, and witness this limitation directly. Thus, [Beggiato et al. \(2015\)](#) suggest that “...non-experienced limitations show a tendency to become less salient and drop out of the mental model network if they are not activated by experience.” They recommend that periodic reminders may be helpful to ensure that drivers' awareness of these exceptions is properly maintained. Such supplemental training on a test track or in a simulator may be the best way to encourage drivers to develop more accurate mental models of the increasingly complicated ADAS and that they remain mindful of their limits.

Appendix A:

Workshop Notes on Behavioral Adaptation to Advanced Vehicle Technology

Introduction

On August 13, 2015 a workshop was held at the AAA Foundation for Traffic Safety Headquarters in Washington, D.C. The overall focus of the meeting was to address issues related to how drivers might be disposed to adapt to advanced driver assistance system (ADAS) technologies in a fashion that might compromise the anticipated safety benefits of the new technology. The workshop was used to gather expert views from academia, government, and industry sources about theories of behavioral adaptation (BA), the empirical evidence and methods used to measure driver adaptation, the effects of automation on driver engagement, and potential interface design strategies used to support and maintain driver engagement. These views and opinions presented at this workshop were sought to help inform and guide a literature review planned for the initial phase of this project.

The workshop was conducted in two sessions—a morning session in which five invited experts made 30-minute presentations on topics related to their expertise and behavioral adaptation, followed by an afternoon panel discussion addressing knowledge gaps, research needs, and options for reducing undesirable driver adaptation. The morning presentations were as follows:

1. Significance and Boundaries of Behavioral Adaptation
Dr. Karel Brookhuis, Professor of Traffic Psychology, University of Groningen
2. Driver Behavioral Adaptation to ADAS and the Potential Benefits of Adaptive Design
Dr. Christina M. Rudin-Brown, Human Factors North, Inc.
3. Modeling the Effect of Drivers' Adaptive Behavior on System Safety
Dr. Linda Ng Boyle, University of Washington
4. Vehicle Technology, Trust, and Driver Engagement
Dr. John D. Lee, University of Wisconsin
5. How to Maintain Driver Engagement—Human Automation Interface Design Using Haptic Shared Control
Dr. David Abbink, Director Delft Haptics Lab, Delft University of Technology

This report will first provide brief summaries of each speaker's presentation, followed by a summary of the key discussion points addressed in each of the afternoon panel discussions.

Morning Presentation Summaries

Significance and Boundaries of Behavioral Adaptation (Dr. Karel Brookhuis)

In this presentation, Dr. Brookhuis reviewed some of the early work on behavioral adaptation, discussing Leonard Evans' (1985) attempt to describe driver adaptation effects in terms of their influence on projected benefit, for instance from an engineering model. In some early theoretical frameworks, adaptation could offset the benefit completely, such as

suggested by Risk Homeostasis Theory (Wilde, 1982); in some models, it could diminish the benefit such that some benefit (albeit less) results; in others, it could leave the benefit unaffected; or it could enhance the benefit. Dr. Brookhuis noted that a major examination of the issue of behavioral adaptation in transportation occurred in 1990 with the release of the OECD report, *Behavioural adaptations to changes in the road transport system* (OECD, 1990). While many theories of driver behavioral adaptation have been proposed, most suffer from two critical flaws—there were serious limitations on the measurement of, mostly only a few, model parameters, and few models were actually falsifiable. The presentation went on to distinguish between adaptation that is driven by utility-based theories that suggest some form of optimization process occurs (e.g., assuming Homo Economicus) versus theories of adaptation that are driven by satisficing processes directed toward achieving an acceptable (but perhaps not optimal) goal to avoid excessive risk. This was followed by a discussion of the rise of “attitude” theories rooted in the *Theory of Planned Behavior* (Fishbein & Ajzen, 1975) which link attitude, subjective norms, and perceived behavioral control in shaping behavior. Such theories include behavioral adaptation theories proposed by Fuller, such as the Threat/Risk Avoidance Theory, the Task Difficulty Homeostasis (TDH) (Fuller, 2005), and the Risk Allostasis Theory (RAT) (Fuller, 2008) including the Task Capability Interface (TCI) (Fuller, 2000). In these theories, drivers strike a balance between perceived task demands and their perceived driving capability to achieve an acceptable level of risk. Some of the issues addressed within these frameworks are whether, for example, the evaluation of the acceptable or perhaps more comfortable level of risk is performed continuously and whether drivers respond discontinuously, as in crossing risk thresholds, versus behaving in a more graded fashion. In this regard, Dr. Brookhuis noted an earlier theory called the zero-risk theory (Näätänen & Summala, 1974) and also suggested similar ideas of risk thresholds that trigger when drivers reach a task difficulty limit. One implication of threshold theories is that nonlinearities would occur in driver behavior, for example, in how drivers manage their following distance to a lead vehicle. Dr. Brookhuis also cited more recent discussions on this topic (Fuller, 2011) and noted Dick DeWaard’s dissertation work on driver workload and performance (de Waard, 1996).

Dr. Brookhuis made a few observations about recent developments with regard to questions about driver behavioral adaptation, noting that there had been many recent efforts to influence driver behavior in Europe as a byproduct of recent field operational tests involving new ADAS technologies. In particular, work on Intelligent Speed Assist (ISA), while effective in influencing driver speed, did not seem to be readily embraced by governments or car manufacturers. Incentives or rewards for good driving is another approach believed to have some positive potential to influence driver behavior. Dr. Brookhuis also noted that drivers may not correctly attribute increases in risk appropriately, citing an experimental study in which drivers appeared to have low awareness that narrower road widths led to lower driving speeds. Drivers instead reported nonexistent differences in road traffic or curved road sections as the reason for the increased risk (Lewis-Evans & Charlton, 2006). These results, as well as some (USA) accident data on the effects of LDWA (lane departure warning assistance), support the suggestion that drivers’ perception of risk may at times be preconscious—evoking an emotional response without a conscious cognitive rationale.

Finally, based on experimental research Dr. Brookhuis raised some serious questions about the “stepping stone” approach of automating motor-vehicles characterized by the SAE.

Human beings, notoriously poor in monitoring task environments, are most probably not able to resume vehicle control in time, should a (semi) automatic in-car system fails.

Driver Behavioral Adaptation to ADAS and the Potential Benefits of Adaptive Design (Dr. Christina “Missy” Rudin-Brown)

In this presentation, Dr. Rudin-Brown focused on the beneficial role that adaptive interface design might have for supporting demographic and inter-cultural variation among drivers, citing earlier work on adaptive interfaces (Jameson, 2009). Dr. Rudin-Brown provided a review of some ADAS, including navigation support systems, vision enhancement systems (Bossi, Ward, Parkes, & Howarth, 1997), backing aids (Mazzae, 2010; Rudin-Brown, Burns, Hagen, Roberts, & Scipione, 2012), and adaptive cruise control (ACC) (Rudin-Brown & Parker, 2004). Dr. Rudin-Brown presented research showing that use of audio- and video-based backing support achieved more accurate reversing performance than when backing was unaided, but that drivers’ reliance on mirrors might decrease and their execution of backing maneuvers may be faster than when such aids are unavailable. Rudin-Brown & Noy (2002) put forth a qualitative model of behavioral adaptation that was later enhanced to include driver-level factors such as gender, culture, education, driver state, and age (Rudin-Brown, 2010). Other factors covered by the model include the influence of personality factors such as *locus-of-control* and *sensation-seeking*, as well as driver trust in the technology. Trust in automation is a central component of the model and is influenced by personality factors which can in turn influence the driver’s mental model of the technology. In a study of behavioral adaptation to adaptive cruise control (ACC) (Rudin-Brown & Parker, 2004), it was noted that use of ACC led to improved performance on a visual search secondary task, though at the cost of less safe braking. The predictions of this behavioral adaptation model were tested using simulator and test track studies, specifically to investigate the ability of lane departure warnings to induce behavioral adaptation in drivers (Rudin-Brown & Noy, 2002). While the presence of reliable warnings did improve lane-keeping performance, drivers also reported high levels of trust in both reliable and *unreliable* systems. Drivers having external locus-of-control and low sensation seeking characteristics were more likely to report trusting the system, regardless of accuracy. Dr. Rudin-Brown also noted that some forms of ADAS such as electronic stability control (ESC) may operate with little driver notice—many drivers may not realize that their vehicle is equipped with it—and so ESC and other similarly inconspicuous technologies would be less likely to be associated with behavioral adaptation than technologies that are more apparent to the driver. There have been limited reports of long-term behavioral changes with ESC, however it was also noted that some drivers have reported an increase in the feeling of added safety and the perception that they could drive an ESC-equipped vehicle faster than one that was not so equipped (Rudin-Brown, Jenkins, Whitehead, & Burns, 2009). Collectively, these results suggest use of caution is warranted when evaluating ADAS benefits since drivers can vary significantly in their inclination to trust unreliable or faulty devices.

Questions following this presentation raised concerns about how a priori individual differences among drivers might be managed by ADAS technologies. Here it was suggested that adaptive interfaces could be useful in accommodating these differences. Other comments from attendees noted that most of the studies looked at individual functions, but not entire systems; that car manufacturers wished to provide features that “do no harm” and are willing to try new things as long as there is some assurance that no unintended

adaptive consequences occur. It was suggested that the best way to anticipate such consequences would require more comprehensive statistical analyses of real-world crash data for those vehicles already equipped with more common forms of ADAS such as, for example, LDW systems, ACC, backing aids, and blind spot warning systems.

Modeling the Effect of Drivers' Adaptive Behavior on System Safety (Dr. Linda Ng Boyle)

Dr. Boyle began her presentation by noting that understanding the safety consequences of behavioral adaptation requires consideration of many conditions and variables that affect a driver's behavior. Some of these factors include environmental factors, experience and frequency of use, and individual driver differences. Modeling these activities should leverage modern data management and analysis techniques that enable researchers to account for spatial and temporal differences. In some respect, this is complementary to Dr. Rudin-Brown's qualitative model in that it introduces integrates the quantitative aspect. One example of this is observed using data from an UMTRI field operational test of ACC ([Xiong & Boyle, 2012](#)).

Dr. Boyle then turned her attention to ADAS-type technologies that are migrating onto smartphones such as the app, *iOnRoad*. One implication of this development is that drivers are able to bring in their own driving support technologies, switching among nomadic-based and OEM systems depending on their preferences. This would add another level of complexity to behavioral adaptation whereby drivers switch among multiple ADAS implementations. On a more positive note, Dr. Boyle also noted that such nomadic technologies also provide for the crowdsourcing of substantial amounts of transportation data that had not been previously available.

Among the comments posed following the presentation, one attendee asked whether driver models are over-specified, and whether there might be an optimum level at which to model. Responses to this comment were that models should be appropriately specific to address the research questions while at the same time, avoiding model saturation (e.g., 40 variables to explain performance of 40 subjects). Others noted that whenever possible, it was best to keep models simple.

Presenters were collectively asked to name key issues related to behavioral adaptation. Reliability of the system was identified as a key factor affecting behavioral adaptation. At the same time, it was pointed out that all systems are somewhat unreliable and the perception of reliability influences a driver's willingness to trust a system, and would likely impede trust. Additional issues were not identified.

Another attendee asked whether drivers should be provided with the ability to customize their on-board assistance systems. Presenters suggested that systems should be able to automatically adapt to the driver (e.g., changing the interface to accommodate poor eyesight), but that there could be challenges to design such a system when both the driver and the system are adapting to each other. A related issue centers on using driver-specific vehicle settings when a different drivers share the vehicle.

Vehicle technology, Trust, and Driver Engagement (Dr. John D. Lee)

For this presentation, Dr. Lee began by describing how automation contributed to the Exxon Valdez disaster. While popular media accounts favored the “drunk captain” explanation, one of the most significant contributions to the disaster was the failure of crew members to recognize that their manual steering efforts did not disengage the automated navigation system. Lee noted that for many car companies, the objective is to sell excitement, not safety. Thus, automation is more often conceived of as a comfort feature rather than a safety feature. Dr. Lee described the recent levels-of-automation framework as having some limitations in describing the real tasks drivers face when dealing with automation. The fine print in the owner’s manual does not guarantee that operators understand how responsibility is distributed under automation. One factor that contributes to delay in developing an understanding of automated systems is the range of time scales under which the automation control loop operates—there are time constants for intervention, frequency of interactions, and frequency of system failure. These time scales contribute to a driver’s perception of system reliability and eventual trust in the system. Dr. Lee also characterized the position of the human within the vehicle control loop in three distinct ways: *in-the-loop*—with the driver in full control; *out-of-the-loop*—with automation in full control; and *on-the-loop*—a state in which the control loop requires the human to *monitor* and *intervene* in the control task when necessary. It is preferred that automation permit the human to be fully *out-of-the-loop*—intermediate states of involvement are fraught with opportunity for error, since the level of monitoring required by the automation is difficult for a human to easily determine.

Dr. Lee also suggested a revision to his earlier work on trust ([Lee & See, 2004](#)) which emphasized perception as input that guides action. He suggested that trust affects the information people seek about automation, and that trust depends on active exploration and interaction with automation. Trust calibration also depends on driver-vehicle interfaces that explicitly reveal operating modes that could otherwise remain hidden to drivers. One example of this is the contrast between key-based starting and pushbutton start of hybrid vehicles; unlike the key-based start, pushbutton operation can hide the vehicle’s on or off state, because it is no longer signaled explicitly by a key physically placed in the ignition. Other considerations mentioned related to metaphors and roles of the human in the automation context—for example, a distinction might be made between driver, passenger, or chauffeur.

How to maintain driver engagement – human-automation interface design using haptic shared control (Dr. David Abbink)

Dr. Abbink began his presentation by pointing out that there will likely be problems with automated cars, because most such engineering endeavors have limitations, and reliance on the driver as a backup is not likely to be a very successful solution. He suggested that use of haptic shared control could help. In haptic shared control, the driver and autopilot are physically coupled through controls, thereby offering an interface that allows mutual awareness and interaction. The driver maintains an understanding of the car’s mode, abilities, limitations, and degree of engagement and vice versa. Dr. Abbink referenced the H-metaphor ([Flemisch et al, 2003](#)), whereby a horse and rider interact such that a balance of control is mediated through the physical contact between the two parties. An initial

application of a haptic-control mechanism was developed as a product for Nissan in 2008 to assist with maintaining a safe distance to a lead vehicle through a haptic gas pedal (Abbink et al., 2011). A version of this product is called, Distance Control Assist (DCA), and features smooth back-pressure on the accelerator pedal related to decreases in separation to a lead vehicle. The driver senses this back-pressure and takes action to correct his following distance to the lead vehicle. A second application of haptic shared control has focused on support for lateral control that employs both force feedback that shifts the neutral point of the steering wheel based on a trajectory from a look-ahead controller, as well as stiffness feedback that increases the 'level of haptic authority' (Abbink et al., 2013). Depending on the design, haptic shared control has part of the benefits of automation such as increased performance and reduced effort (Mulder et al., 2012), but also potentially suffers from part of the downsides (de Winter & Dodou, 2011). Dr. Abbink presented research he and his colleagues conducted to examine the effect of various forms of haptic steering feedback on execution of evasive maneuvers (Penna, van Paassen, Abbink, Mulder, & Mulder, 2010). In more recent work, he has also looked at the cost of haptic shared control aftereffects under continuous and bandwidth haptic control (Petermeijer et al., 2015), finding both costs and benefits in each approach.

In concluding, Dr. Abbink suggested that the effects of haptic shared control keeps drivers comfortably engaged in their driving tasks, with perhaps light or mixed results on behavioral adaptation. For example, drivers do not appear to speed more when their control task requires less effort.

Appendix B: Panel Discussions

Knowledge gaps and research needs/questions

This discussion focused on research priorities and identified a few key themes. One theme that emerged was that ADAS technologies vary in the degree to which they assist or automate the driver's task; and that ADAS themselves are evolving quickly, making it difficult to satisfactorily research each new system's effects on the driver population. One suggestion to address this rapid change was that automobile manufacturers might share early test results of different ADAS technologies with NHTSA. In this regard, a panel member noted that while automobile companies undoubtedly collected data, they are generally disinclined to share data with others for competitive reasons. However, it was also noted that the Insurance Institute for Highway Safety (IIHS) had evaluated many of the ADAS technologies and more or less concluded that the systems are generally working—that is, insurance claims associated with the vehicles equipped with these technologies seem to be lower. Another suggestion was to look to other industries that have introduced substantial amounts of automation (such as aviation) for some research guidance.

Another issue identified in the discussion was that ADAS systems vary in the degree to which they make their presence felt to the driver. For example, a lane departure warning (LDW) system can be safely “experimented” with by drivers to learn the system's competence without endangering the driver. On the other hand, drivers cannot as easily experiment with a forward collision warning (FCW) system, because that would involve closing in on a forward vehicle at a dangerous rate of speed. The driver's exposure to the operation of each of these warning systems will therefore vary substantially. One implication of this variation in exposure is that the function of each ADAS technology may be learned and understood by drivers at different rates, which will vary given the kind of driving environments to which individual drivers are exposed. If a driver's understanding of an ADAS influences behavioral adaptation, then behavioral adaptation will develop at different rates for different ADAS. Behavioral adaptation to ADAS technology cannot be thought of as a single generic adaptation effect (as suggested by earlier risk models of behavioral adaptation). Instead, behavioral adaptation must be studied as a set of responses to specific ADAS technologies.

Panelists also pointed out that behavioral adaptation to ADAS technologies might play out over very different time scales depending on whether they affected driving behavior that was skill, rule, or knowledge-based ([Rasmussen, 1983](#)), or alternatively the control, tactical, or strategic driving levels ([Michon, 1985](#)). One implication is that the adaptation at higher behavioral levels would likely take longer to develop. One example of strategic change that might be observed is that as older drivers come to trust an ADAS system, they may increase their willingness to drive at all hours, under conditions of higher risk (e.g., during hours of darkness).

Another important theme that emerged among the panelists was a general concern about the effect of growing complexity of control automation, a feature of many ADAS technologies. It was anecdotally noted that in aviation, when systems become too complex, pilots abandon efforts to understand the system and revert to a rote push-button strategy.

(In this context, it is possible that what was meant by “complexity” was the pilot’s lack of clear understanding about what or why the automation was performing a task.) Some of this problem was associated with less-than-transparent modes of operation. In the car, it was suggested that given the limited degree of training and sophistication of the average driver, only one operating mode should be allowed. When more than one operating mode is permitted, there is a greater opportunity for confusion. For example, ACC systems may operate differently in low speed versus high speed conditions. The mode issue was extended to the issue of customization of vehicle settings to accommodate the individual driver and the problem of sharing vehicles among different sets of drivers. The key concern is that heterogeneity of function within (and across) vehicles could easily lead to confusion.

Taking up the issue of system complexity, the discussion then shifted to how individual drivers might cope with complexity. Concern was expressed that older drivers had particular difficulty understanding the complexity of new technologies. One concern raised was that current level of training may be limited to absorbing details buried in owner’s manuals, which most participants believed are seldom read by drivers.

The panel and audience seemed to arrive at a few final conclusions:

- Real-world testing of specific ADAS technologies has the best chance of revealing behavioral adaptation effects when compared to other approaches such as simulator and test track experiments.
- There is a need to examine behavioral adaptation over longer periods of time (e.g., months rather than days). Behavioral adaptation can change over time in response to changes in the driver’s understanding of ADAS operation.
- Priority should be given to identifying changes in behavior that are undesirable (i.e., adaptation that undermines driver safety), beyond any specific driver-interface issues.

Promising methods to address unwanted driver adaptation

At the start of this panel discussion, initial points were made that not all behavioral adaptations necessarily result in compromises to safety. It was pointed out, for example, that long term exposure to FCW resulted in a decline in the frequency of warnings and an increase in following distance to a lead vehicle. It was also suggested that some form of reward might be considered for such positive adaptation effects. The idea of rewarding drivers for good behavior was echoed later in the discussion.

Panelists raised the issue that driver understanding of the functionality of ADAS is important. If such understanding is poor, drivers’ expectations about how the ADAS will intervene may be unreasonably high. It was also suggested that any misunderstandings about ADAS function need to be quickly corrected. Some suggested that dealers provide car buyers with a more formal review of the system operations. By doing this, dealers may both ensure that drivers do not mistakenly report system faults and the ADAS is used correctly.

Suggested ways to address unwanted behavioral adaptation were enumerated as follows:

- Provide reinforcement. Reward drivers for good driving behavior, and give drivers demerits for poor driving behavior. This would perhaps raise a driver's awareness of negative behavioral adaptations that might otherwise escape awareness.
- Monitor drivers. Systems that monitor drivers are already being marketed to detect drivers falling asleep at the wheel. The same head-pose evaluation can be used to determine if the driver is looking at the roadway or engaged in a non-driving secondary task.
- Do not fully release control to the driver. This suggestion rejects the notion that any system function should be fully automated. It endorses Dr. Abbink's approach in which control is shared and never fully delegated to the automation. It sharply contrasts with the automobile manufacturers' inclination to shift responsibility between the driver and automation such that one or the other is mostly in control, with the driver always retaining full responsibility.

Some of the discussion veered out of scope, considering macro-level changes in traffic flow management that might be affected by ADAS technologies. The goal to examine near-term effects of L2 and L3 ADAS automation was brought up at this point. How best to look at these issues was discussed.

The problem of individual differences was also raised in this panel discussion—specifically, how much effort should be expended looking at driver outliers? For example, differently motivated drivers may not be “interested in driving” and remain disengaged even when there are no ADAS technologies involved. The ubiquity of mobile phones was raised as an issue that increased driver incentive to engage in secondary tasks while driving. The combination of ADAS automation and mobile phones seemed to raise additional concerns about driver disengagement.

A final list of research priorities was developed by the end of the meeting. The priorities included:

- Conduct real-world longer-term evaluations of the relationship between ADAS technologies and crash risk. Simulator and test track evaluations are usually limited in their ability to capture temporal changes and changes based on varying roadway characteristics. This limits the tools' capability to identify significant changes in behavior as observed in real driving.
- Recognize that there are differences among ADAS technologies. Behavioral adaptation effects are likely to be highly variable across ADAS technologies.
- Examine and evaluate options for informing drivers about ADAS operations on their vehicles, with emphasis on ADAS limitations.
- Place highest research priority on operational (e. g., headway management, control of lane position) and tactical (e.g., maneuvering to pass, gap acceptance) forms of behavioral adaptation. Most strategic-level adaptations (e.g., deciding travel routes) are less likely to be critical for safety.
- Distinguish between different driver personality types. Identify people more likely to exhibit behavioral adaptation from those who are less likely.

- Explore reliability issues related to ADAS technologies—how do people adapt to imperfect technology?
- Consider examining the macro-level adaptation (change to the entire system) to the micro-level adaptation (change to the individual).
- Examine misuse, abuse, and disuse issues with ADAS technologies, including training and design to prevent misuse. Parasuraman and Riley (1997) describe automation misuse as monitoring failures and overreliance. Automation abuse is described as the inappropriate application of automation in a manner that disrupts the driver's normal task. Disuse occurs when a driver elects to ignore the automation or deactivate it.

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