Fall 2009

Supporting operator reliance on automation through continuous feedback

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SUPPORTING OPERATOR RELIANCE ON AUTOMATION THROUGH CONTINUOUS FEEDBACK

by

Bobbie Danielle Seppelt

An Abstract

Of a thesis submitted in partial fulfillment
of the requirements for the Doctor of
Philosophy degree in Industrial Engineering
in the Graduate College of
The University of Iowa

December 2009

Thesis Supervisor: Associate Professor John D. Lee

ABSTRACT

In driving, multiple variables in automated systems such as adaptive cruise control (ACC) and active steering, and in the environment dynamically change and interact. This complexity makes it difficult for operators to track the activities and responses of automation. The inability of operators to monitor and understand automation's behavior contributes to inappropriate reliance, i.e. when an operator uses automation that performs poorly or fails to use automation that is superior to manual control. The decision to use or not use automation is one of the most important an operator can make, particularly in time-critical or emergency situations, therefore it is essential that an operator is calibrated in their automation use. An operator's decision to rely on automation depends on trust. System feedback provided to the operator is one means to calibrate trust in automation in that the type of feedback may differentially affect trust. The goal of this research is to help operators manage imperfect automation in real-time and to promote calibrated trust and reliance. A continuous information display that provides information on system behavior relative to its operating context is one means to promote such calibration. Three specific aims are pursued to test the central hypothesis of this dissertation that continuous feedback on the state and behavior of the automation informs operators of the evolving relationship between system performance and operating limits, therefore promoting accurate mental models and calibrated trust. The first aim applies a quantitative model to define the effect of understanding on driver-ACC interaction failures and to predict driver response to feedback. The second aim presents a systematic approach to define the feedback needed to support appropriate reliance in a demanding multi-task domain such as driving. The third aim assesses the costs and benefits of presenting drivers with continuous visual and auditory feedback. Together these aims indicate that continuous feedback on automation's behavior is a viable means to promote calibrated trust and reliance. The contribution of this dissertation is in providing purpose, process, and performance information to operators through a continuous, concurrent information display that indicates how the given situation interacts with the characteristics of the automation to affect its capability.

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CERTIFICATE OF APPROVAL

PH.D. THESIS

This is to certify that the Ph.D. thesis of

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has been approved by the Examining Committee
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To Jeremy, Oliver, and Hazel

ACKNOWLEDGMENTS

I would like to thank my advisor, John D. Lee, for his continued wisdom and guidance, and for his exemplified model of studied, integrated, thought-provoking research. To my cognitive systems laboratory (CSL) members, I thank you for your friendship, advice, and collaborative efforts. I learned volumes from each of you in our many discussions and interactions. I look forward to our future collaborations and continued friendships. And to my family, this dissertation is as much yours as it is mine: thank you for your unwavering support and love. Together, through God's grace, we moved a mountain (Matthew 17: 20).

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CHAPTER I. INTRODUCTION

Automation—as intended in its design—promises increased efficiency, accuracy, and control. In practice, however, people tend to misunderstand automation and to rely on it inappropriately, compromising safety and performance. Identifying how to support people so they can capitalize on automation is a fundamental challenge with broad implications.

In driving, as in other domains such as air traffic control, aviation, advanced manufacturing, and teleoperations, multiple variables in the automated system and in the environment dynamically change and interact. This complexity often makes it difficult for operators to understand the behavior of automation. Automation also tends to induce a shift from active engagement in a task to a passive role of monitoring, removing operators from directly interacting with the system and at times physically and mentally isolating operators from the activities of the automated system and its controls. This isolation further diminishes operators' understanding of how the automation and environment interact, which is needed to ensure appropriate use of automation (Sarter, Woods, & Billings, 1997).

Operator understanding of automation's behavior can be defined in terms of explicit understanding (i.e., mental models) and implicit understanding (i.e., trust)—cognitive mechanisms that guide decision-making under uncertainty (Kahneman & Frederick, 2002; Stanovich & West, 2002). These two types of understanding operate in parallel, influencing operator expectations and guiding the use of automation. Trust is a form of implicit understanding that guides operators' expectations when system complexity and situational uncertainty make complete understanding of the automation impractical (Lee & See, 2004). Appropriate trust—trust that corresponds to the capacity of the automation—is particularly important when managing complex, imperfect automation. Trust in automation develops according to the information available; its attributions are dependent on the degree to which the purpose of the automation, its underlying mechanisms, and the performance of the automation are apparent to the operator. Explicit understanding is an operator's knowledge of the functional structure of the automated system, i.e., mental model (Rouse and Morris, 1986). An operator's expectations of system behavior are guided by the completeness and correctness of this mental model, which allows operators to predict the automation's behavior (Sarter et al., 1997).

Poor explicit and implicit understanding of automation contribute to inappropriate reliance (Parasuraman & Riley, 1997). Misuse and disuse represent two important types of inappropriate reliance. Misuse refers to instances when operators use automation that performs poorly or fail to monitor it effectively. Disuse refers to instances when operators neglect or underutilize the automation, turning off or ignoring automated alarms or safety systems (Parasuraman & Riley, 1997). The decision to use or not use automation has profound consequences for system performance (Endsley & Kaber, 1999; Stanton & Marsden, 1996), particularly in time-critical or emergency situations, therefore it is essential that operators rely on automation appropriately.

In complex, dynamic domains such as driving, the context and its interplay with an automated system factor into the definition of appropriate reliance. Figure 1 depicts a timeline of key events that occur during use of automation as it interacts with its operating environment. The dynamic, interacting variables in the automation and environment often cause changes of condition that make reliance on the automation inappropriate because it is prone to fail. A precipitating event is one that induces such a failure. Use of the automation following a precipitating event constitutes misuse. Prior to any change in condition, however, it is appropriate to use the automation and not doing so is disuse.

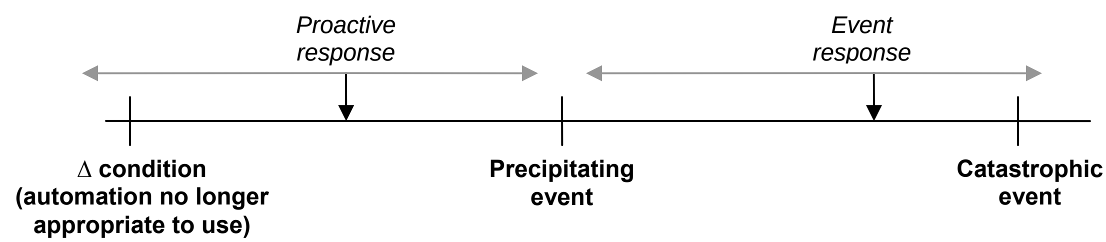

Figure 1. Timeline denoting key events that occur during use of imperfect automation as it interacts with its operating environment. The horizontal arrows above the timeline indicate time periods during which an operator is likely to resume manual control; turning automation off prior to a precipitating event represents a proactive response while turning it off following this event represents an event response.

Understanding influences operator response to imperfect automation. An operator that turns the automation off prior to a precipitating event in anticipation of a failure—a proactive response (see Figure 1)—demonstrates an adequate level of understanding of the automation. An operator that turns the automation off following a precipitating event in reaction to the event—an event response—demonstrates poor understanding; delayed long enough, such an ill-timed response will result in a catastrophic event. A calibrated response would occur at the change in condition. And while a proactive response indicates improved understanding as compared to an event response, both represent breakdowns in human-automation interaction (i.e., interaction failures).

To respond appropriately to imperfect automation, operators need information that informs of the status and behavior of the automaton and of the process the automation controls. Essentially, knowing about the inputs to the automation, the internal process and state transitions, and the outcomes permits operators to predict the automation's behavior which in turn allows them to anticipate what parameters and conditions to monitor to prime their response (Gopher, 1991; Sarter et al., 1997). Adequate feedback on the state and behavior of automated systems is important to promoting appropriate explicit and implicit understanding for guiding attention and supporting effective responses (Norman, 1990; Sarter et al., 1997).

Researchers have explored various types of feedback to inform operators about automation to promote appropriate reliance (Bagheri & Jamieson, 2004; Bisantz & Seong, 2001; Cohen, 2000; Dzindolet, Peterson, Pomranky, Pierce, & Beck, 2003; Masalonis, 2000; Moray, Inagaki, & Itoh, 2000; Wickens, Gempler, & Morphew, 2000). One approach to informing operators is to alert them to unexpected events (designed so they can be recognized and appropriately handled), i.e., warnings. Despite desired attention-capturing effects, the literature points to the fact that warnings, as used during driving, do not keep drivers properly informed of the behavior of in-vehicle automated systems nor adequately aware of the driving situation (Brown, Lee, & McGehee, 2000; Walker, Stanton, & Young, 2007); essentially, they fail to support explicit understanding. Feedback provided to operators in information displays of modern equipment should indicate task requirements and clearly display the way in which the system responds to a variety of situations to keep them 'in the loop' (Norman, 1986). For drivers, warnings require them to examine the roadway to determine cause for their issuance, and the relevance of the warning with respect to the current situation. Warnings and the delays associated with their confirmation force a reactive response, which is particularly harmful in many imminent collision situations. By failing to support explicit understanding of the automation's behavior, warnings force operators to rely more on their implicit understanding, which is less precise.

Another approach to informing operators is to provide continuous information regarding the automation's behavior. Providing operators with a more complete representation of the system, including such information as proximity to state transition points and operating boundaries—information not available from discrete warnings—would support explicit understanding. To the extent that a continuous information interface provided operators cues of the automation's impending behavior, it would relieve them of the time required to extract information from the environment and prompt a proactive control response (van der Hulst, Meijman, & Rothengatter, 1999).

In a visually-demanding, multi-task domain like driving, continuous feedback would need to be both peripheral and easily understood to avoid distracting drivers. Because drivers must manage their attention to automated systems and to the driving task, they may have little attentional capacity to devote to feedback provided on automated systems (Verwey, 2000). As such, provided feedback must be carefully designed not to distract drivers. Tactile and auditory modalities are conducive to presenting non-obtrusive feedback to drivers (Arroyo, Sullivan, & Selker, 2006). For visual feedback, the potential for distraction is greater as the driving tasks of vehicle navigation, vehicle control, and hazard identification are primarily visual. Display techniques are required that minimally demand drivers to focally attend to and integrate information.

Continuous, concurrent information interfaces are a novel approach to informing drivers in which the effect of information content and modality on driver attention, understanding, and control response behaviors are unknown. It is further unknown how driver understanding interacts with driving situation to affect the driver's response.

My long-term goal is to help operators manage imperfect automation by promoting appropriate reliance. A central premise of this goal is that breakdowns in human-automation interaction result from a lack of continual feedback (Norman, 1990). In this dissertation, I present a continuous, concurrent information display as one means to promote appropriate reliance in the face of a dynamic context that influences its capability (Lee & See, 2004). This research fills an important gap in the literature: use of concurrent feedback that informs operators of the automation's behavior in the environmental context. To fill this gap, I applied a quantitative model to define the effect of driver understanding of ACC's behavior on interaction failures, and to predict driver response to feedback type, of varied modality and content, and mediated by attention. Quantitative modeling of driver behavior offers a valuable alternative to more labor-intensive, participant-based studies for understanding and evaluating these effects. I further developed displays to convey continuous, multivariate feedback to mitigate interaction failures with particular consideration of the attentional demands posed by a multi-task domain such as driving. The central hypothesis of this research is that continuous feedback on the state and behavior of the automation informs operators of the evolving relationship between system performance and operating limits, therefore promoting accurate mental models and calibrated trust. This central hypothesis was investigated through the following specific aims using adaptive cruise control (ACC) as the example control automation:

Specific Aim 1

Apply a quantitative model to define the effect of understanding on driver–ACC interaction failures and to predict driver response to feedback (see Chapter III). A quantitative model provides the ability to develop a deeper understanding of driver–ACC interaction to guide the design of an ACC continuous information display. This model shows how interface design and driving condition contribute to driver–ACC interaction failures. This model of driver interaction with an automated control device considers the effect of feedback type and driver understanding (mental models mediated by attention) on driver behavior (control response); it estimates driver response time to ACC behavior in a variety of driving situations. The distraction potential of provided feedback is modeled as attenuated attention. State transition diagrams, according to the systematic approach described in Degani and Heymann (2002, 2007), are used to model driver understanding, associated with the provided feedback. Response strategies based on perceptual processing factors form rules for when to trigger a control response. The model predicts that a more accurate mental model results in more appropriate driver response to ACC behavior.

Specific Aim 2

Develop a systematic approach to define the feedback needed to support appropriate reliance in a demanding multi-task domain (see Chapter IV). A systematic approach to the design of an interface to inform operators of the constraints that govern driver–ACC interaction is needed. Representation aiding principles offer a structured methodology to create a visual interface, and sonification—continuous auditory feedback—is a means to design an auditory counterpart. The interface designs consider the attentional demands present in driving.

Specific Aim 3

Assess the costs and benefits of continuous visual and auditory feedback (see Chapter V). Continuous feedback has the potential to increase drivers' cognitive load and undermine their driving performance (Arroyo et al., 2006; Corbett & Anderson, 2001). The degree to which continuous feedback imposes visual and cognitive distraction and the timing of the driver's response relative to event boundaries indicate the cost of providing this feedback. The degree to which drivers trust the automation respective to the accuracy of their mental model indicates the benefit of this feedback. A participant-based study that compares warnings to a continuous interface assesses these costs and benefits for both visual and auditory modalities.

Contributions

As a theoretical contribution, this dissertation advances a quantitative model to describe human-automation interaction failures. This model shows the benefit of feedback to promote appropriate operator response to imperfect automation. This research also provides a novel design approach to support explicit understanding (mental models) and implicit understanding (trust) of automation behavior in the driving domain.

As a practical contribution, this research informs on the design of automation support displays—the type of feedback to provide in domains defined by uncertainty, complexity, and time intensity (Lee, 2006). Results will help designers to define what type of information to provide to promote appropriate reliance, and in practice, how to make imperfect automation more effective to increase the reliability of joint human-automation performance.

Supporting Publications

The following papers underlie this research:

1) Seppelt, B.D., Lees, M.N., & Lee, J.D. (2005). Driver distraction and reliance: Adaptive cruise control in the context of sensor reliability and algorithm limits. Honda outstanding student paper award. In *Proceedings of the Third International Driving Symposium on Human Factors in Driver Assessment, Training, and Vehicle Design*, 255-261.

2) Seppelt, B.D., & Lee, J.D. (2007). Making adaptive cruise control (ACC) limits visible. *International Journal of Human-Computer Studies, 65(3)*, 192-205.

3) Seppelt, B.D. (2008). Modeling human-automation interaction: Evaluating driver response to adaptive cruise control failures. First place student paper award. *Transportation Scholars Conference 2008.* Iowa State University, Ames, IA.

4) Lee, J.D., & Seppelt, B.D. (2009). Human factors in automation design. In S.Y. Nof (Ed.), *Handbook of Automation.* Springer. p. 417-436.

CHAPTER II. BACKGROUND AND RATIONALE

As automation is increasingly used to support control, decision-making, and information processing in complex environments such as driving, aviation, and manufacturing systems, designers must address the question of how to design these systems to foster human-automation coordination (Dekker & Woods, 2002). Automation alters the nature of tasks, and forces operators to adapt in novel ways. Specifically, operators are required to monitor the automated tasks and manage those tasks that remain using the feedback that is available from the automated system, which is often altered in type and extent to that of manual control. These changes in tasks and their structure invoke behavioral, cognitive, and emotional responses (Lee & Seppelt, 2009).

Of particular interest in this dissertation is the influence of trust in automation and mental models on automation use. Trust influences the way people interact with automation much the same as it affects human-human relationships (Lee & See, 2004; Sheridan & Hennessy, 1984). People tend to rely on automation they trust and to disuse automation they do not trust (Lee & Moray, 1992; Lewandowsky, Mundy, & Tan, 2000; Muir & Moray, 1996); it is therefore important to consider the role of trust in the interaction between operator and automated system. Mental models influence the way people allocate their attention to automated systems (Moray, 1986), and in turn influence their response, where an operator's response reflects their prediction of system behavior (Gentner and Stevens, 1983). Multiple factors that affect the development of human trust in automation systems and their mental models involve how and what information is presented to operators. This chapter reviews human-automation interaction literature, specific to problems of automation that result in operator's inappropriately relying on the automation, and on informing strategies to mitigate potential human-automation interaction failures. A section on gaps in the literature concludes the chapter.

Human-Automation Interaction

Automation is any "sensing, detection, information-processing, decision-making, or control action" (Moray et al., 2000: 44) that is performed by a machine but could be performed by a human. This technology offers increased benefits of efficiency, accuracy, and control (Endsley & Kiris, 1995). In aviation, for example, introduced automation is credited with reducing flight times and increasing fuel efficiency (Nagel, 1988). Benefits including improved precision and economy of operations are realized through the introduction of automation; however, these benefits of automation are those aspects of system operation that do not involve much interaction between human and machine. Automated systems, even those at high levels of autonomy, require operator involvement and consequently communication and coordination between the human and machine (Sarter et al., 1997). Operators are tasked to supervise the automation. In supervisory control, where operators only intervene if they believe the system to be faulty or desire to improve efficiency (Sheridan, 1975; Sheridan & Johannsen, 1976), there is a tendency of humans to misunderstand the automation and to rely inappropriately on the automation, resulting in reduced safety and performance.

Problems of human-automation interaction

Multiple variables dynamically change and interact both in automated systems and in the environment in complex, multi-task domains such as driving, making it difficult for operators to track the activities and responses of these systems. Operators are removed from directly monitoring variables in the environment due to the shift from active engagement in a task to a passive role of monitoring the automation. A monitoring role creates new attentional and knowledge demands: operators must understand how different elements of complex systems operate and interact in addition to the effect of their inputs on system behavior (Sarter et al., 1997). Empirical research indicates that operators often have gaps and misconceptions in their mental models of automated systems (Sarter & Woods, 1994a) due to the cognitive demand and complexity of operating these systems in real-time. As a consequence, operators are sometimes surprised by the behavior of the automation and uncertain of what the automation is doing and what it will do next (Wiener, 1989). Essentially, the problems with human-automation interaction originate from monitoring and management costs of automation, including increased task complexity, and from changes in feedback that result from its use.

Monitoring and management costs

Use of automation can induce increased workload because of the cognitive workload associated with monitoring the automation. Operators must monitor the automated system, its performance, and the process it controls (Wickens, 1992). These new attentional demands require that operators know more about systems in order to understand, predict, and manipulate their behavior (Sarter et al., 1997).

Automation can also shift the pattern of workload between work phases, creating pronounced workload peaks and troughs. When workload is low, automation can reduce workload further (e.g., cruise control during highway driving). When workload is high, automation can increase workload at critical phases (e.g., takeoff and landing in airplanes; Parasuraman, Molloy, Mouloua, & Hilburn, 1996). For example, in high-workload, dynamic phases of flight pilots reported an increase in workload from use of automation systems (Wiener, 1989). This effect of automation on workload—increased monitoring at high workload, high criticality periods—is referred to as "clumsy automation" (Sarter et al., 1997). More specifically, it is the poor coordination between the operator and machine in the control of dynamic processes in which the costs imposed by the technology surface during periods of high workload, high criticality, or fast-paced operations (Cook & Woods, 1996; Sarter & Woods, 1994b). For clumsy automation, the pattern of workload shifts because the nature and structure of tasks have changed—easy tasks are easier and hard tasks are more difficult. Automation is often used in place of operators for simple physical tasks, but the more complex cognitive tasks are left for operators to perform. These tasks are made even more difficult for operators by the reduced experience and impoverished context that is a consequence of automating the easy tasks.

An effect of clumsy automation is to mask the continuous attentional demands that monitoring imposes. Clumsy automation can induce operators to disengage from the automation during the low workload periods, increasing the likelihood that they will be surprised by the automation's behavior. An example of this effect is seen in use of driving technologies that assume partial control of the vehicle, leaving the driver in the role of monitoring the automation. These technologies reduce driving workload. Drivers are under-loaded and therefore devote less attention to the driving task (Rudin-Brown & Parker, 2004), a consequence that degrades their understanding of the system's operation, and in turn their ability to intervene in failure situations (Stanton, Young, & McCaulder, 1997). Operators must stay engaged during the low workload periods to ensure appropriate response during the high-workload periods. These monitoring costs that automation imposes reinforce the need for adequate feedback on its behavior.

Changes in feedback

The required feedback for operators to adequately monitor the automation is often unavailable as automation changes the nature and extent of available feedback. Automated systems can eliminate the critical cues present in manual operation; this loss of feedback results in difficulties tracking automation status and behavior, and a failure to understand when and how to intervene to avoid undesirable actions by the automation or to achieve required performance. For example, Kessel and Wickens (1982) reported that for a tracking task, the loss of haptic information in the automated mode degraded control as compared to that of manual control, which included haptic information. Further, automated systems can occlude needed raw system data in favor of processed, integrated information; these types of system designs often lack sufficient information to keep the operators aware of system actions.

Inadequate feedback contributes to serious errors when the automation fails because the information operators need to detect the problem and to take over manual control is not available. Operators show reduced ability to detect malfunctions when not actively controlling a process compared to when they are engaged both in control and in monitoring (Parasuraman, Molloy, & Singh, 1993). The limited proprioceptive and other forms of feedback under conditions of passive monitoring are a likely contributor to this poor failure detection. This decreased ability to detect system errors and to intervene and perform the tasks manually in response to failures compared to those who manually perform the same tasks is referred to as out-of-the-loop unfamiliarity (Endsley & Kiris, 1995; Wickens, 1992; Wiener & Curry, 1980). Operators may also require a significant period of time to reorient themselves to the current system state following a failure and to develop adequate understanding of the state to act appropriately, thus potentially reducing the effectiveness of actions taken and prohibiting operators from carrying out required actions. For example, drivers removed from active steering and speed control with active steering (AS) and adaptive cruise control (ACC) systems, respectively, fail to effectively intervene in response to failures, largely a result of missing haptic feedback in control of the steering wheel and of raw data on the automation's low-level processing in control of speed (Stanton & Young, 1998).

Operators may develop inaccurate mental models, over- or under-trust the automation respective to its capabilities, display complacent behavior, and adapt their behavior in safety-degrading ways as a consequence of their qualitative shift from active processor of information to passive recipient of information, and the associated loss or change in the type of feedback received on the state of the system (Lee & Moray, 1994; Norman, 1990; Parasuraman, Mouloua, & Molloy, 1994; Sarter et al., 1997). These cognitive and emotional responses of operators are symptomatic of breakdowns in interaction between operators and automated systems, and all can lead to inappropriate reliance. Though not a complete list, those mentioned depict the complexity of how technology can affect human performance, particularly as related to dynamic, complex domains such as driving.

The described problems of automation are particularly relevant for automated systems that place the operator in the role of deciding when and how to use the automation—a supervisory or monitoring role. In this role, human operators are to assume responsibility for safety of a human-machine system to prevent situations where the automation is unable to control the complex system. To attain this safety, operators must correctly understand the operating conditions. It is difficult to maintain correct understanding at all times, particularly when a process is controlled with a complex system with inherent uncertainty (e.g. process control plant, aircraft, nuclear power plant, automobiles). Consequently, operators may inappropriately rely on the automation.

Understanding and relying on automation

For judgments made under uncertainty, such as the decision to rely on automated systems that control all or part of a complex, dynamic process, two types of cognitive mechanisms—intuition and reasoning—are at work (Kahneman & Frederick, 2002; Stanovich & West, 2002). Intuition (System 1) is characterized by fast, automatic, effortless, and associative operations—those similar to features of perceptual processes. Reasoning (System 2) is characterized by slow, serial, effortful, deliberately-controlled, and often relatively flexible and rule-governed operations. System 1 generates impressions that factor into judgments while System 2 is involved directly in all judgments, whether they originate from impressions or from deliberate reasoning.

Trust and mental models align with the intuitive mode and the controlled mode of the two-system view, respectively. They represent two types of understanding that govern reliance decisions: implicit understanding (i.e., trust) and explicit understanding (i.e., mental models). Consistent with the two-system view, these two types of understanding operate in parallel, influencing operator expectations and guiding the use of automation.

Implicit understanding

Trust is a form of implicit understanding that guides operators' expectations when system complexity and situational uncertainty make complete understanding of the automation impractical (Lee & See, 2004). It is defined as "the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability" (Lee & See, 2004). Trust is an internal mechanism that allows operators to reduce their feelings of uncertainty and vulnerability related to the potential consequences of their control decisions, and is inversely related to system uncertainty (Uggirala, Gramopadhye, Melloy, & Toler, 2004). Trust in automation develops according to the information available; its attributions depend on the degree to which the purpose of the automation, its underlying mechanisms, and the performance of the automation are apparent to the operator. Trust influences the way people interact with automation much the same as it affects human-human relationships (Lee & See, 2004; Sheridan & Hennessy, 1984): people tend to rely on automation they trust and to disuse automation they do not trust (Lee & Moray, 1992; Lewandowsky, Mundy, & Tan, 2000; Muir & Moray, 1996).

Whether or not reliance is appropriate is partly defined by the match between trust and the capabilities of the automation (Lee & Moray, 1994; Lee & See, 2004). Trust that is calibrated leads to appropriate use of automation. Similar to definitions of misuse and disuse in describing appropriate reliance, overtrust and distrust are instances of poor calibration. Overtrust is trust that exceeds system capabilities; overtrust leads to misuse. Mistrust is trust that falls short of system capabilities; distrust leads to disuse. Appropriate trust depends on matching the level of trust to the capability of the automation; ideally, both change in the same direction and in proportion to one another (Lee & See, 2004).

Explicit understanding

Explicit understanding is an operator's knowledge of system purpose and form, its functioning and associated state structure, i.e., mental model (Johnson-Laird, 1983; Rouse & Morris, 1986). For operators who interact with automation that in turn interacts with the environment, such as drivers, it is important that their mental models include the environment's effect on the automation's behavior. Mental models are constructed from information provided in the environment and from instructions (Norman, 1986). Such knowledge guides attention allocation (Moray, 1986), directing an operator where and when to look for information on the status and behavior of the automation and the system being controlled, thus allowing operators to account for and to predict the behavior of physical systems (Gentner & Stevens, 1983; Sarter et al., 1997). In allowing an operator to predict and explain system behavior, and to recognize and remember relationships between system components and events (Wilson & Rutherford, 1989), mental models influence people's expectations (Wickens, 1984).

Mental models assist people in how they interact with their environment (Cannon-Bowers, Salas, & Converse, 1993). These models facilitate an operator's ability to estimate all variables central to system control, to assume strategies to control the system, and to select appropriate responses relative to the particular strategy (Veldhuyzen & Stassen, 1977). According to Johnson-Laird (1983), mental models enable people to draw inferences and make predictions, to decide on their actions, and to control system operation. These are functions involved in a reliance decision.

The means of organizing knowledge into structured patterns (i.e., mental model) affords rapid and flexible processing of information that translates into rapid response such as the decision to rely when operating an automated system (Rumelhart & Ortany, 1977). These patterns serve to classify situations, objects, and environments into retrievable relationships amongst the concepts and their features (Rips, Shoben, & Smith, 1973). Consequently, ill-constructed patterns prompt inappropriate reliance.

Inaccuracies in mental models increase in likelihood the more unreliable the automation (Kazi, Stanton, & Harrison, 2004). Failures, particularly those non-predictive or unspecified as to a cause, create uncertainty in the interpretation of the automation's behavior. Kazi et al. (2004) exposed drivers to different levels of reliability of an ACC system and found that failures involving random accelerations of the ACC led to varied mental models of its operation, which were predominately flawed. Accurate, well-developed mental models are critical to successful interaction between human operators and automated systems as inaccuracies lead to ill-formed operator expectations and inappropriate use.

Driver–ACC Interaction

The problems of human-automation interaction apply to how drivers interact with automation in their vehicles. Unlike domains such as air traffic control, aviation, advanced manufacturing, and teleoperations, in which the timescale of interactions with automation occur more at strategic and tactical levels, in driving, operational, or moment-to-moment, interactions with automation dominate. The temporal demands of driving necessitate drivers to react to automation failures within seconds to milliseconds; drivers must remain vigilant to variants in automation's state on this level. Contributing to the high attentional demands of driving is the need for drivers to monitor the surrounding environment, which is both dynamic and uncertain. Drivers need to predict how variables in the environment will change to know how to adapt their behavior in how they interact with automated systems. An important concern is how drivers manage their attention to automated systems and to the driving task.

Technology that automates vehicle control relieves drivers of some of the demand of moment-to-moment control but imposes attentional demands associated with the need to monitor the status and behavior of the automation (Moray, 1986). Control automation in vehicles are those systems that replace primary driver functions of braking, steering, and accelerating (e.g., active steering, collision avoidance systems). Adaptive cruise control (ACC) is such a system—it automates headway maintenance—but because ACC operates effectively in only a subset of driving situations, drivers must monitor the system and intervene periodically. Sensors positioned on the front of the vehicle detect the presence of preceding vehicles and determine their range and speed. If no vehicle is detected, the ACC operates like a conventional cruise control system, maintaining a set speed. If a preceding vehicle is detected, the ACC modulates vehicle speed to maintain a preset time headway. ACC's technical limitations include: the ACC does not work at low speeds, vehicles in adjacent lanes and those in a curve outside the detection area of the ACC's sensors are not detected, and the braking authority of the ACC is limited to less than 0.3 g.

Because of the limitations of this device, drivers are responsible for vehicle control and consequently for their decision to use or not use automated control. In particular, the dynamics of the driving domain create a variety of situations of use of the

ACC system that are not predictable by the driver, thus preventing them from knowing in real-time the appropriate allocation of function. This incomplete knowledge of how the system will respond in interaction with the driving situations that arise causes uncertainty. This uncertainty can lead to improper use of ACC.

Improper use of ACC is predominately a product of inadequate driver understanding of its behavior and design limitations (Rudin-Brown & Parker, 2004; Stanton et al., 1997). Nilsson (1995) introduced drivers to three critical scenarios that each required driver intervention. These scenarios were approaching a stationary queue of traffic, a car pulling out in front of the driver's vehicle, and a hard braking lead vehicle—all scenarios likely with routine use of ACC. Drivers over-relied on the ACC and delayed their response when confronted with the first scenario, resulting in near collisions. Rudin-Brown and Parker (2004) observed similar decrements to hazard response with use of ACC; drivers maintained overly high levels of trust in the hazard situation, shifting their response priorities to a secondary task. Hoedemaeker (2000) showed that drivers are prone to adapt their behavior when using the ACC; they drive faster and adopt shorter headways, using the system beyond its intended design parameters. Such behavioral adaptation can increase crash likelihood. Drivers also failed to recognize the limitations of the ACC for overtaking maneuvers on rural roads and in detecting traffic coming from the right at an intersection. As a consequence to the first situation, unsafe headways were a result, and as a consequence to the second situation, drivers delayed their response to the traffic. Stanton et al. (1997) classified situations in which the ACC contradicts drivers' expectations as those in which the sensors either do not detect targets in the path of the vehicle (e.g., motorcycle) or respond to non-vehicle targets (e.g., bicyclist). These studies show the need for drivers to understand the limits of ACC and when it is required to disengage (i.e., turn off) the system. The feedback available from current ACC systems is inadequate to helping drivers develop appropriate mental models that will enable them to understand its limitations, and to predict its behavior (Kazi et al., 2004; Stanton et al., 1997; Stanton & Young, 2005).

Multiple limits of ACC exist which may lead to breakdowns in driver-automation interaction. While previous studies have identified subsets of driving situations in which ACC did not operate effectively in relation to driver expectation, these studies did not specifically consider the role of the environment in its effect on automation capability. Environmental context can affect the reliability and behavior of the automation, the operator's perception of the automation, and thus the overall effectiveness of human-automation interaction (Flach, 1990; Kirlik, Miller, & Jagacinski, 1993; Lee & See, 2004; Vicente & Rasmussen, 1990). An initial study was run to assess how an environmental situation interacts with the characteristics of the automation to affect its capability, and in turn, how this differing capability affects drivers' use of the automation and their driving performance (Seppelt, Lees, & Lee, 2005). Two limits of ACC that are realized through its interaction with the environment are braking algorithm limits as induced from heavy traffic, which produces frequent, intense lead vehicle braking, and sensor detection limits as induced from heavy rain, which degrades sensor quality with periodic malfunction. Both limits within their respective environmental contexts lead to ACC failure, i.e., a loss of THW between the driver's vehicle and the lead vehicle. Results showed that drivers' expectation of failure and their reliance differed between the two. In traffic, drivers over-relied on the ACC; they waited to disengage the ACC when failure occurred, but without decrement to driving safety as measured with THW and TTC at failure response. This wait-and-see behavior suggests that drivers perceived the failure cause and managed their response based on the severity of the situation. In rain, drivers under-relied on the ACC; they were quick to disengage the ACC when failure occurred, but did not readily re-engage. Such behavior suggests that drivers were uncertain of the failure cause and may have lost trust in the ACC.

Minimal research is available on the relationship between ACC capability and driver response. Of that available, it is clear that driver expectation is formed from experience with ACC in various traffic situations and from a perceived understanding of how ACC's control algorithms will react (Marsden, McDonald, & Brackstone, 2001; Zheng & McDonald, 2005). Driver intervention can occur in situations that ACC is able to manage due to an incompatibility between a driver's expectations and ACC control. The situation dynamics determine if use of ACC is appropriate in how they affect its performance. Drivers must continually attend to the performance of the ACC to intervene when needed.

Mitigating Human-Automation Breakdowns

Feedback is a means to mitigate discrepancies in understanding (Norman, 1990). For implicit understanding, feedback on function and intention, in making automation more reliable and predictable, would promote trust (Sheridan, 1995). For explicit understanding, feedback that informed of the automation's behavior in a variety of situations would promote improved mental model accuracy (Stanton & Young, 2005). Together, feedback on the automation's purpose, process, and performance would support both types of understanding.

In the past, operators have been provided with feedback on the automation's reliability (Bagheri & Jamieson, 2004; Moray et al., 2000; Dixon & Wickens, 2006), system confidence (McGuirl & Sarter, 2006; Wickens et al., 2000), the automation's performance relative to that of the operator's performance (Dzindolet et al., 2003), specific situations when the automation performs poorly (Masalonis, 2003), an explanation of why the automation might fail (Bisantz & Seong, 2001; Dzindolet et al., 2003), etc.. These studies vary in the frequency and timing with which operators are provided feedback: asynchronously—pre-experimental training or following each trial, concurrently—immediate to a value crossing a threshold or an event-specific trigger. What to feed back and when to feed it back is to a large extent domain-specific and situation-specific. In a highly-regulated industry such as aviation, for example, training is a practical and useful strategy for providing operators appropriate feedback on automation behavior. In a domain such as driving in which drivers are minimally regulated, however, training is a more problematic strategy as it is inconsistent in amount and quality (e.g., drivers study user manuals to a varied degree). Specific to the situation, multiple researchers have asserted that feedback should be adaptive in amount and form in relation to the events in the environment (e.g., Kaber & Endsley, 2004; Moray et al., 2000; Norman, 1990; Woods, 1996).

Multiple studies point to the need to provide information on the purpose, process, and performance of the automation (e.g., Bagheri & Jamieson, 2004; Dzindolet et al., 2003; Lees & Lee, 2007; Masalonis, 2000; McGuirl & Sarter, 2006; Moray & Inagaki, 1999; Moray et al., 2000; Wiegmann, Rich, & Zhang, 2001). This information in separate often leads to inappropriate reliance. Operators trained on system reliability—

performance information—commonly disuse the automation, their trust below that of the system's capabilities (Moray et al., 2000; Dixon & Wickens, 2006). In these instances, operators seemingly apply reliability as a relative indicator of the automation's utility, consequently the benefits to task performance it provides are often unrealized and overall task performance suffers. This disuse is present even if operators are updated on automation's reliability on a regular basis (Dzindolet et al., 2003, study 2). In these instances, operators must rely on their understanding of the current operating conditions to interpret feedback that is in the form of a single indicator such as reliability or system confidence without more descriptive variables of its behavior. Those studies that provide a rationale for the automation's behavior—process information—report misuse of the automation, in which operators' trust is above the system's capabilities (Dzindolet et al., 2003, study 3; Masalonis, 2003). Operators seemingly over-extend the reasoning for failure and rely on the automation despite its apparent costs to overall performance. These patterns indicate that operators require information on system performance and process unambiguously related to its real-time operation to properly understand the automation and in turn to use it appropriately.

The attentional costs that real-time information on system purpose, process, and performance impose on driving control may offset its provided benefit. Because continuous feedback has the potential to increase drivers' cognitive load and undermine their driving performance (Arroyo, Sullivan, & Selker, 2006; Corbett & Anderson, 2001), it is important to design support interfaces that are processed peripherally, with minimal interpretation and integration required. Configural displays, which use emergent features, are designed to exploit perceptual processes. Emergent features are a product of interaction between display elements and provide a high-level aggregated view of a system (Cummings, Brzezinski, & Lee, 2007). Use of configural displays is a promising approach to providing drivers with non-obtrusive visual feedback. In the auditory domain, sonification—continuous auditory information coded into perceived relationships in sound (Barrass & Kramer, 1999; Kramer, 1994)—is a promising approach. But because auditory information imposes obliging and transitory stimulus on an individual, sonification interfaces must be designed to control attention properly over time. Techniques such as semantic mapping and representational aiding are means to map information to aural forms that demand attention at the desired level (Guerlain, Jamieson, Bullemer, & Blair, 2002; Reising & Sanderson, 2002a; Watson & Sanderson, 2007).

In describing human-automation interaction, this chapter has discussed concepts of attention, feedback, operator understanding, and control behavior. The relationship among these concepts is complex and meaningful, and important to understand to support operator reliance on automation. Informed from the Neisser perceptual circle (1976), Figure 2 captures the relationship between these concepts. This cyclical model of actions and events depicts the importance of the operator's current understanding of the situation, which determines what response the operator enacts and dually affects an operator's evaluation of the information available (from the automated system and the environment) as it is perceived. Attention tempers observation and response and so permeates all functions of the perceptual circle. Essentially, what information from the interface is perceived or observed by operators influences their implicit and explicit understanding, modulating expectation and response. An operator's response alters the environment and in turn affects the information available and perceived.

To more concretely define these relationships, a functional model of operator interaction with an automated control device is presented in the next chapter.

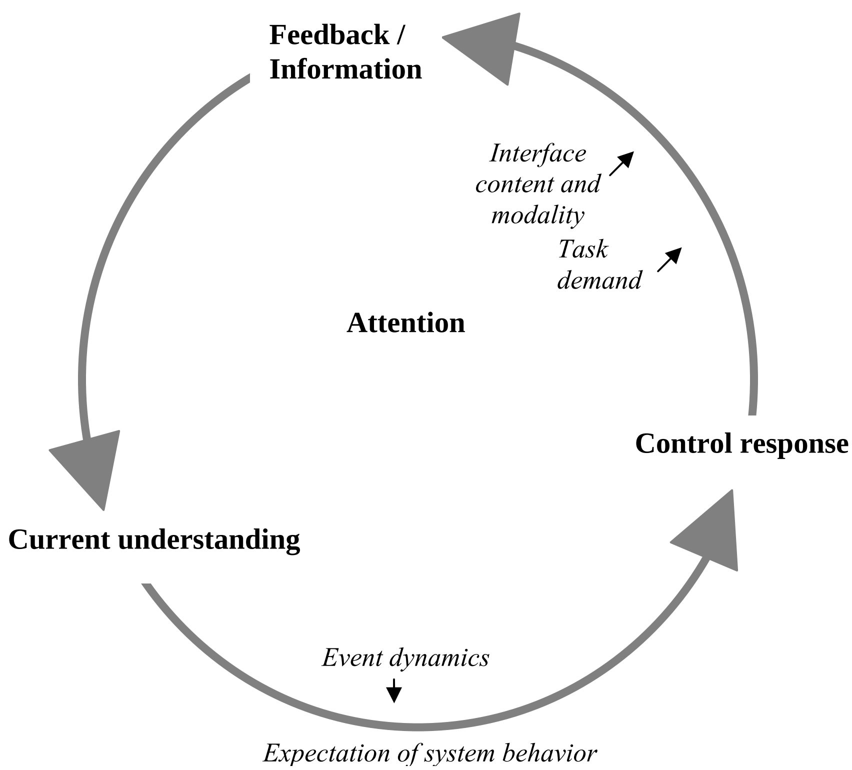

Figure 2. Model of operator interaction with automation as a function of their attention and understanding of the automation's behavior, conceptually coherent with the perceptual circle of Neisser (1976).

Gaps in Literature

A quantitative approach modeling driver–ACC interaction, capturing both a driver's explicit and implicit understanding of automation behavior, has not been applied to understand failures in use of ACC. In the next chapter, I present a model to predict driver response to imperfect control automation.

Multiple strategies exist on what to feed back to operators. There is a gap, however, in terms of how to present feedback to operators that is specific to the situation, yet non-intrusive. Continuous visual and auditory displays are proposed to both support understanding of automation behavior and to account for the particular attentional demands of driving.

The contribution of this dissertation is in providing purpose, process, and performance information to operators through a continuous, concurrent information display that indicates how the given situation interacts with the characteristics of the automation to affect its capability. The intended goal is to keep drivers informed, not to alert them or "wake them" from a complacent state with an occasional alarm or warning. As evidenced in other domains, providing continuous information (visual and/or auditory) to operators is an effective way to encourage appropriate reliance on automation (e.g., Lee, See, Crittendon, Marquard, & Folmer, in review; Watson & Sanderson, 2007).

CHAPTER III. MODELING HUMAN-AUTOMATION INTERACTION

This chapter presents a modeling analysis intended to develop a deeper understanding of driver–ACC interaction. This analysis reveals situations in which a driver's inadequate understanding of the ACC's function and operating capabilities leads to imminent (or likely) collision. Such situations indicate the need to properly inform drivers of the ACC's behavior.

Modeling Approach

The driver–ACC interaction model presented in this chapter is composed of a driver component and an ACC component. The driver is modeled as a function of attention, understanding of ACC's behavior, and consequent control response in failure situations. ACC is modeled according to its operational states (Off, On, Standby) and control algorithms.

Driver component

Figure 3 provides an overview of the driver component. A driver's attention is modulated based on roadway demand and in-vehicle demand. These factors influence the amount of information drivers process related to ACC's behavior. In turn, the information drivers encode into a mental representation, i.e., model, is affected. State transition diagrams, as seen in Figure 3, are used to represent a driver's model of ACC; this model articulates the driver's current understanding of ACC. A comparison of this model to the ACC system model reveals any errors in the driver's understanding. A continuous data stream of dynamic ACC behavior in car-following situations is used to dynamically transition through the driver model, producing a real-time update of the driver's expectation of ACC's current system state. Based on the accuracy of the moment-to-moment expectation, and the driver's perceptual processing of situation dynamics, drivers form response strategies that act as rules for initiating a control response. The driver's response falls along an event timeline—the boundaries of which are used to classify its appropriateness and to calculate reaction time. The following sections provide greater detail of this driver model.

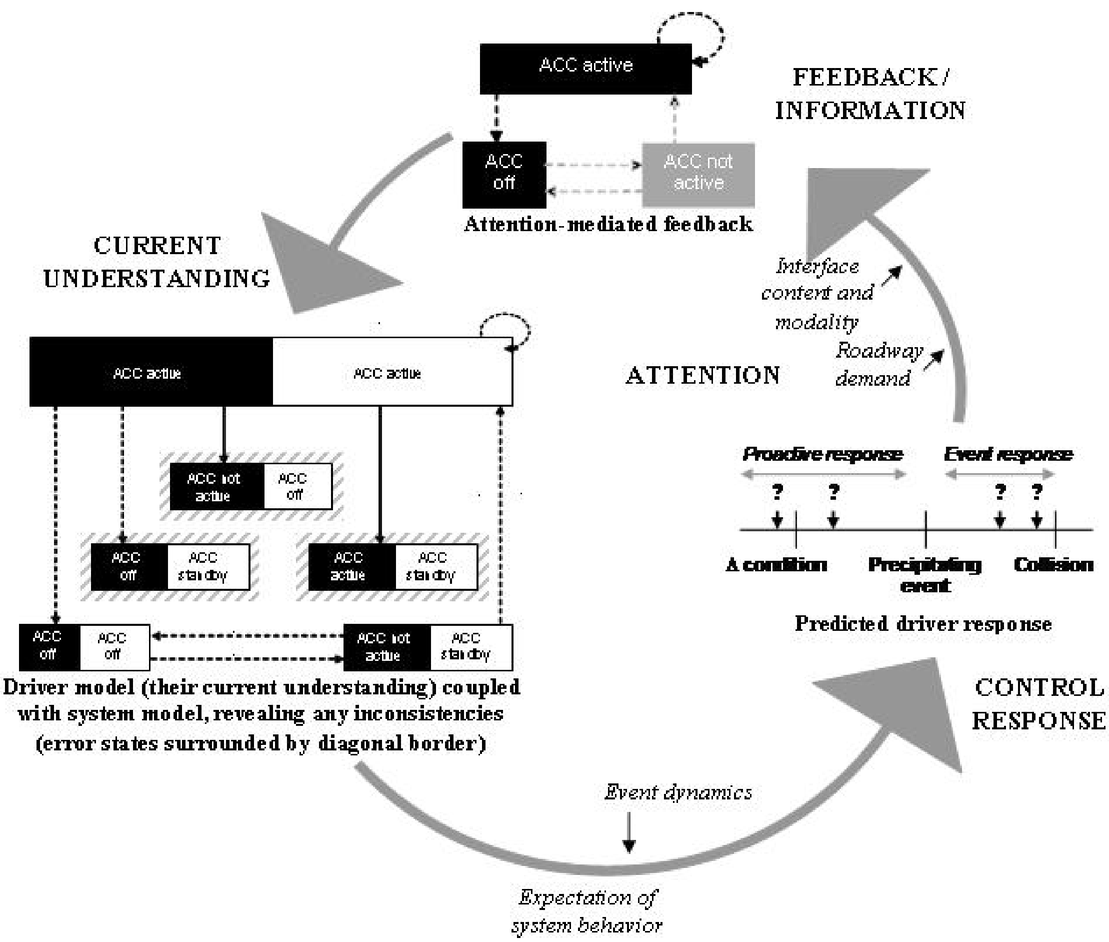

Figure 3. Model of driver interaction with ACC as a function of their attention and understanding of ACC's behavior.

Attention-mediated feedback/information

A driver must attend to the forward view to successfully maintain a safe distance when following a vehicle—particularly as car-following is a perceptual, visual task (see Michaels, 1963). Driver attention, however, is often not focused on the forward view, resulting in missed visual cues that alert to impending collision situations. The rate of visual sampling depends largely on the rate that information changes. When monitoring ACC, this sampling rate reflects the uncertainty regarding system state. Uncertainty increases as a function of roadway demand (i.e., information density of the road), the velocity of the driver's vehicle, time elapsed from last forward view, and a driver's memory decay (Senders et al., 1967). A driver returns attention to the forward view once uncertainty reaches an unacceptable level. At higher speeds and with increased information density of the roadway—a function of traffic, roadway curvature, lane width, and roadway layout (McDonald & Ellis, 1975, Tsimhoni & Green, 2001)—drivers must sample the forward view more frequently.

In-vehicle interface content, according to properties of form and complexity, affect a driver's attention distribution. Interfaces that require focal attention to perceive and interpret information demand more visual attention than those that allow for peripheral processing. Text-based and complex graphical interfaces are examples of displays that obviate undue visual attention. Object-based interfaces like configural displays may speed detection and information processing because people are able to code object properties of color, orientation, size, and direction of movement automatically, without attention (Treisman & Gelade, 1980). An increase in the complexity of interface information is associated with a transfer of attention away from the roadway, re-directed to the display (e.g., Horrey et al., 2006). Degraded driving control often results from such increased side-task demand.

In-vehicle interface modality also affects driver's attention distribution. Visual and auditory interfaces require different perceptual processes. A visual interface often competes for driver attention to the forward view. To the extent that a visual display uses ambient vision, however, the relevant information does not need to be fixated in order to be processed (Leibowitz & Post, 1982). Peripheral vision can engage in object recognition, albeit degraded (Sekuler & Blake, 1994). An auditory interface demands additional memory resources to that of its visual counterpart due to its transient nature; drivers may need to rehearse auditory information, requiring attention resources to keep the information in working memory, in a way that is not necessary for more lasting visually displayed information (Latorella, 1998). An auditory interface may consequently invoke a less precise (i.e., accurate) mental model than a visual interface.

Table 1 summarizes, according to information modality, information content, and roadway demand levels, attention requirements and the expected effect of these factors on driver understanding. The length of the arrows translates to effect magnitude. The individual factors in Table 1 combine to produce additive effects. A complex visual display used in a high-demand driving context would require, of these factors, the greatest amount of driver attention to both the in-vehicle interface and the driving task. Related to effects on driver understanding, a complex auditory interface audible during high roadway demand is expected to compromise driver understanding the most due to the transient nature of the auditory information in a situation in which a driver lacks the capacity to fully attend to its meaning.

Table 1. Feedback/Information Demands

	Modality		Information content		Roadway demand	
	Visual	Auditory	Simple form and low information bandwidth	Complex form and high information bandwidth	Low	High
Required Attention	↑	▲	▲	↑	▲	↑
Effect on Driver Understanding	▼	↓	▼	↓	▼	↓

A simple time delay is used to model driver attention. A 300-ms time delay is applied to model the differential processing time of a driver fully attentive to the roadway compared to a driver whose attention is compromised due to interface content or form. This delay duration is the approximate time it takes for a human to switch attention from one task to another (Klapp, Kelly, & Netick, 1987; Pashler, 1998). The added 300 ms represents a situation in which a driver is focused on the interface information and must redirect his/her attention to the roadway to determine that the ACC is not functioning properly.

Driver understanding of ACC

The formal, systematic approach of Degani and Heymann (2002, 2007) to describe human-automation interaction is applied to define driver understanding of ACC. In the work of Degani and Heymann, state transition systems model the internal configuration of automation and the state changes that occur in response to events that trigger them. As an operator interacts with automation through an interface, observing and triggering state transitions, it functions as the operator model. The operator and system models combine (according to state pairs) to form a composite model. The composite model reveals any discrepancies in the two models, which indicate interaction failures as a result of inadequate or missing information. Essentially, mismatches between the system model and the operator's model of the system show where display information is needed or is incorrect.

State transition systems are a means to formally represent an operator's knowledge of automation but do not necessarily encode its full extent or form. Other viable formalisms for representing operator models of automated systems include state-transition systems (e.g., automata, Statecharts, object-oriented methods), rule-based formalisms, Petri-nets, lattices, and temporal logics (e.g., Moray, 1999). State machines are used in this modeling work as they are the most basic and commonly-applied formalism.

State transition model of ACC. Figure 4 depicts a state transition model of ACC. This model includes four *states*, which represent internal configurations: speed control, distance (or following) control, off, and standby. The *transitions* to and from these states, which represent discrete state changes, are triggered either by the operator (depicted in Figure 4 as dashed lines) or automatically (depicted in Figure 4 by solid lines). The transition lines are labeled by the event that triggers the state change. Automatic transitions can be classified into two types: those triggered by the automation's internal dynamics, and those triggered by the external environment. The state transition model in Figure 4 is consistent with recent patents for Adaptive Cruise Control Systems (King et al.,2000; Richardson et al., 2000) and with the ISO standard for performance requirements and test procedures for Adaptive Cruise Control Systems

(ISO/PWI 15622, 2007). Figure 5 shows the detailed view of the states and transitions internal to the 'ACC active' state.

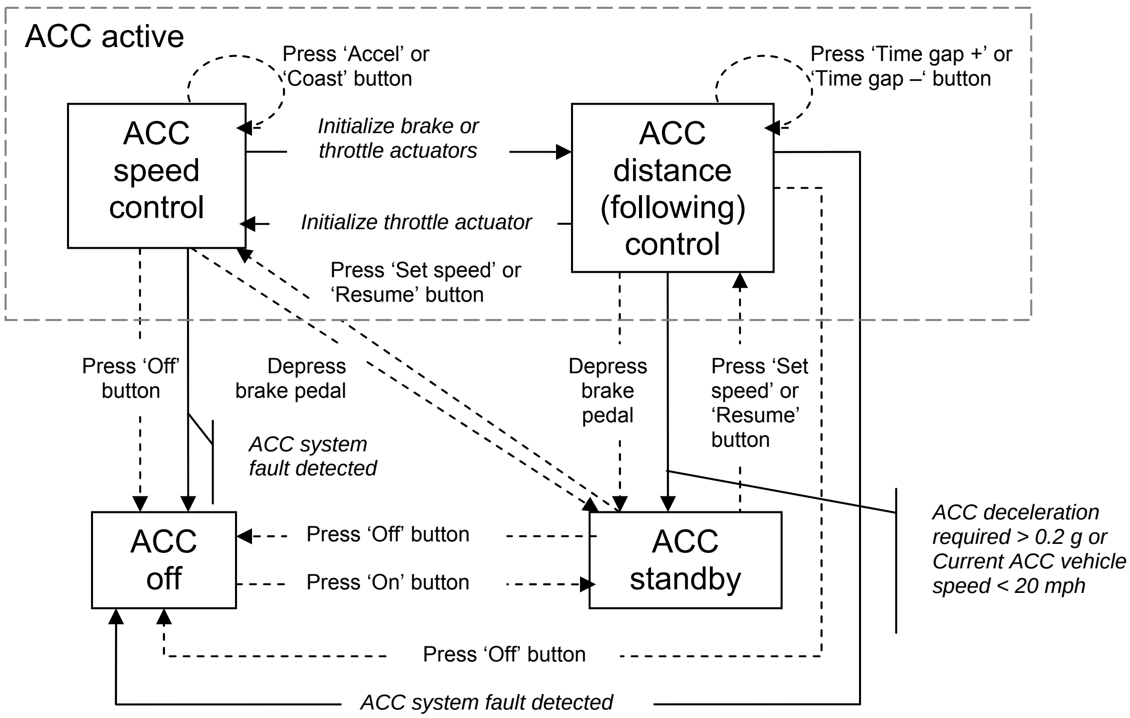

Figure 4. ACC states and transitions. Dashed lines represent driver-triggered transitions while solid lines represent ACC-triggered transitions.

In the 'ACC off' state, there is no direct access for activation of the 'ACC active' state, which is disabled. In the 'ACC standby' state, the ACC system no longer controls longitudinal variables, though the system is ready for activation by the driver. In the 'ACC active' state, the system controls speed and/or headway.

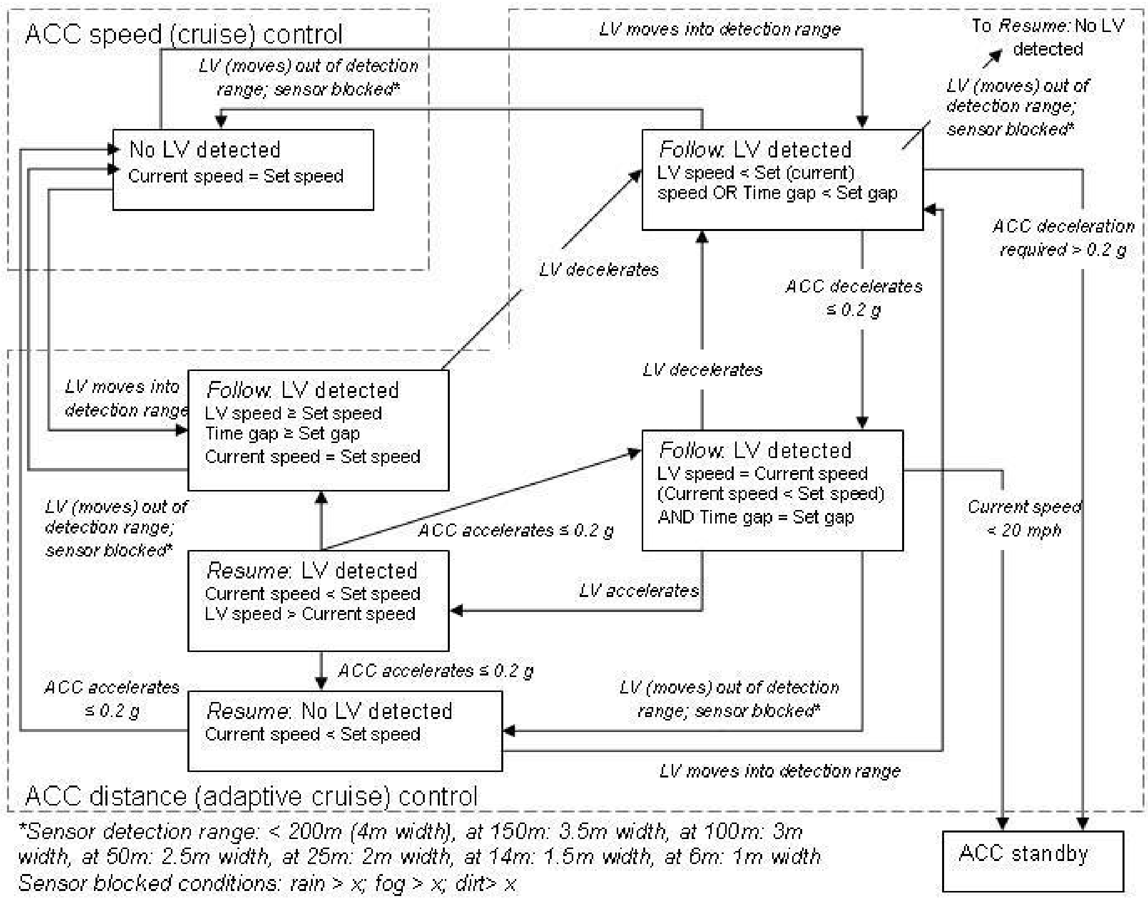

Figure 5. Detailed states and transitions within ‘ACC speed control’ and ‘ACC distance control’.

There are multiple states and transitions internal to the ‘ACC speed control’ and ‘ACC distance control’ states. In the ‘ACC speed control’ state, the systems maintains the set speed, essentially a conventional cruise control mode, while in the ‘ACC distance control’ state, the system controls the headway to a target vehicle according to a select time gap and/or to maintain a set cruise speed. ACC operates according to both a reference vehicle speed signal and a range signal, controlling velocity and headway dependent on the driver settings and the inter-vehicle dynamics. Internal to the ‘ACC distance control’, the system functions to assume a set following distance when a LV is detected (i.e., follow modes) or to return the vehicle into the conventional cruise control mode if the LV is no longer detected (Resume modes). All transitions between the states in Figure 5 are triggered either by the automation's internal dynamics or by the external environment. *Note*: In the top-right of Figure 5, the system transitions from 'Follow: LV detected' to 'Resume: No LV detected' if ACC started to decelerate, and to 'No LV detected' if there was no deceleration before the event (LV out of detection range or sensor blocked) occurred.

Driver state transition models. Automation interfaces often present abstracted information on the underlying complexities of automation state, structure, and response; they provide a model of the automation for the operator. Operators use interfaces as a sufficing means to capture their mental model because of the time and resource demand required to update their models to capture conflicting or additional information (Besnard et al., 2004). It is therefore important that an interface capture the automation's behavior adequately. When the model of automation the interface provides is divergent from the actual model by which the automation operates, breakdowns in human-automation interaction can occur.

The ISO standard for ACC systems is to provide drivers at a minimum an indication of the ACC's activation state (e.g., on, off), and set speed. An example of such an interface is a display of set speed that is only visible when ACC is active. Drivers are also to be informed if the ACC system is not available due to a subsystem failure. A potential driver model of the ACC system that would originate from use of the controls and through an interface containing the ISO-specified feedback is shown in Figure 6.

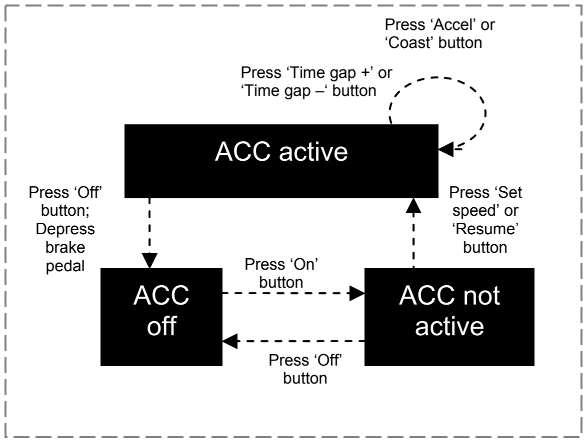

Figure 6. Driver model of ACC.

The automatic transitions from follow control to cruise control are internal to the 'ACC active' state. Figure 7 shows two different driver models of this state from interfaces described in Richardson et al. (2000) and King et al. (2000), respectively; see

Figure 8 for the schematics of these interfaces. This example illustrates, dependent on the information provided in the interface, both the disparity of models that can occur, and the over-simplification of the actual complexity of the 'ACC active state' as compared to the system model in Figure 5.

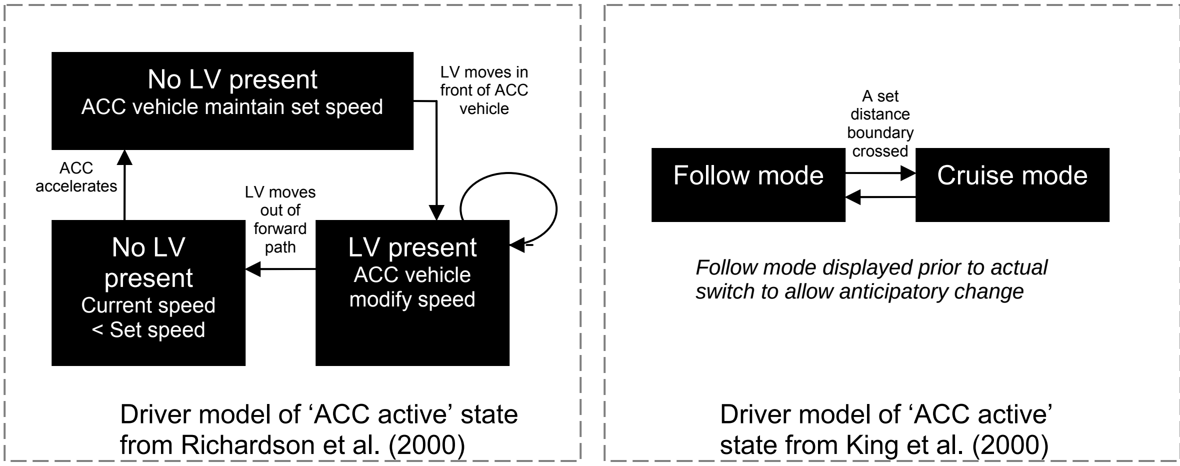

Figure 7. Two different driver models of the 'ACC active' state. In the Richardson et al. (2000) driver model, the internal state transitions of the 'ACC active' state are based on the presence of the LV while in the King et al. (2000) driver model, the two states and associated transition involve the switch between a steady state and transition state of a set cruise speed.

Figure 8. Schematics of the Richardson et al. (2000) and King et al. (2000) ACC interfaces, respectively. *Note*: for the Richardson et al. (2000) interface, no visual is provided so the photograph shown is assumed consistent to the interface description provided in the text.

In the Richardson et al. (2000) driver model, drivers are only provided information on when ACC is active and therefore are left to infer the ACC's behavior internal to this mode based on its interaction with the environment, i.e., the presence of a

LV. In the King et al. (2000) driver model, cruise mode acts like conventional cruise control and controls the vehicle to a desired set speed. Follow mode is where the speed of the vehicle is reduced below the set speed because of another vehicle or object in the vehicle's path within a set range, i.e., the speed of the vehicle is controlled to maintain a set distance from a preceding target vehicle. Thus, cruise mode is equated to set velocity control; any deviations in speed are ascribed to the follow mode.

A comparison of the ACC system model figures and the driver model figures indicates that there are a number of unobserved events. Unobserved events are those that are not displayed in the interface and consequently not represented in the operator model. Unobserved ACC events include (dependent on the particular interface): sensor limits, braking algorithm limits, and most of the transitions between follow and cruise modes internal to 'ACC active'. Without such information on the system's performance and the factors that dictate this performance, drivers are susceptible to confirmation bias, and are likely to develop inaccurate mental models (Kazi et al., 2007).

Composite state transition models. A composite model of each of the driver models presented in the previous section reveals their inconsistencies to that of the system model. To create a composite model, the driver model states and ACC model states are combined into state pairs. If these state pairs are inconsistent, i.e., the driver's model of ACC indicates that ACC is in a state that is incorrect to the underlying true state of the ACC model, there is an inaccuracy in the driver's model, referred to as an error state.

Inconsistencies between the driver's model and the system model may exist so long as the transitions of the driver's model conform to task requirements. An operator may have a reduced (but still correct) model of the system if their model transitions to—consistent with the system model—those states that are involved in performance of a particular task. Essentially, the task the model is used to perform determines its accuracy (Degani & Heymann, 2002). A driver's task in use of ACC is to engage ACC only when it can handle the driving situation and to disengage ACC if it is unable to operate properly, i.e., not able to maintain a set following distance to a lead vehicle in accord with its operating limits. To perform this task, drivers must know ACC's current operational state (Off, On, Standby) and limits.

Error states for the driver model in Figure 6 and for the 'ACC active' state models from Figure 7 are indicated with a vertical hashed border in Figure 9, and in Figure 10 and Figure 11, respectively. In Figure 9, the 'ACC not active—ACC off' and 'ACC off—ACC standby' error states results because the interface does not visibly differentiate between standby and off states. The 'ACC active—ACC standby' error state results from missing feedback on the conditions that automatically deactivate the ACC system. In Figure 10, the 'LV present—No LV detected' error states result from the conflicting presence of the LV and either an acceleration response or lack thereof by the ACC system, a result of failed or occluded sensors or a move of the LV outside of the sensor range. In Figure 11, the 'Follow or Cruise mode: No LV detected' error state represents a mismatch between the cue of a LV present and the ACC's behavior that occurs when the LV moves out of detection range or sensors are blocked, i.e., ACC will begin to accelerate the driver's vehicle despite the presence of the LV, which indicates that a deceleration is the appropriate behavior. Inconsistencies between the driver's model and the system model that are inconsequential to task performance are indicated with an irregular dashed line in Figure 11; these inconsistent state pairs, provided a different task definition, may constitute error states. The ‘Cruise mode—LV detected’ state pair results from the misconception that once the cruise speed is achieved, ACC is in cruise mode; if a LV is detected, the system is in follow mode. The ‘Cruise mode—Resume: LV detected’ and ‘Cruise mode—Resume: No LV detected’ state pairs result from the misconception that if the LV speeds up or if there is no LV present, ACC reverts back to cruise mode without considering that ACC accelerates the vehicle back up to the cruise speed, which is a function within the follow mode; acceleration of ACC is considered part of the cruise mode within the driver model.

An ACC system that issues discrete warnings when its braking and setting limits are exceeded and that indicates its on/off states produces a driver model consistent with the Richardson et al. (2000) model, with the exception that the deceleration and setting conditions that trigger a state change out of ‘ACC active’ result in an ‘ACC off—ACC standby’ error state instead of the ‘ACC active—ACC standby’ error state (see Figure 10).

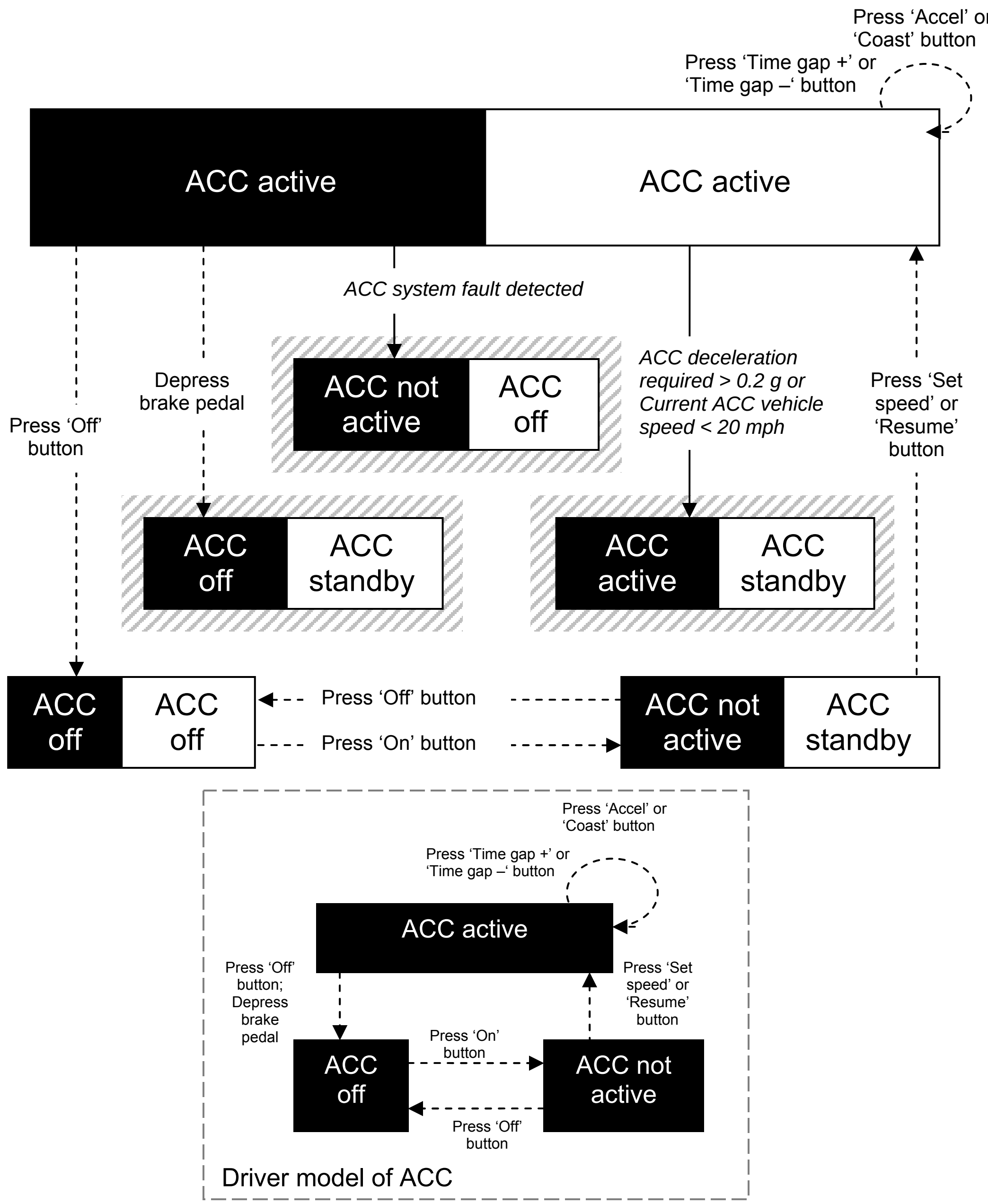

Figure 9. Composite of the driver model (black boxes) and ACC system model (white boxes). Error states are indicated with a vertical hashed border. The driver model is provided as a reference on the right-hand side within the dashed box.

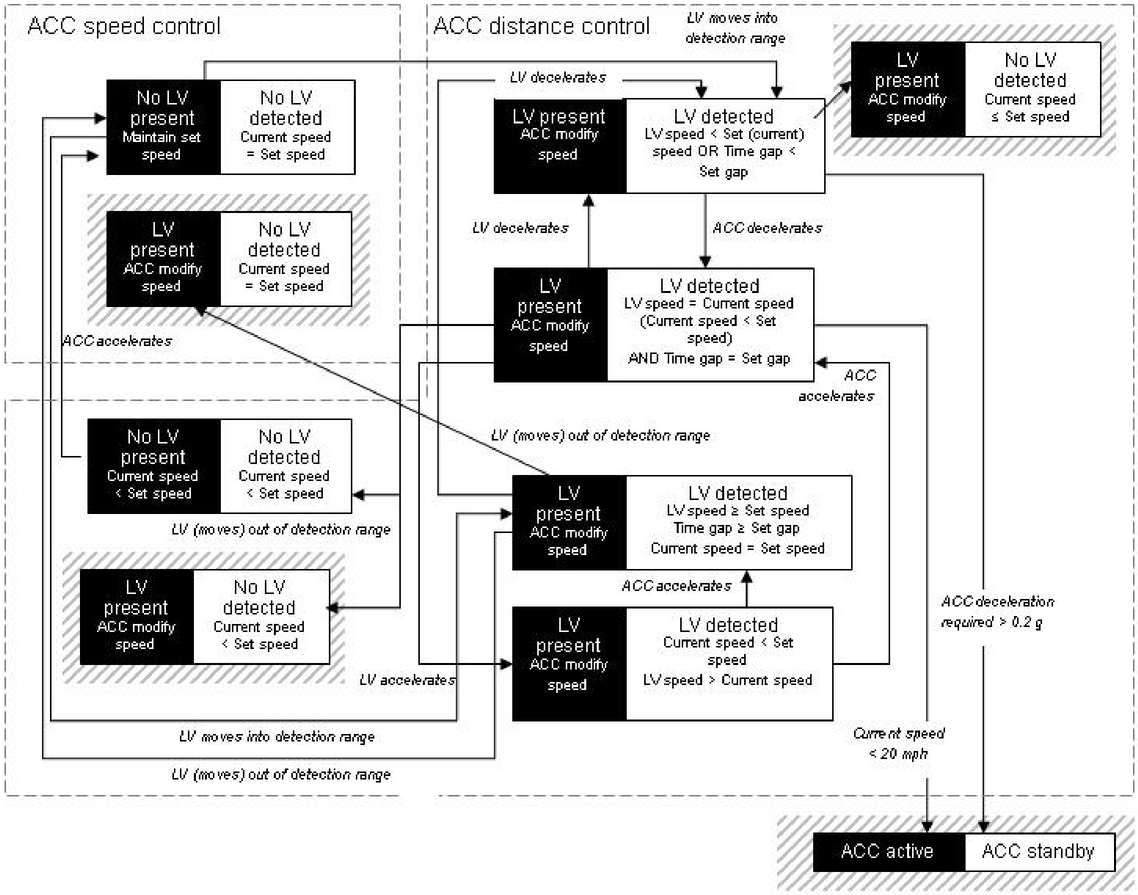

Figure 10. Composite of the Richardson et al. (2000) driver model (black boxes) and ACC model (white boxes), detailed states and transitions within 'ACC speed control' and 'ACC distance control' states. Error states are indicated with a vertical hashed border.

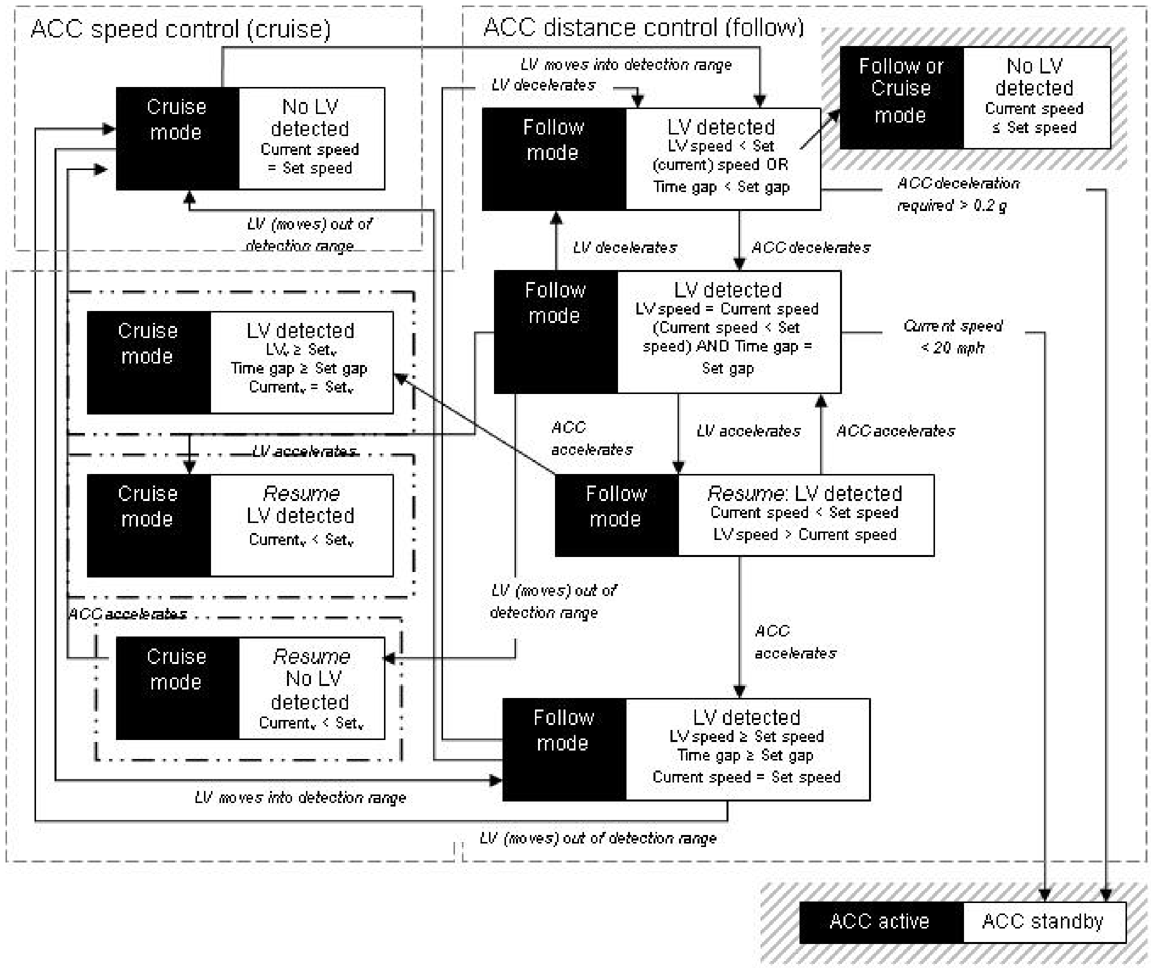

Figure 11. Composite of the King et al. (2000) driver model (black boxes) and ACC model (white boxes), detailed states and transitions within 'ACC speed control' and 'ACC distance control' states. Error states are indicated with a vertical hashed border.

This systematic modeling approach revealed what feedback is currently missing or incorrect as supplied from standard ACC interfaces. Each driver model of ACC represented driver understanding of ACC as informed from the respective interface. Gaps or inconsistencies in understanding were any error states that occur within the composite model. To conform to the ACC system model and to unambiguously inform drivers of the ACC's behavior, an ACC interface should indicate set speed, current speed, set headway, current headway, ACC activation (on, off, standby), if the LV is detected, and the events/conditions that trigger transitions, i.e., the boundary operating conditions of ACC. A correct mental model is not simply a matter of providing all the needed cues but also of how those cues are displayed, as discussed in the next chapter.

Expectation and Control Response

Because a mental model represents understanding, shaping operator prediction of automation behavior and control responses (Carrol & Olson, 1987; Gentner & Stevens, 1983; Moray, 1998; Park & Gittleman, 1995; Wickens & Hollands, 2000), compatibility must exist between the physical system itself, the mental model, and the interface between the two. The driver's mental model is shaped from provided information within an interface. The driver model and the ACC system model (i.e., a model of the physical system itself) combine to produce the composite model that reveals inconsistencies between the two models, e.g., error states (Degani & Heymann, 2002, 2007). Figure 12 shows a high-level model of the components that are involved in producing the driver's expectation of ACC behavior. Inputs to the ACC system model in Figure 12 (desired THW, driving event) represent the dynamic, continuous update of the automated system as it interacts with the environment. Driver expectation of ACC behavior resides within the transitions that produce state changes as part of their mental model. Dynamic ACC behavior either conforms to or contradicts such initial expectation according to the accuracy and completeness of the driver's mental model. An inaccurate or incomplete (or both) mental model, with for instance missing transitions between states or missing states, leads drivers to expect behavior contrary to that observed. ACC behavior conforms to driver expectation when the states and transitions internal to their mental model are consistent with those of the ACC system. Output from the composite model is driver expectation of ACC behavior—a product of the accuracy and completeness of the driver model as compared to the system model.

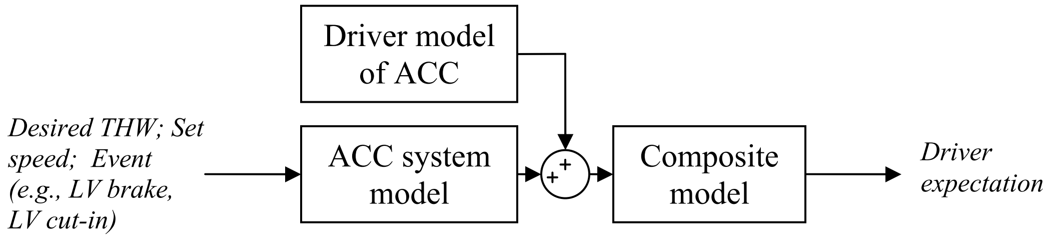

Figure 12. High-level model of 'Mental model' component in Figure 3; this is a model of the driver's expectation of ACC behavior.

The timing of drivers' control responses is a product of their understanding. The location of drivers' responses in relation to the driving events that induce ACC failure indicates the degree to which their understanding of ACC behavior is accurate to its actual behavior. A response prior to an event but following a change in driving condition that heralds the event's occurrence represents a latent interaction failure. With accurate understanding, a driver should recognize the driving conditions that make ACC inappropriate to use and disengage ACC at or prior to such changes. Any response following the precipitating event represents a response interaction failure; a driver is simply reacting to the deteriorating driving conditions to avoid a collision. Figure 13 depicts the time-based relationship between driver response and driving event and its implications for interaction failure type.

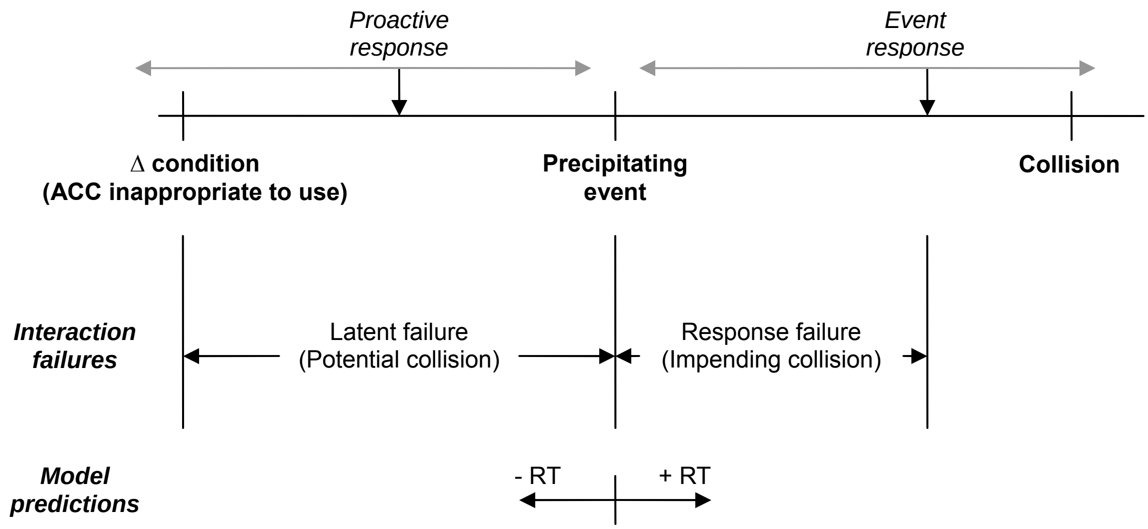

Figure 13. Driver response timeline. Interaction failures include latent failures and response failures. Model predictions indicate the difference between anticipatory responses (-RT) and delayed responses (+RT). RT is reaction time.

Driving events that induce ACC failures vary according to their environmental predictability and situation dynamics. In terms of Figure 13, these differences are represented according to the temporal spacing of the response boundaries (i.e., change in condition, precipitating event, collision): for environmental predictability, by the timing between change in condition and precipitating event, and for situation dynamics, by the timing between precipitating event and collision. The variance between these boundaries necessitates that driver reaction time (RT) be interpreted relative to the response boundaries. The precipitating event, as the failure-inducing event, is the zero point for calculating RT (see the boundary for -RT and +RT in Figure 13).

Calculating response threshold. The lower bound for a driver's control response (i.e., disengaging ACC) is at the point where an event is first perceptible—a just-noticeable difference (JND). Essentially, such a response occurs provided the perception of a change in a particular variable. For dynamic visual objects, the JND is based on the visual angle subtended by the object at the eye of the following driver (θ) and the rate of change of this visual angle ($d\theta/dt$). These quantities are defined, according to Hoffmann and Mortimer (1996), as:

$$\theta = W/H \tag{1}$$

$$d\theta/dt = \dot{\theta} = WV_r/H^2 \tag{2}$$

where W is the width of the object, V_r is the relative velocity between the driver's vehicle and the object and H is the distance between the following driver's eye and the rear of the object. The visual angle and the angular velocity subtended by the observed object are perceptible above the threshold values of approximately 0.017 degrees (Hills, 1975) and 0.17 degrees/second (Hoffmann & Mortimer, 1994), respectively.

In tasks involving approaching objects, humans use visual angle and expansion rate (i.e., rate of change of visual angle) as cues to determine when to initiate an avoidance response (Smith, Flach, Dittman, & Stanard, 2001). Humans respond on the basis of these two variables differentially, favoring one as the primary source of information, dependent on approach dynamics (i.e., approach speed and initial distance) and object size. Essentially, the situation dynamics determine the degree to which visual angle and expansion rate are used alone or in combination to determine the threshold for (a collision-avoidance) response. This relationship is defined as:

$$\varphi_1 = \alpha_1 * \theta + \alpha_2 * \dot{\theta} \tag{3}$$

where φ_1 is the threshold for driver response and α_1 and α_2 are the weights for visual angle (θ) and expansion rate ($\dot{\theta}$), respectively.

In driving, visual angle and expansion rate are effective information sources for detecting deceleration of a lead vehicle only when they exceed the lower bound thresholds (0.017 degrees and 0.17 degrees/second). The perceptual system is flexibly attuned to specific properties of the task environment in response to a looming event or stimulus, whereby angle and expansion rate strategies are used alone or in combination (Smith et al., 2001). While the information drivers use to detect deceleration may differ for near and far lead vehicles (see Hoffmann, 1968), including such depth cues as occlusion or discrete cues such as brake light onset, the primary cues used are visual angle and expansion rate, to which the model is constrained to simplify calculations.

Visual angle and expansion rate, alone or in combination, define a perceptual response threshold: a response at a value greater than or equal to 0.017 degrees and/or 0.17 degrees/second is in reaction to a perceptible event but less than these values is in reaction to cues that predict the event prior to its being perceptible. Responses on opposing sides of this boundary are meaningfully different because they indicate different driver strategies for when to respond.

Another type of response threshold pertinent to driving is that of a threat threshold. Time-to-collision (TTC) is often applied as a safety indicator for longitudinal control using a determined minimum TTC (e.g., van Winsum & Heino, 1996; Hirst & Graham, 1997).

$$\mathrm{TTC} = R \,/\, (V_{\text{driver's vehicle}} - V_{\text{lead vehicle}}) \qquad (4)$$

where R indicates range from the driver's vehicle to the lead vehicle. TTC indicates collision potential, being inversely related to accident risk (higher TTC values indicate a higher accident risk and vice versa). A minimum TTC of 3 or 4 seconds is often cited as the boundary discriminating instances in which drivers unintentionally find themselves in a dangerous situation and those in which they remain in control (Hirst & Graham, 1997; Horst, 1984; Maretzke & Jacob, 1992). As with the perceptual threshold, responses on opposing sides of a TTC boundary are telling to different response strategies.

Response strategies. The value of the response threshold (φ) at which drivers will initiate a control response depends on response strategy. This strategy is a function of their implicit (trust) and explicit (mental model) understanding of ACC's behavior. For instance, drivers with inaccurate mental models are likely to initiate control responses based on their JND of a driving event that signals an ACC failure rather than on their perception of a change in driving condition that precedes an ACC failure. As another example, drivers with accurate mental models may delay their control responses, despite perceiving a change in driving condition, because they over-trust the ability of ACC to account for the changing condition (essentially placing greater importance on their implicit understanding than on their explicit understanding). In the examples mentioned, JND for a precipitating event and JND for change in condition, respectively, could be used as the response thresholds (based on JND calculations from formula 3: φ_1). Perception of a variable change does not ensure response, however, particularly if the dynamics of the situation do not necessitate a response. Drivers may decide to postpone a response to assess the severity of the situation against their better judgment and counter to what experience predicts will happen. In this situation, a driver response relative to the threat threshold would differentiate between an intentional (> 4 s *TTC*) versus a required response (< 4 s *TTC*). Ideally, a driver's response threshold is more conservative than the JND for a precipitating event, resulting in a response prior to this event.

There are seven response strategies that are expected from the interaction of implicit and explicit understanding. The timing of a control response relative to the boundaries in the response timeline (from Figure 13) defines each strategy. These strategies and their timing along the response timeline are listed in Table 2 and shown in Figure 14 below. The strategies are hypothesized categories that differentiate driver response to ACC failure; the experiment in Chapter V generated data to determine if these strategies accurately capture the groupings of driver responses and in turn, each strategy's assumed level of explicit and implicit understanding. The perceptual response threshold (φ_1) is the predicted response trigger for inaccurate mental models, and is used to operationalize the boundaries in the response timeline (see the 'Response trigger' column of Table 2). For instances in which the threat response threshold, which separates threat situations (< 4 s *TTC*) from non-threat situations (> 4 s *TTC*), occurs prior to φ_1 due to the dynamics of the situation, the threat threshold is the predicted response trigger, essentially replacing 'JND' in Table 2 with '4 s *TTC*'.

Table 2. Response Strategies and Their Triggers within the Proposed Model

Strategy	Response trigger
1. Informed (accurate mental model)	Before JND for event
2. Uninformed (inaccurate mental model)	*After* JND for change in condition; JND for event
3. Over-trust	*After* JND for event
4. Under-trust	Before JND for change in condition
5. Informed, calibrated trust	JND for change in condition
6. Informed, over-trust	*After* JND for change in condition
7. Additional (unknown) cues within environment or interface used to determine response	Before JND for change in condition

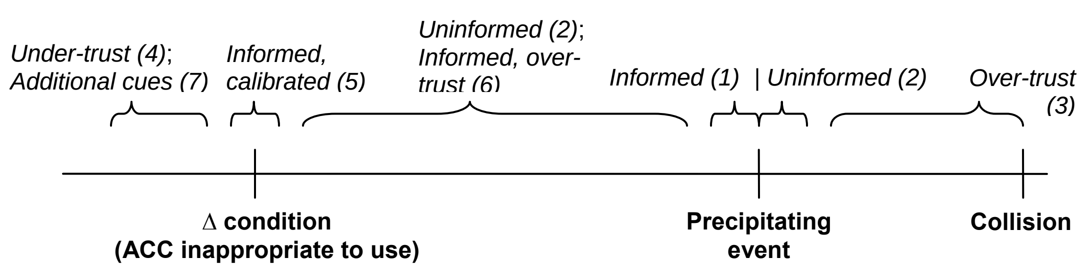

Figure 14. Response strategies, defined by their timing relative to the boundaries in the response timeline.

Calculating control response. Of the possible values for α_1 and α_2 in formula 3, three sets of scaling constants are used to examine the possible rankings of visual angle (θ) and expansion rate ($\dot{\theta}$) as information sources for determining when to initiate an avoidance response. The following weights for θ and $\dot{\theta}$ are tested for each response trigger:

- visual angle only: $\varphi_1 = 1.0 * \theta + 0.0 * \dot{\theta}$

- expansion rate only: $\varphi_1 = 0.0 * \theta + 1.0 * \dot{\theta}$
- visual angle and expansion rate weighted equally: $\varphi_1 = 0.5 * \theta + 0.5 * \dot{\theta}$

Threat threshold values of TTC = 3 s and TTC = 4 s are also included in the model calculations of driver RT. Essentially, for every event tested in the model, three perceptual response thresholds and two threat response thresholds are used to calculate driver RT.

To determine the specific values of φ_1 (thresholds that trigger a response), and of α_1 and α_2 (relative importance of the two perceptual variables), an additional modeling exercise would be to use the data from the experiment described in Chapter V to train a genetic algorithm to determine parameters values. This is a potential extension of the current model.

The use of response thresholds with values for which drivers initiate a control response based on their explicit and implicit understanding allows the model to make predictions that are testable in a participant-based study. Within this section, expectation of system behavior is shown to affect driver RT to imperfect ACC behavior, revealing how interaction failures can occur.

ACC component

The control aspects of the ACC system model that determine its response behavior that trigger state transitions are briefly described below. The two-level longitudinal control model from Zheng and McDonald (2005) was adopted to simulate ACC behavior. The upper level controller computes acceleration using inputs of range (headway), and range rate (relative speed). The lower level controller determines the throttle (or brake) commands that are required to track the upper level of command. The upper level control algorithm is based on a proportional derivative (PD) control law:

$$a_{\text{cmd}} = K_v(\dot{x}_{DV} - \dot{x}_{LV}) + K_d(x_{DV} - x_{LV} - T_h * \dot{x}_{LV}) \tag{5}$$

where a_{cmd} is the acceleration command input, K_v and K_d are feedback gains, x_{DV} and x_{LV} are the position of the driver's vehicle (*DV*) and lead vehicle (*LV*), respectively, $\dot{x}_{DV}$ and $\dot{x}_{LV}$ are the velocity of the *DV* and *LV*, respectively, and T_h is the set time headway.

The lower level controller is approximated by a first-order lag τ, set to 0.5 s based on experimental results from work of Rajamani and Shladover (2001). This set delay value encompasses delay caused by sensors, brake actuator or engine time delays, and controller delay. The open-loop ACC control law that includes both controllers is as follows:

$$\dddot{x}_{LV} = \frac{1}{\tau}\left[K_v(\dot{x}_{DV} - \dot{x}_{LV}) + K_d(x_{DV} - x_{LV} - T_h * \dot{x}_{LV}) - \ddot{x}_{LV}\right] \tag{6}$$

where $\dddot{x}_{LV}$ is the rate of change of acceleration of the *LV* as a function of time. Based on the results from Zheng and McDonald (2005), K_v and K_d are set to 0.75 and 0.1, respectively. The time headway (T_h) is set to 1.5 s. The maximum acceleration of the ACC system is 0.2 g.

Model outputs

The described model outputs driver reaction time to failures of the ACC system to maintain the set THW, and a composite model profile, which indicates state changes over time and any resulting error states. The model also outputs velocities and relative positions of the lead vehicle and the driver's vehicle for the duration of a driving event (or until disengagement), allowing for calculation of collision frequency—a driver safety measure.

The purpose of the driver–ACC interaction model analysis is to reveal how interface design and driving condition lead to driver–ACC interaction failures. The resulting improved understanding of driver–ACC interaction will guide the design of an ACC continuous information display. The following four questions are addressed by the implemented driver–ACC interaction model:

1) What event conditions lead to collisions with use of ACC?
2) In what conditions are drivers' perceptual abilities ineffective?
3) What are the implications of an inattentive driver?
4) What are the potential benefits of continuous feedback?

Method

The model used for these analyses was developed using Simulink 6.0 and Stateflow, 6.0, as part of MATLAB 7.0 (Mathworks Inc., Natick, MA). All parameters relating to the driver component and ACC component are controllable. The driver models and system model of ACC were implemented using Stateflow. The basic ACC system model is shown in Figure 15. The 'On' state is shown in Figure 16. The open-loop control law for ACC (formula 5) was implemented using Simulink as shown in Figure 17. Figure 18 shows the interaction of these two components within MATLAB.

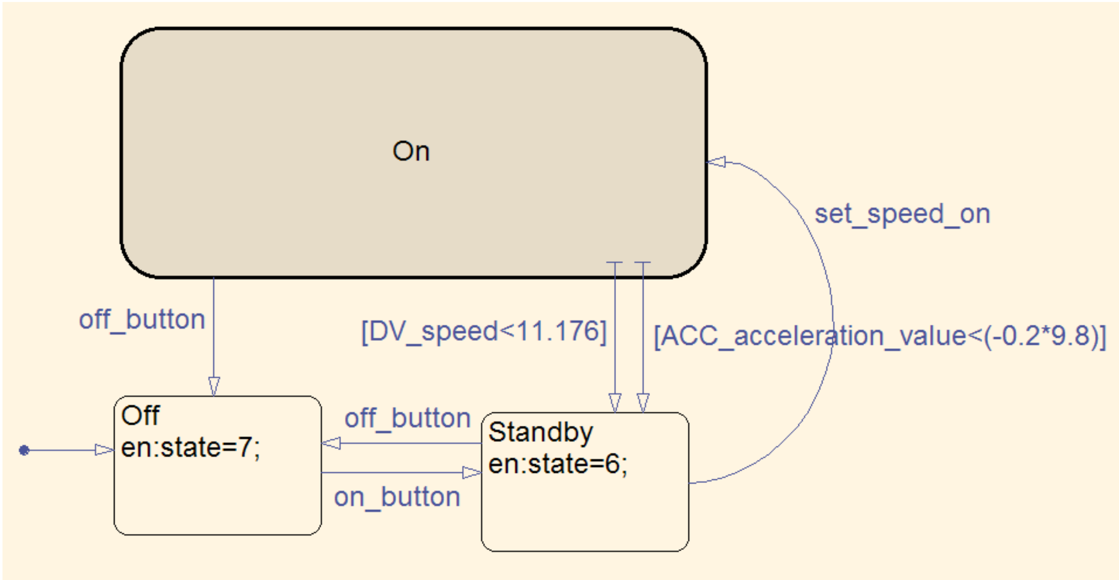

Figure 15. Stateflow implementation of ACC system model (i.e., accurate driver model of ACC).

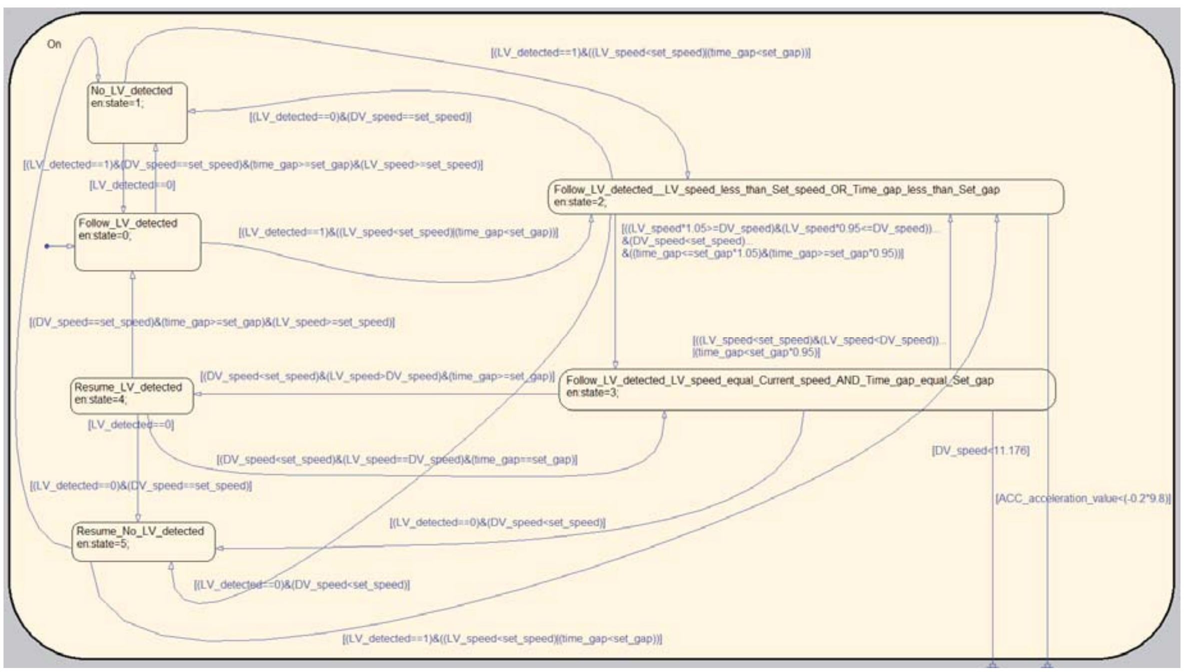

Figure 16. Stateflow implementation of 'On' state of ACC system model (i.e., accurate driver model of ACC).

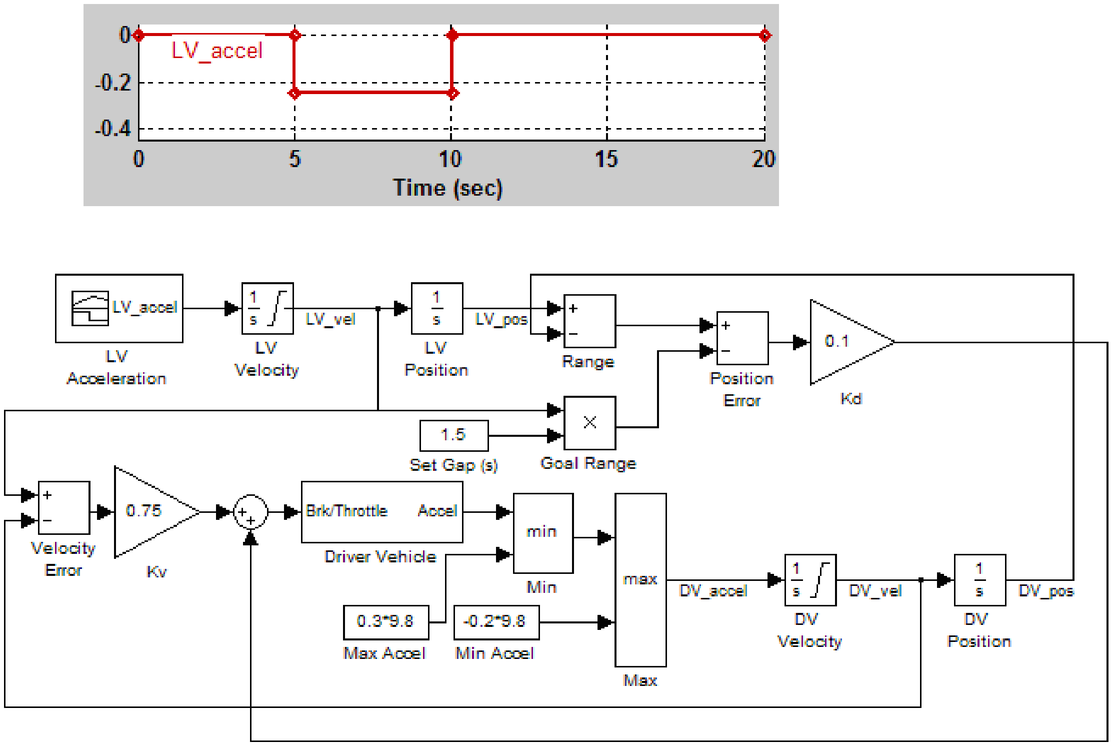

Figure 17. Simulink model of Zheng and McDonald's (2005) ACC algorithm with expanded detail of an example LV acceleration profile shown in the gray box above.

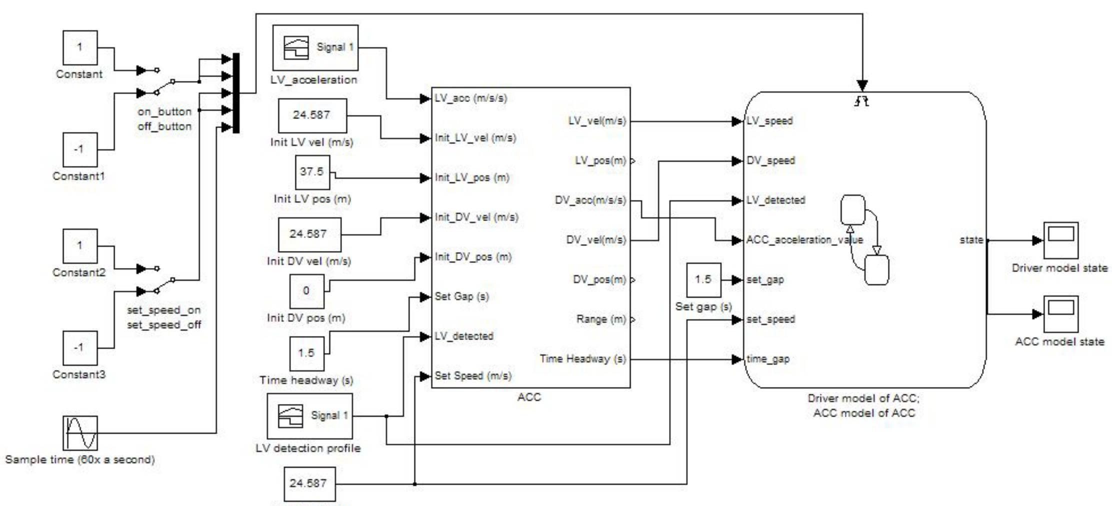

Figure 18. Simulink model of ACC and its interaction with the driver and system models of ACC.

Initial event conditions were input into the ACC component, which output an acceleration profile for the driver vehicle. This profile and event parameters were input into the driver model and into the ACC system model to dynamically transition through their respective states and transitions. Driver reaction time to ACC failure events were calculated from the precipitating event to the control response.

Independent variables

The independent variables examined in this study were event type, driver model, and control response.

Event type

Each event type is characterized by lead vehicle (LV) acceleration, LV velocity, driver vehicle (DV) velocity, initial time headway (THW) to LV, initial range rate to LV, set velocity, and an ACC sensor operation profile (i.e., this input is a series of numerical constants that denote if the sensor is fully functioning—a non-zero value—or in failure mode—a null value; this sensor operation profile specified the failure duration of the sensors). The event types and their associated conditions are listed in Table 3. These event types were selected based on their differential effect on ACC's braking, sensing, and setting limits. Additionally, the event conditions resulted in differing ACC response behaviors at failure: 1-second maximum deceleration followed with transition to standby, acceleration to set velocity within active state, and immediate transition to standby for braking, sensing, and setting failures, respectively. In their unique behavioral implications to ACC, these event conditions test the specificity of a driver's mental model. Further, the event types in Table 3 articulate the situational factors and vehicle dynamics that are reported in the literature as problematic to drivers in use of ACC. Events cited as inducing driver confusion and ACC misuse are degraded sensors (Stanton, Young, & McCaulder, 1997), braking limit exceedances (Nilsson, 1995; Rudin-Brown & Parker, 2004; Zheng & McDonald, 2005), offset LV outside sensor field, LV in curve outside sensor field (Stanton, Young, & McCaulder, 1997), lateral incursion of a LV not detected by sensor field (Zheng & McDonald, 2005), and set velocity deviant from LV velocity (Hoedemaeker, 2000). For all event types, the initial conditions represent a following situation in which the driver's vehicle and a lead vehicle are at 1.5 s THW to each other at equal velocity. LV deceleration rate and duration, sensor failure time, and velocity difference to set speed are varied for the braking limit exceedence, degraded sensor/lateral range limit exceedence, and setting exceedence event types, respectively.

Table 3. Event Inputs to Model of Driver–ACC Interaction

Driving Event Type	Description of Driving, Initial Conditions, and ACC response	Number of Conditions
Braking limit exceedance	THW_o = 1.5 s; RR_o = 0.0 m; Set V_o = 24.59 m/s [55 mph] DV V_o = 22.35 m/s [50 mph] LV V_o = 22.35 m/s [50 mph] d_{LV} = 0.0 : 0.01 : 0.85 g T_{decel} = 0 : 0.1 : 10 s T_F = 0 s Individual condition run time: 60 s (at 60 Hz)	8,686
Degraded sensor / Lateral range limit exceedence (LV in curve)	THW_o = 1.5 s; RR_o = 0.0 m; Set V_o = 24.59 m/s [55 mph] DV V_o = 22.35 m/s [50 mph] LV V_o = 22.35 m/s [50 mph] d_{LV} = 0.0 : 0.01 : 0.85 g T_{Decel} = 0 : 0.1 : 10 s T_F = 1, 5, 10 s Individual condition run time: 60 s (at 60 Hz)	26,058
Minimum velocity setting exceedence	THW_o = 1.5 s; RR_o = 0.0 m; Set V_o = 13.41 m/s [30 mph] DV V_o = 13.41 m/s [30 mph] LV V_o = 13.41 m/s [30 mph] d_{LV} = 0.0 : 0.01 : 0.85 g T_{Decel} = 0 : 0.1 : 10 s T_F = 0 s Individual condition run time: 60 s (at 60 Hz)	8,686

THW = time headway; *RR* = range rate; *DV* = driver's vehicle; *LV* = lead vehicle;

V_o = initial velocity; d_{LV} = deceleration rate of LV; T_{decel} = time of LV deceleration;

T_F = sensor failure time; a_{ACC} = acceleration response of ACC

Note: Numbers nested between two numbers with colons on either side are the step sizes

The equations of motion for the driver and lead vehicles were solved using a fixed step size of 0.01667 s. The accelerations of the lead and driver vehicles were constant over the step size. The acceleration of the lead vehicle changed over time according to a predetermined profile. The shape of the profile was a rectangular function in which the height and width of the rectangle were varied with each simulation run. The height of the rectangle corresponded to the deceleration rate and the width of the rectangle corresponded to the deceleration period (see Figure 19). The acceleration of the driver vehicle was set by the adaptive cruise control model which is described in the next section.

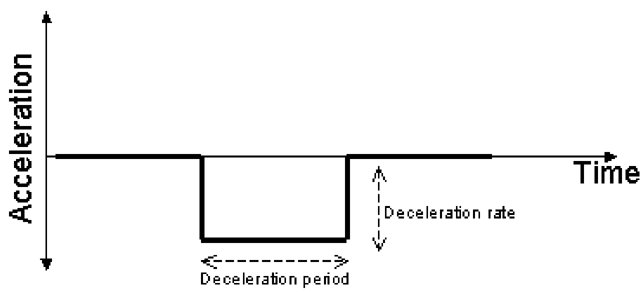

Figure 19. Lead vehicle acceleration profile.

The following equation was used to solve for the velocity of the lead and driver vehicles at each step in the simulation.

$$v_i = v_{i-1} + a_i \Delta t \tag{7}$$

where v_i was the current velocity of the vehicle, v_{i-1} was the previous velocity, a_i was the current acceleration and Δt was the step size. The position of each of the vehicles was computed with the following equation.

$$s_i = s_{i-1} + v_i \Delta t + \frac{1}{2} a_i (\Delta t)^2 \tag{8}$$

where s_i was the current position of the vehicle, s_{i-1} was the previous position of the vehicle, v_i was the current velocity of the vehicle, a_i was the current acceleration and Δt was the step size.

ACC model implementation. The acceleration of the driver vehicle was computed at each time step based on a fixed-base simulator vehicle model. To create the vehicle model, the subject vehicle acceleration response to throttle and brake levels were measured in a fixed-based driving simulator. Figure 20 shows the raw data collected from this simulator.

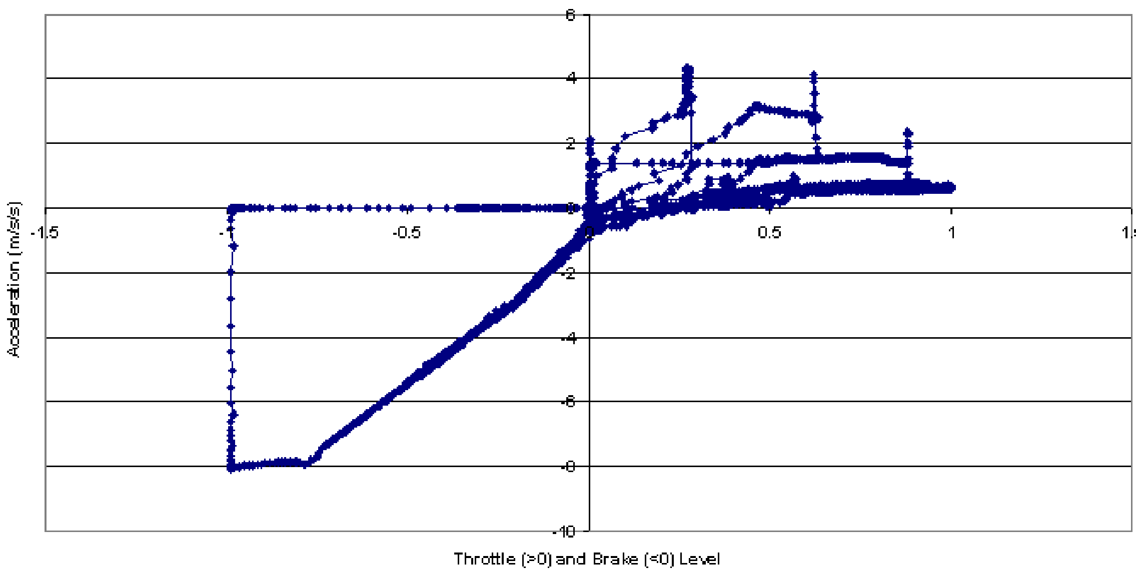

Figure 20. Driver vehicle acceleration as a function of throttle and brake levels.

The positive x-axis represents throttle levels while the negative x-axis represents brake levels. The y-axis represents the acceleration response of the driver vehicle. The acceleration is a different function of throttle level depending on the state of the vehicle's transmission. As expected, in lower gears, the vehicle accelerated more for a given throttle level than in higher gears. Because ACC operates at higher speeds, and thus higher gears, the high-gear relationship between throttle level and acceleration was assumed. Figure 21 shows the piecewise linear approximation of the vehicle that was used in the driver–ACC interaction model.

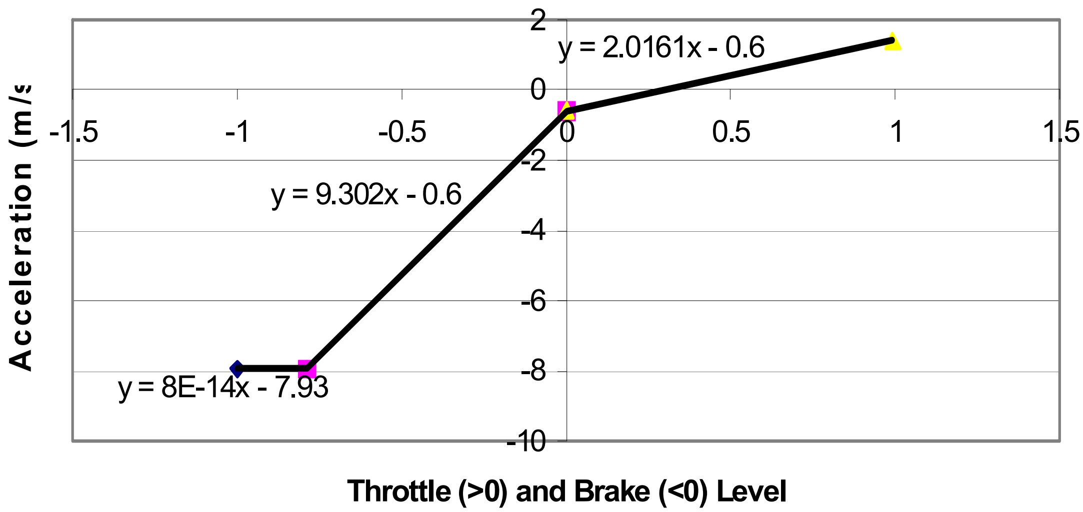

Figure 21. Piecewise linear approximation of the driver vehicle acceleration as a function of throttle and brake levels.

The ACC error value was computed as the weighted sum of the THW and range rate errors (i.e., see formula 5, Zheng & McDonald, 2005). Throttle and brake levels were adjusted by the ACC PD control loop to force the ACC error value to zero. The vehicle approximation served as a transfer function to convert throttle and brake levels to driver vehicle accelerations. The acceleration was then used to compute the velocity and position of the driver vehicle using the equations of motion described above. The acceleration profile of the lead vehicle was used to compute its current velocity and position using the same equations of motion. Given the new velocity and position of the driver and lead vehicles, the ACC error value was computed and this process repeated. To verify the stability and response time of the ACC model, three test cases were developed. Test case 1 was a step change in velocity of the lead vehicle. Test case 2 was a slow change in velocity of the lead vehicle. Test case 3 was a sinusoidal variation in the velocity of the lead vehicle for a period of 10 seconds. Timeline plots of longitudinal-control variables were evaluated for each test case; an example of a composite plot is shown in Figure 22. These timeline plots were used to visualize the response of the ACC algorithm to each of the test cases and to verify that the ACC responded efficiently and remained stable. Figure 22 shows a test case in which the ACC system reached its deceleration limits in response to a LV deceleration event but was able to recover THW and range rate control.

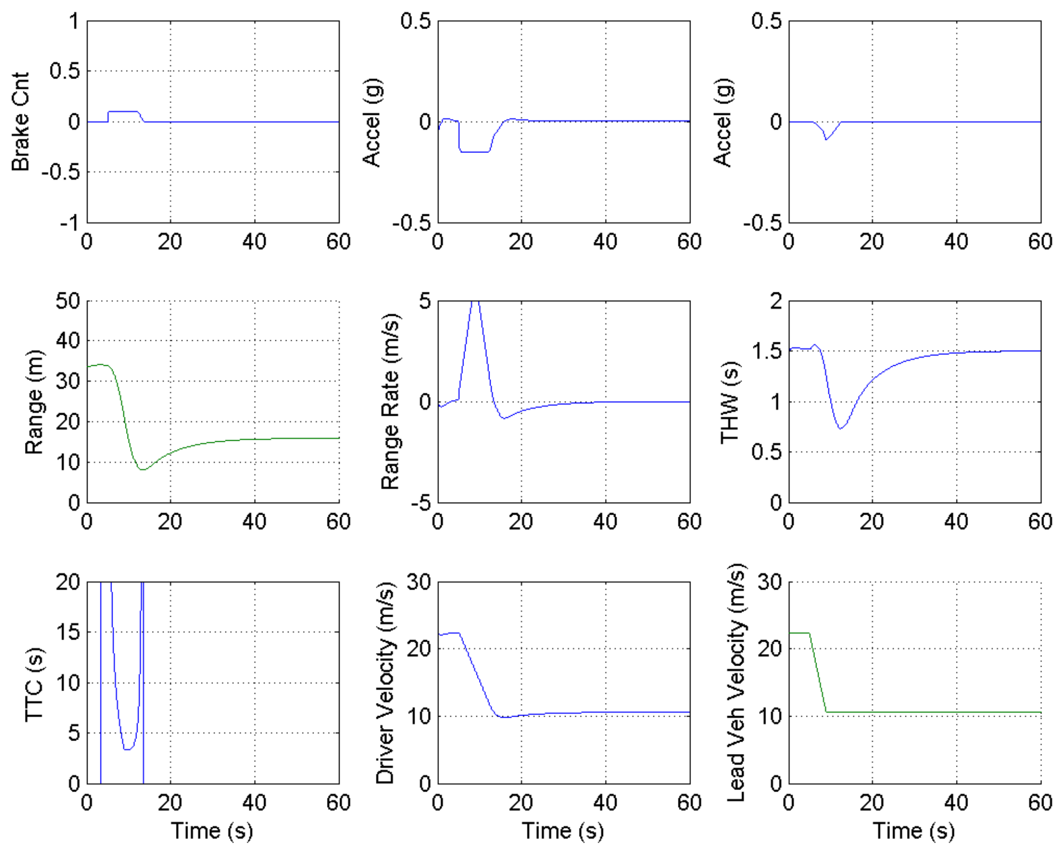

Figure 22. Longitudinal-control variables plotted as a function of time for the sharp lead vehicle deceleration: test case 1. The upper left plot is ACC's acceleration scaled from 0 to 1, the upper middle plot is the driver vehicle acceleration (g), and the upper right plot indicates the acceleration required to avoid a collision. The plots below indicate, moving from left to right across each row, range between the lead vehicle and the subject vehicle, range rate, THW, TTC, driver vehicle velocity, and lead vehicle velocity.

Driver model

Two driver models of ACC were implemented in Stateflow for the driver component of the interaction model:

1) A driver model as predicted to result from use of an ACC system that issued discrete warnings when its limits were exceeded;
2) A driver model as predicted to result from use of an ACC system that provided continuous feedback on its activation state, settings, and operating limits.

Control response

Initial model runs indicated that visual angle was not a viable information source for determining when to initiate an avoidance response because it exceeded the perceptual threshold in all event conditions. Consequently, only the expansion rate form of formula 3 was used for a perceptual threshold.

Seven control responses were tested: 1) no response (a control condition); 2) JND of expansion rate (a perceptual threshold); 3 and 4) TTC = 3 s, TTC = 4 s (threat response thresholds); 5) state change from inaccurate model; 6) state change from accurate model, and 7) state change from accurate model with inattention delay. To more accurately model driver response time to ACC failures, a 1.5 s time delay was added to each control response calculation of reaction time to account for cognitive processing and movement time to initiate a brake response (McGehee, 1995; Brown et al., 2001). The independent variables were manipulated in four analyses to address the model questions.

Dependent measures

From the driver–ACC interaction model output, driver reaction time to ACC failure (mean and standard deviation) and collision outcome are reported.

Results and Discussion

The total number of event conditions produced from the initial conditions listed in Table 3 was 43,430. A driver reaction time was calculated for each of these initial conditions for each of the seven control responses. These data were summarized into a single figure for each event type by control response that indicated collision outcome percent and mean driver RT. Table 4 summarizes these statistics by control response and event type. These results are discussed according to analysis question.

Table 4. Summary of Model Findings

Collisions	No Response	Expansion Rate	TTC=3	TTC=4	Inattentive	Discrete Warnings	Continuous Feedback
Braking	0.54	0.527	0.351	0.183	0.483	0.463	0
Sensing 1	0.591	0.578	0.367	0.181	0.037	0	0
Sensing 5	0.785	0.768	0.545	0.366	0.122	0	0
Sensing 10	0.903	0.889	0.545	0.366	0.122	0	0
Settings	0.636	0.603	0.378	0.162	0.48	0.472	0

Mean RT for Response Required Conditions	No Response	Expansion Rate	TTC=3	TTC=4	Inattentive	Discrete Warnings	Continuous Feedback
Braking	-	7.024	4.438	3.967	4.814	4.524	3.063
Sensing 1	-	6.649	3.985	3.603	2.228	1.928	0.428
Sensing 5	-	7.565	4.305	3.744	2.306	2.001	0.501
Sensing 10	-	10.973	5.317	4.59	2.306	2.001	0.501
Settings	-	5.856	3.952	3.717	3.813	3.633	2.438

Standard Deviation of RT for Response Required Conditions	No Response	Expansion Rate	TTC=3	TTC=4	Inattentive	Discrete Warnings	Continuous Feedback
Braking	-	0.231	0.164	0.03	0.041	0.049	0.125
Sensing 1	-	0.247	0.152	0.015	0.001	0	0
Sensing 5	-	0.314	0.351	0.361	0.035	0.014	0.014
Sensing 10	-	0.3	0.446	0.55	0.035	0.014	0.014
Settings	-	0.24	0.081	0.007	0.238	0.267	0.134

ACC Capable	No Response	Expansion Rate	TTC=3	TTC=4	Inattentive	Discrete Warnings	Continuous Feedback
Braking	-	0.448	0.436	0.415	0.459	0.459	0.459
Sensing 1	-	0.369	0.382	0.359	0.27	0.27	0.27
Sensing 5	-	0.199	0.181	0.155	0	0	0
Sensing 10	-	0.082	0.069	0.055	0	0	0
Settings	-	0.355	0.347	0.324	0.364	0.364	0.364

What event conditions lead to collisions with use of ACC?

This question was addressed by event type. In situations in which drivers do not initiate a control response, ACC is required to handle the driving condition. For each event type, the 'No Response' column in Table 4 lists the percent of conditions that result in a collision ('Sensing 1', 'Sensing 5', and 'Sensing 10' denote the duration of the sensor failure in seconds). See also Figure 23, Figure 24, and Figure 25; in these figures, the white area represents situations that ACC is capable of responding to given its operating limits; the black area represents collisions that occur due to ACC exceeding its limits; the percent of conditions that result in a collision is noted above the plot. From these findings, it is evident that ACC is incapable of responding to a large number of LV following situations. The braking capabilities of ACC are sufficient to handle only half of the LV decelerations at a higher velocity. As sensor failure durations increase, collisions become inevitable for a wider range of lead vehicle deceleration profiles. At slower speeds, the minimum velocity limit of ACC is quickly reached. These results confirm the selection of event types for situations that are likely to induce driver–ACC interaction failures. The prevalence of situations in which ACC's limits are exceeded indicates the need for drivers to remain vigilant to its moment-to-moment state and behavior.

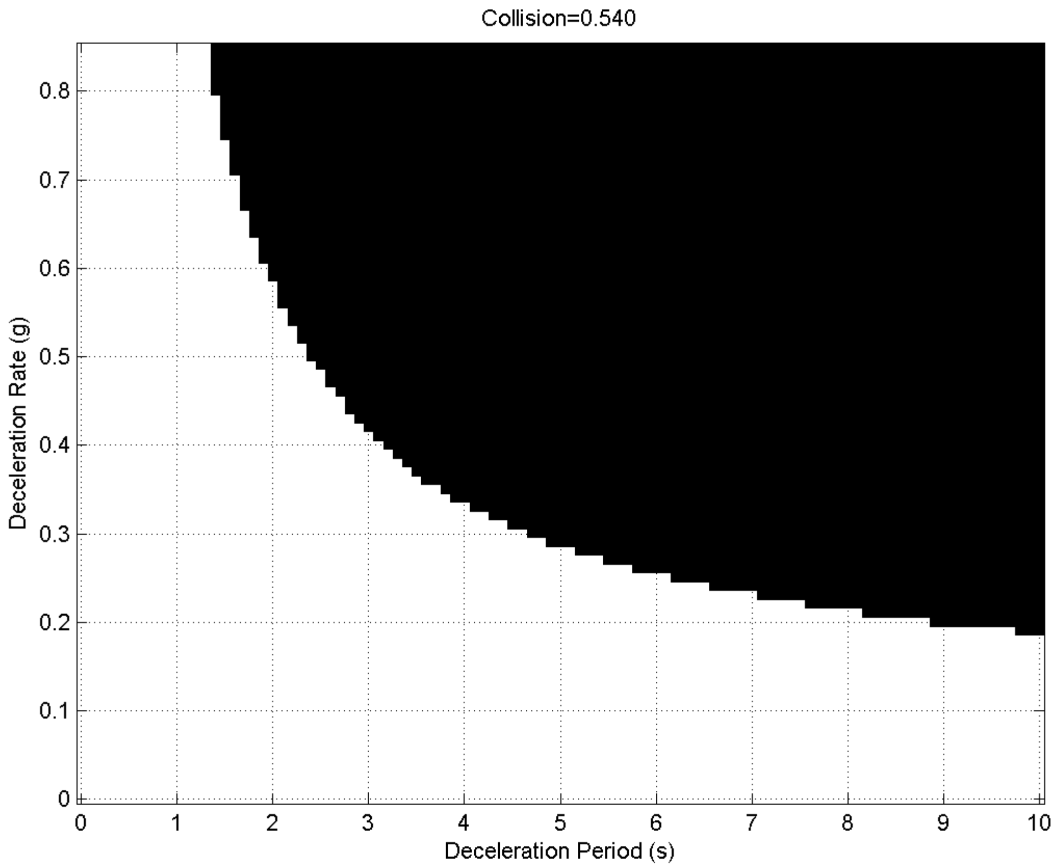

Figure 23. Driving conditions (defined by LV deceleration period and deceleration rate) that resulted in a collision given no driver intervention for the braking event type.

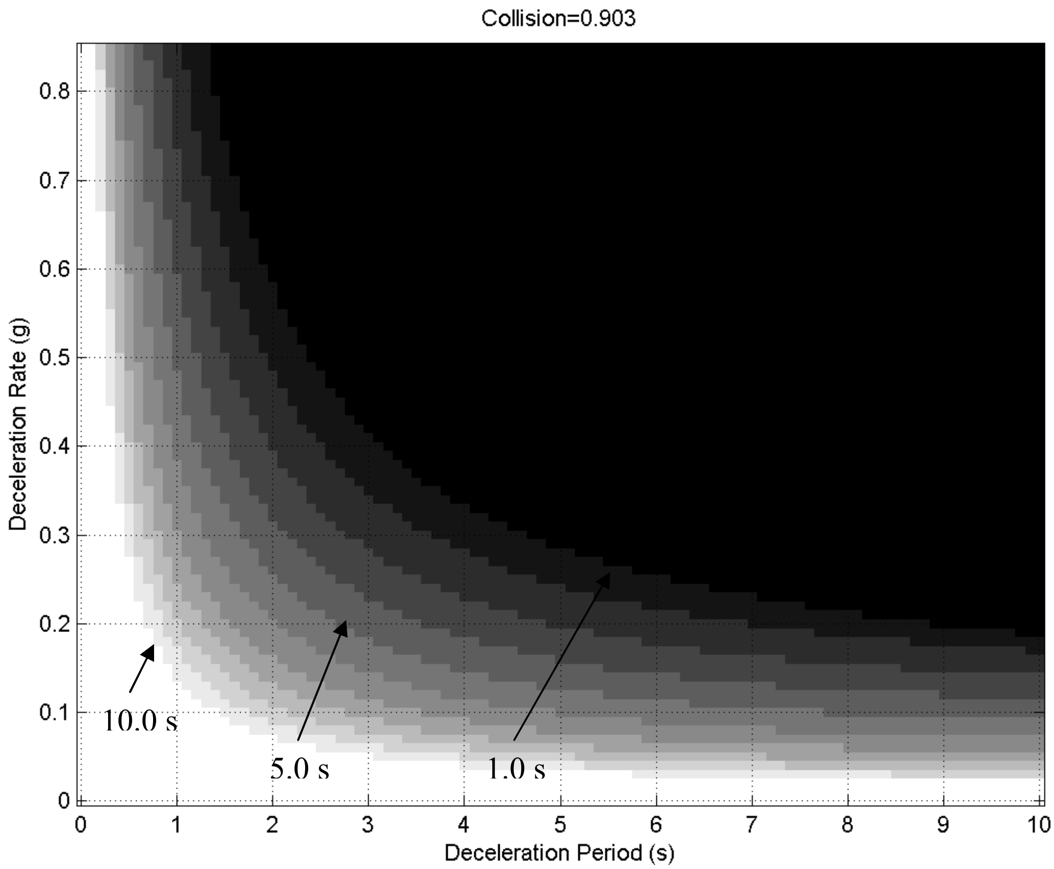

Figure 24. Driving conditions (defined by LV deceleration period and deceleration rate) that resulted in a collision given no driver intervention for the sensing event types. The shades of gray correspond to the different sensor failure times (1 – 10 s).

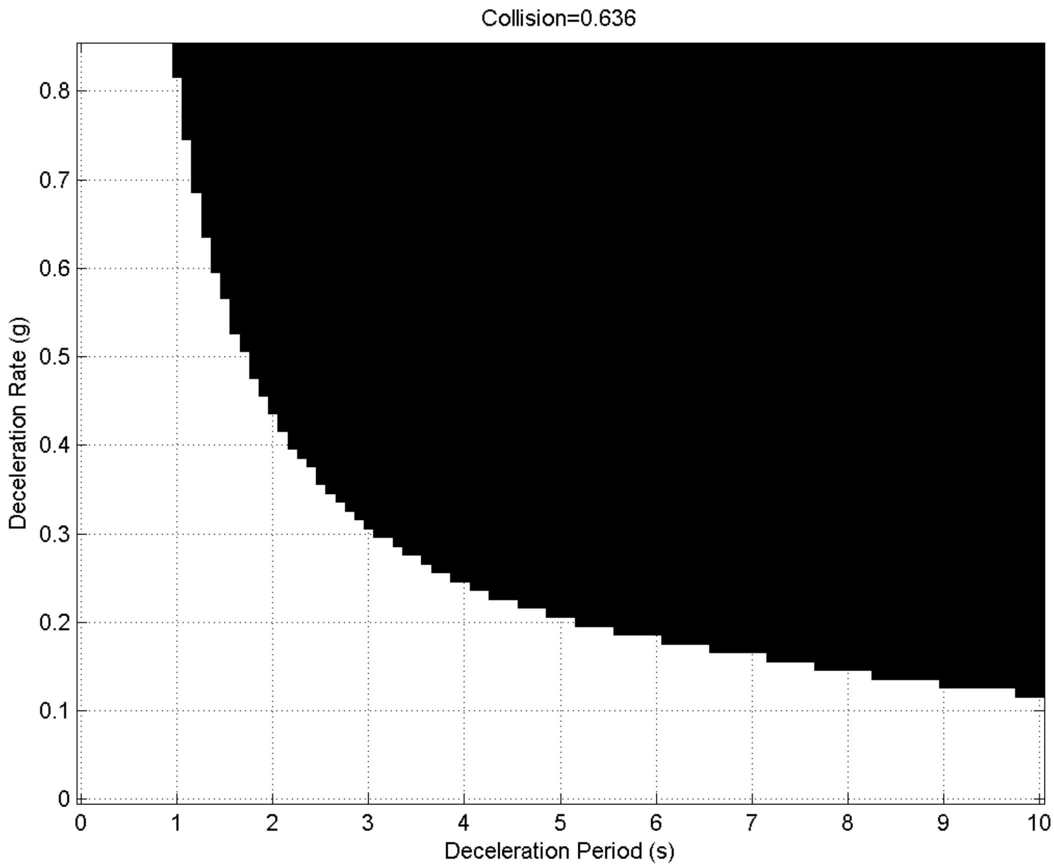

Figure 25. Driving conditions (defined by LV deceleration period and deceleration rate) that resulted in a collision given no driver intervention for the settings event type.

In what conditions are drivers' perceptual abilities ineffective?

Drivers who rely on their perceptual abilities to detect and respond to failures of ACC are likely to over-estimate its ability to operate within its limits. The 'Expansion Rate', 'TTC=3'and 'TTC=4' columns in Table 4 detail the consequences for driver control responses initiated at these perceptual/threat thresholds (*Note*: RTs include the 1.5 s delay to respond following response triggers). A figure of the results for each perceptual and threat threshold for the braking event type supplements the discussion of these data (see Figure 26, Figure 27, and Figure 28). A TTC=4 response threshold results in the fastest reaction times across event types and consequent lowest number of collision situations. Numerous event conditions still exceed drivers' ability to respond safely with use of this threat boundary as a threshold for when to initiate a control response.

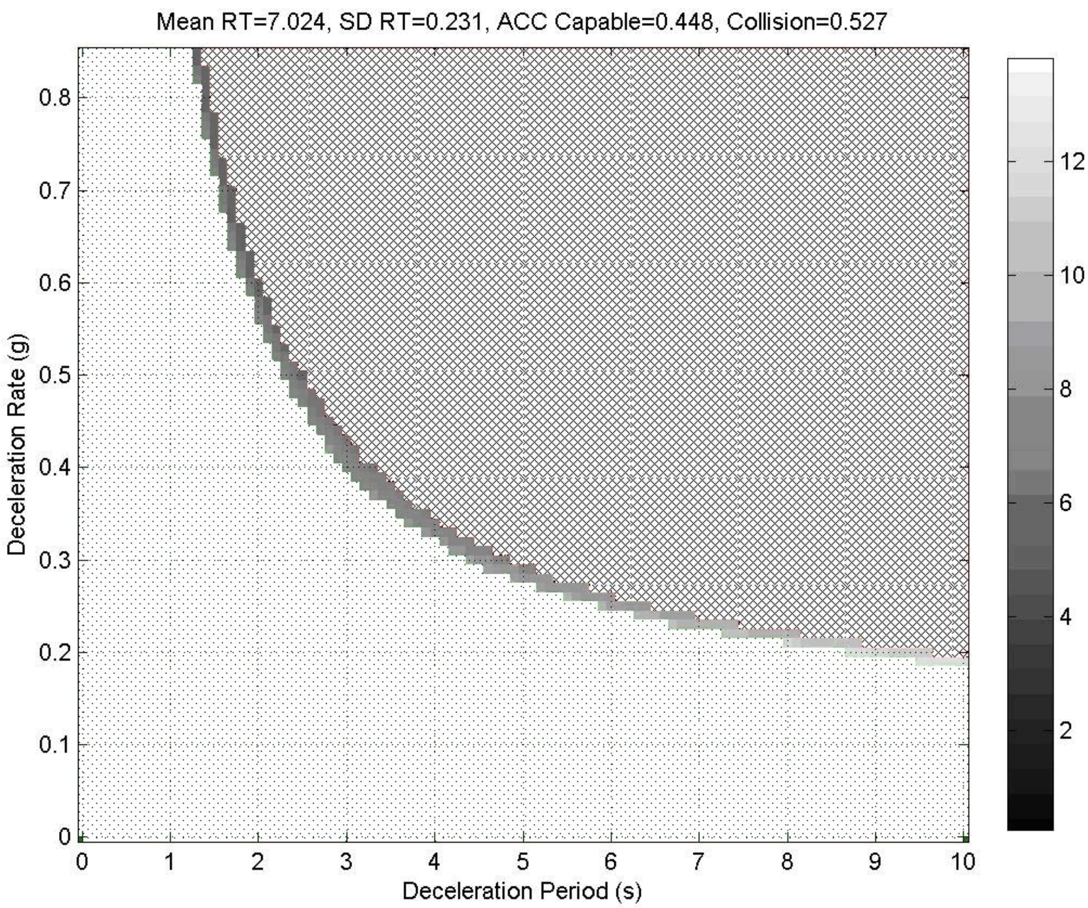

Figure 26. For braking event types, as defined by LV deceleration period and deceleration rate, conditions when ACC is operating within its limits (dotted area), when, if the driver reacted at 1.5 seconds after the JND expansion rate threshold, a collision would occur (cross-hatched area), and the driver response time in conditions where the driver was able to respond to avoid a collision (gray-scaled area). The shade of gray indicates RT value as noted in the scale on the right.

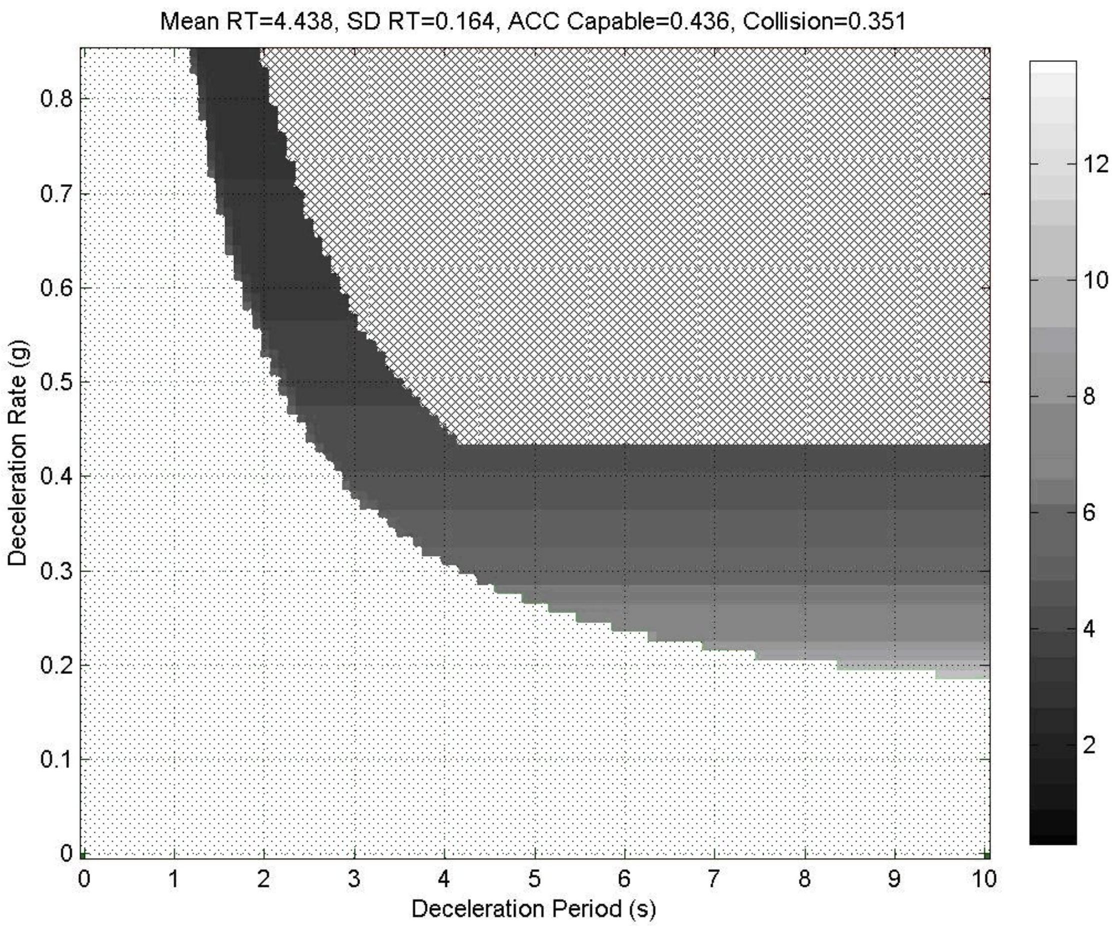

Figure 27. For braking event types, as defined by LV deceleration period and deceleration rate, conditions when ACC is operating within its limits (dotted area), when, if the driver reacted at 1.5 seconds after the TTC=3 s threshold, a collision would occur (cross-hatched area), and the driver response time in conditions where the driver was able to respond to avoid a collision (gray-scaled area). The shade of gray indicates RT value as noted in the scale on the right.

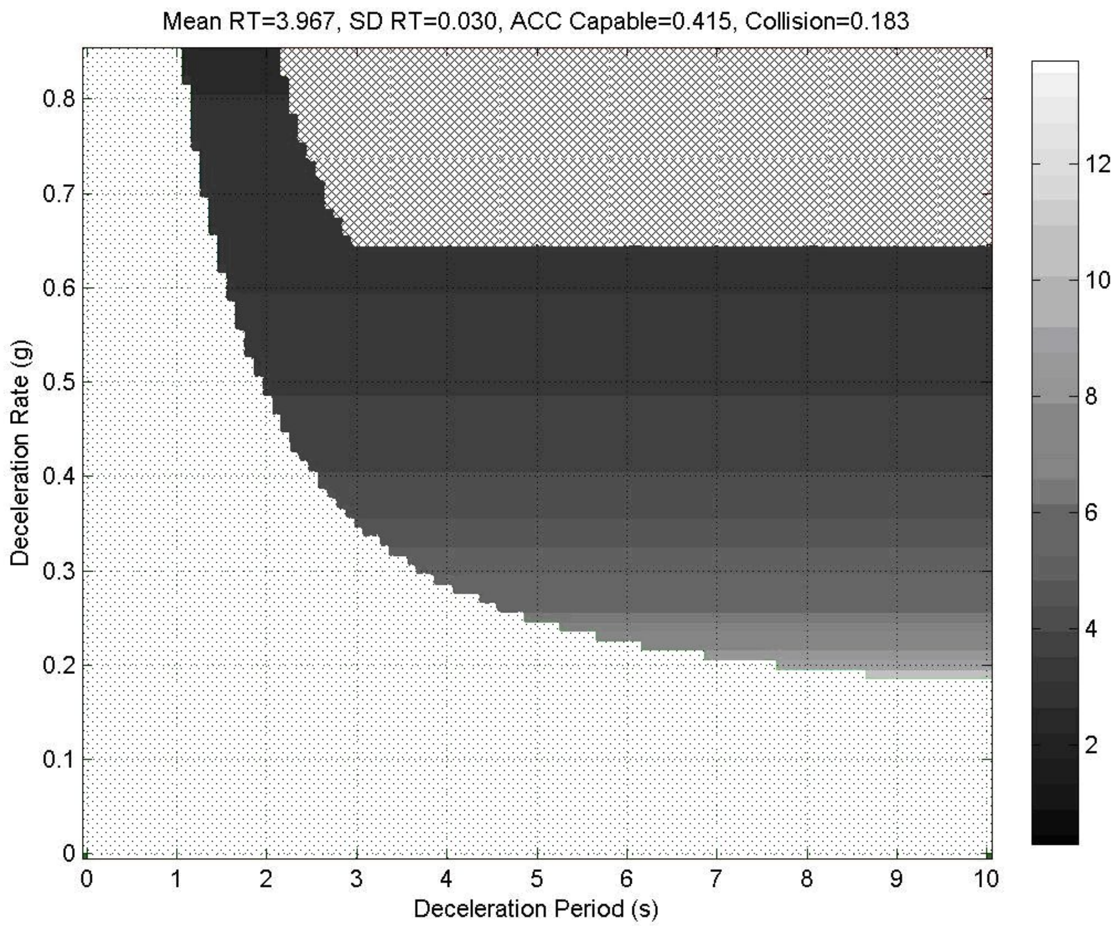

Figure 28. For braking event types, as defined by LV deceleration period and deceleration rate, conditions when ACC is operating within its limits (dotted area), when, if the driver reacted at 1.5 seconds after the TTC = 4 s threshold, a collision would occur (cross-hatched area), and the driver response time in conditions where the driver was able to respond to avoid a collision (gray-scaled area). The shade of gray indicates RT value as noted in the scale on the right.

What are the implications of an inattentive driver?

If drivers are inattentive to the driving task and are required to switch their attention back to the roadway to verify a need to initiate a control response, their response will be delayed by 300-ms, which increases the risk of collision. For situations in which drivers are alerted to ACC's limits with discrete warnings, as represented in the column entitled ‘Discrete Warnings’ in Table 4, an additional 300-ms following a discrete warning to respond to sensor failures 5-seconds or longer results in a 12% increase in collisions (see the ‘Inattentive’ column in Table 4). This effect occurs because of the event dynamics associated with ACC’s acceleration response in failure situations. These results indicate how quickly a driving situation can degrade when ACC is engaged, requiring drivers to remain aware of the environment and its effect on ACC.

What are the potential benefits of continuous feedback?

For the driver model predicted to result from use of an ACC system that issued discrete warnings when its limits were exceeded (as from Figure 10), control responses were initiated at the point of ACC’s state change from ‘On’ to ‘Standby’ when braking and setting limits were exceeded. Discrete warnings that indicate braking and setting limits do not prevent collisions in all situations (again, assuming drivers take 1.5 s to respond following the warning). In fact, initiating control responses based on TTC is a better response strategy than relying on warnings that notify of limit exceedences, resulting in faster RTs and consequent fewer collisions. For situations when drivers are notified of ACC’s sensing limits (the ‘Sensing’ rows in the ‘Discrete Warnings’ column in Table 4), drivers are able to avoid collisions. For the driver model predicted to result from interaction with discrete warnings, however, drivers were unaware of ACC’s sensing limits (refer to the ’LV present—No LV detected’ error states in Figure 10), and therefore remained in the ‘On’ state during the sensing failures. Drivers are expected to remain in this state until either a perceptual or threat threshold is crossed alerting them to their incorrect expectation of ACC’s state. In these situations, driver RTs would conform to the predicted RT results defined by the perceptual/threat thresholds.

The 'Continuous Feedback' column in Table 4 lists the predicted RTs and consequent collision outcomes that result from use of a continuous feedback interface. Given that continuous information would prime drivers to the accelerating event conditions that lead to ACC failure, RTs reflect responses initiated at the point that ACC's limits are exceeded without the 1.5-second processing/movement delay. These RTs result in collision-avoidance responses for all of the tested event conditions.

Conclusion

The purpose of the analysis presented in this chapter was to develop a deeper understanding of driver–ACC interaction. The model findings revealed driving situations that are problematic to drivers in use of ACC. These situations form the basis for the situations included in a driving simulator study (Chapter V). The most hazardous situations had high deceleration rates, long failure periods, and long deceleration periods. A high deceleration rate with a low deceleration period (braking event type), a long failure period (sensing event types), and a low deceleration rate with a high deceleration period (setting event type) were conditions included in the study. This modeling exercise also generated a set of expectations for driver response to discrete and continuous forms of feedback on ACC's state and behavior. Continuous feedback is expected to promote more accurate mental models of ACC than discrete feedback. Accurate mental models are expected to prompt proactive driver responses, initiated before ACC exceeds its limits. Inaccurate mental models are expected to prompt reactive driver responses, initiated after ACC exceeds its limits.

The modeling analysis indicated that ACC failures that occur as a result of normal use of the system in common driving situations can result in significant consequences to safety for drivers if they do not have a complete understanding of its function and operating capabilities. Because of the limited time to respond to ACC failures (given a following distance of 1.5 s), it is important for drivers to understand ACC and to disengage it prior to failure. The rapidly-devolving driving situations that ensue following an ACC failure indicate the need for an attentive and proactive driver. Even attentive drivers will not always be able to avoid a collision if an ACC failure occurs. Drivers who rely simply on their perceptual capabilities and who do not actively develop accurate models of the ACC's behavior are at risk for collision. Drivers, in addition to remaining attentive to the driving task, must anticipate situations that will lead to failure based on an adequate understanding of how the ACC interacts with the driving environment to ensure safe driving.

Simply alerting drivers to ACC's limit exceedences is not effective. In situations in which a LV initiates a high deceleration rate for more than a few seconds, for example, drivers who initiate a maximum deceleration based on a warning will be unable to avoid a collision. In the same way that rear-end collision avoidance systems are limited in their ability to assist drivers in potential collision situations due to the non-linear relationship between driving situation, warning algorithms, and driver response (Brown et al., 2001), ACC warnings are limited in their ability to properly inform drivers of when to disengage the system. Certain driving situations combined with inadequate driver response based on impoverished or inaccurate mental models predestine collisions situations. This model demonstrates the need for drivers to receive additional information on ACC's behavior in a more continuous fashion. The next chapter describes an interface design approach to informing drivers of ACC's state and behavior in real-time—in a minimally distracting form—to promote appropriate reliance.

In terms of its extensions to empirical testing: this model allowed for efficient, iterative design and testing of a stable ACC controller for use in a fixed-based simulator environment. With use of the model, ACC algorithm changes were tested over many conditions in fractions of a second, as compared to the minutes for each algorithm change that development in a simulator would have required. Performance of the algorithm in a simulator was used to validate algorithm changes.

In addition to streamlining algorithm development, the model helped to guide the selection of driving conditions used in an empirical evaluation of continuous feedback (Chapter V). The driving conditions for failure trials used in this study were selected based on the predicted driving conditions that resulted in collisions without driver intervention; those conditions that were predicted by the model to result in near-collisions were chosen for non-failure trials.

CHAPTER IV. ENHANCED FEEDBACK TO PROMOTE APPROPRIATE RELIANCE

This chapter discusses the use of feedback to promote appropriate reliance. Principles of representation aiding structure the description of a designed peripheral visual display and comparative auditory display. Cue selection for each display is described. For each display modality, the display decisions are discussed with reference to the attentional demands of driving.

Continuous Visual Display

Applying principles of representation aiding is one means to map the many constraints of the ACC system into a meaningful display. Representation aiding uses abstraction and integration, which support visual perception, to convey complex information. The goal of this approach is to represent relevant "domain, task, and systems constraints through visual properties of the display, and thus encourage people to perceive these relationships with little cognitive effort" (Guerlain et al., 2002). Guerlain and colleagues (2002) describe three principles to support monitoring, understanding, and adjusting tasks involved in human-automation interaction, including: 1) create visual forms in which emergent features (i.e., symmetries or patterns that form from combined individual variables or data elements) correspond to higher-order relationships and provide a high-level aggregated view of a system, 2) represent the dimensional properties of variables appropriately (e.g., magnitude with line length rather than color), and 3) place data in an appropriate context (e.g., add references, set points, and expected or allowable ranges to variables). Dekker and Woods (2002) list ways to present automation activities so that they are observable; these design recommendations align with those of Guerlain and her colleagues. The recommendation to use pattern-based representations that allow operators to synthesize complex relationships perceptually rather than through difficult mental transformations is consistent with principle 1. The recommendation to include event-based representations that highlight changes is an extension to principle 3. The recommendation to include historical and predictive information to help operators project future states is an additional consideration to that of the principles above.

Display techniques such as representation aiding that afford direct perception of system state improve operator understanding of the automation's behavior, which may in turn reduce overreliance (Vicente & Rasmussen, 1990). Conversely, if feedback is poorly or excessively presented, operator workload can increase, thus reducing the benefits of automation (Entin, Entin, & Serfaty, 1996). Integrated components that form emergent features (Bennett & Flach, 1992; Woods, Wise, & Hanes, 1981) reduce the attentional demand of detecting automation failures. Displays that do not use emergent features often require operators to use memory, integration, and inference processes to make decisions (Gibson, 1979).

In Seppelt & Lee (2007) drivers were presented with a continuous information display that abided by the principles of representation aiding. This display informed operators of the behavior of ACC as conditioned on the environmental context; it provided automation state relative to its operating limits. The results of this experiment indicated that operators better understood failures with use of the designed display. This experiment also indicated that providing drivers with continuous information about the state of the automation is a promising alternative to the more common approach of providing imminent crash warnings when it fails. For automation management (i.e., appropriate reliance and effective transition between driver and automation control when failures occur), informing drivers with respect to the environmental context was proposed as more effective than warning drivers.

Without trust measures collected on a trial-by-trial basis, an assessment of driver understanding of ACC and its operating limitations, a direct comparison with a warning interface, and a formalized classification of failure types, however, it was unclear what benefit the display might have in helping operators manage imperfect automation. The experiment described in Chapter V was designed to address these issues.

The continuous information display for ACC from Seppelt & Lee (2007) and its revised version (

Figure 29 below), which incorporates additional process information, abides by the representation aiding principles as follows:

1) Create visual forms in which emergent features (i.e., symmetries or patterns that form from combined individual variables or data elements) correspond to higher-order relationships.

Range rate (relative velocity between vehicles), TTC, and THW variables combine to form two emergent shapes: 1) triangle shape—this form indicates a potentially hazardous LV following situation as the driver's vehicle is traveling faster than the lead vehicle, 2) trapezoid shape—this form indicates a non-hazardous LV following situation as the LV is moving away from the driver's vehicle.

The TTC, THW, and range rate variables were derived from a Cognitive Work Analysis (CWA) of the control tasks associated with headway maintenance, situation assessment, and collision avoidance (Seppelt et al., 2005). Ecological Interface Design (EID)—a theoretical structure that identifies environmental constraints that define the information requirements for both normal operations and unexpected situations (Vicente & Rasmussen, 1992)—a similar design concept to representation aiding—informed the configuration of these variables. THW, TTC, and range rate indicate the distance (m) and speed (m/s) that defines the state of the driver's vehicle in relation to the LV. Further, these variables provide the basic information needed to control speed and distance in highway driving (Fancher, Bareket, & Ervin, 2001).

Each variable is mapped onto the display as follows:

$THW = distance / velocity_{\text{driver vehicle}}$: defines the vertical position of the shape within the display. As THW decreases, the shape moves closer to the bottom of the display, and as THW increases, the shape moves to the top of the display. At a THW > 7.0 s the shape moves off the display, alerting drivers that THW is no longer detectable given the large time distance between their vehicle and the LV.

$TTC^{-1} = (distance / (velocity_{\text{driver vehicle}} - velocity_{\text{LV}}))^{-1}$: defines the height of the object within the display. As TTC decreases (or as the rate of closure increases), the shape expands vertically (at TTC=0, the point of collision, the shape is maximally expanded to the height of the display), and as TTC increases, the shape contracts vertically. At a TTC > 20, the shape contracts to a minimum fixed height.

$Range\ rate = velocity_{\text{driver vehicle}} - velocity_{\text{LV}}$: defines the width of the object within the display. As range rate increases, the shape expands horizontally, and as range rate decreases, the shape contracts horizontally. This effect, coupled with the vertical movement associated with the TTC^{-1} variable, creates a looming effect and indicates potentially hazardous braking events. See Seppelt & Lee (2007) at http://www.engineering.uiowa.edu/~csl/publications/pdf/Seppelt%20Lee%202007.pdf for more detail on how the shape moves within the display, specifically its transition from the triangle to the trapezoid shape and vice versa.

2) Represent the dimensional properties of variables appropriately (e.g., magnitude with line length rather than color).

Object shape, a categorical representation, is used to represent two general categories of situations, those (potentially) hazardous and those non-hazardous, respectively, for drivers to better understand the behavior of ACC over time for a variety of situations.

3) Place data in an appropriate context.

Dashed lines in the display convey the limits of the ACC's braking authority. The dashed line near the bottom of the display indicates a minimum (~1.5 s) THW boundary of the ACC's braking limits. When the shape exceeds the two triangular reference lines, the ACC's braking power has reached the 0.2 g limit. These reference lines remain fixed, representing the fixed braking limits of ACC, and the shape moves in relation to the fixed lines. Differences in time to reach the braking limits with varied speed differentials and THWs are reflected in the rate of change of the shape. For example, if THW is shorter than 1.5 s and the LV brakes, the TTC and range rate variables will change more rapidly—and thus the braking limits will be exceeded more rapidly—than if the THW were equal to or longer than 1.5 s. The dashed triangular lines represent the situation where TTC^{-1} and range rate are hazardous—when the shape exceeds their position vertically and horizontally, respectively. All hazardous situations are thus bounded by these lines (i.e., the lines do not form a closed shape); either a horizontal or vertical movement of the shape beyond the reference lines indicates that the 0.2 g braking limit of ACC has been reached.

The display conveys sensor degradation in two ways: 1) color dilution and 2) display update rate failure. As the intensity of the rain increases, the color of the shape diminishes from a bright yellow, the normal operating color, to a light yellow to a light gray during the two highest rain levels. To increase the salience of the shape as the color dilutes, contrast is added through means of a degraded shape image; the border of the shape is dashed in its light gray state, revealing the white background at intervals around the shape's border, and at is most degraded state, the gray shape is perforated throughout. The color dilution, in degrading the image, provides drivers with a continuous measure of the reliability of the displayed information; people are able to understand uncertainty conveyed through degraded icons (Finger & Bisantz, 2002). When a sensor failure occurs, as a result of the rain temporarily attenuating the radar signal, the shape is not visible for the duration of the sensor failure. The shape then reappears in the appropriate position following the sensor failure.

In the revised display (Figure 29: bottom-left panel), the shape moves horizontally to reflect the position of the LV; these lateral movements are constrained to indicate the detection boundary of the sensors (Figure 29: bottom-right panel). Additionally, a horizontal black bar is under-laid on the top range rate axis to indicate the difference between the set speed and the ACC adapted speed, a difference which reflects the magnitude of departure from the desired speed. This black bar is not visible if the driver's speed is equal to the set speed. See Table 5 below for a detailed list of ACC constraints and the display features that inform drivers of these constraints. The constraints in Table 5 can be summarized into a list of conditions that characterize ACC's current state, shown in Table 6; corresponding display cues are also included.

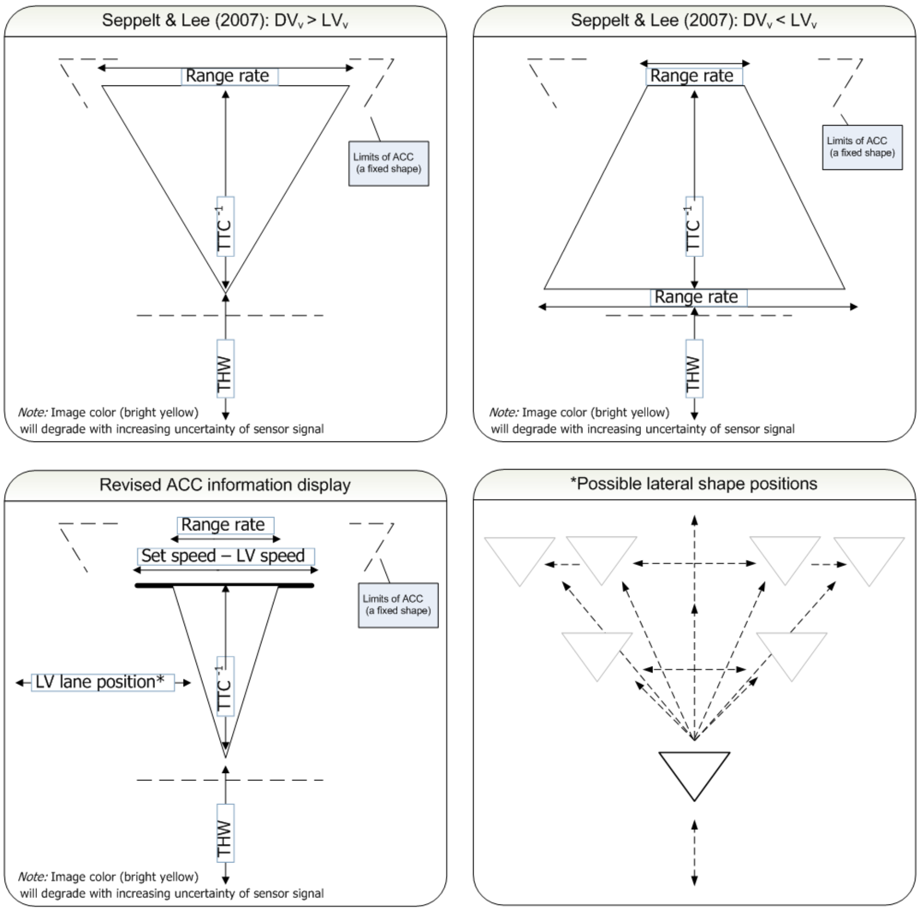

Figure 29. Top-right and top-left panels: ACC information display concept from Seppelt & Lee (2007). Bottom-left panel: revised ACC information display concept for Chapter V experiment. Bottom-right panel: possible lateral positions for the shape to convey sensor lateral range constraints. DV denotes "driver's vehicle"; LV denotes "lead vehicle"; subscript v denotes "velocity".

Table 5. ACC Constraints and Associated Display Features

Constraint	Display feature
Measurements of range, range-rate, and velocity (or equivalent) provide the basic information drivers needed to control speed and distance in highway driving.	Range rate, THW, and TTC variables combine to form the triangle and trapezoid emergent-features shapes
Time headway settings between 1.0 and 2.0 seconds provide an adequate margin for driver comfort and convenience as well as for driver response to unexpected events.	A dashed horizontal line indicates a ~ 1.5 s THW
If no vehicle is detected in front of the participant vehicle, ACC operates like a conventional cruise control system, maintaining the set speed as selected by the operator. If a slower moving vehicle is in front of the participant vehicle, ACC reduces vehicle speed.	A black bar expands and contracts to indicate set speed minus LV speed. If the set speed is equal to the driver's velocity, the black bar is not visible.
Variables that describe car-following situations are velocity of the preceding vehicle, velocity of driver's vehicle (or of ACC-equipped vehicle), range, desired range (of ACC-equipped vehicle), and range rate.	Range rate, THW, and TTC variables combine to form the triangle and trapezoid emergent-features shapes
Braking algorithm applies maximum of 0.2 g or 20% of vehicle's braking power.	Dashed triangular lines convey the limits of the ACC's braking authority
The radar beam widens from its installation point at the front, center, of the car, forming a triangular cone that emanates out to a distance of 300 ft.	The shape moves laterally to reflect LV position, constrained to positions that reflect the triangular shape of the radar beam
Radar signal, which is used to detect objects, is compromised from heavy rain or snowfall	A degraded image provides drivers with a continuous measure of the reliability of the displayed information (Finger & Bisantz, 2002)
Moving vehicles beyond 300 ft, the longitudinal range of the radar, are not detected	The shape moves up off the screen as the LV moves away from the driver's vehicle; it is not visible at 300+ ft
Stationary objects (0 mph) are not recognized	The shape is not visible

Table 6. Visual Display Cues

Condition	Visual Cue
If LV is detected	Presence of shape on display screen
(x,y) location of detected vehicle, relative to boundary	(x,y) position of shape within display screen
Braking intensity, relative to capacity	Shape form within triangular reference lines
Sensor quality	Color dilution, update rate
Difference between set speed and ACC adapted speed	Length of underlaid black bar
Deviation from 1.5s THW setting	Vertical distance from THW line
Hazardous level of the LV following situation (a combined output of TTC^{-1}, THW, and RR)	Shape size, shape form (triangle, trapezoid)
Off to Standby state	No shape; gray background; limit lines visible
Standby to On state	Shape visible; white background (If no LV in sensor field, then no shape is visible)

Continuous Auditory Display (Sonification)

An auditory complement to the peripheral visual display was created using sonification. Sonification—a continuous stream of sound adjusted according to dynamic variables (Barrass & Kramer, 1999)—is a design approach used to help operators monitor complex systems in multi-task situations. This approach has been shown to help operators maintain awareness of system state in demanding, multi-task environments (e.g., process control plant, operating room; Lee et al., in review; Watson, Sanderson, & Russell, 2004; Watson & Sanderson, 2007).

The application of representation aiding principles in creating the visual continuous information display for ACC provided the rationale for the selected variables to map into the auditory domain. The list of conditions that characterize the ACC's current state (the same as those presented in the first column of Table 6) and corresponding cues mapped into the auditory modality are shown in Table 7.

Table 7. Auditory Display Cues

Condition	Auditory Cue
If LV is detected	Presence of signal
(x,y) location of detected vehicle, relative to boundary	x→pan (lateral orientation); y→ loudness (longitudinal orientation)
Braking intensity, relative to capacity	Change in tone (whole step up) if the capacity is exceeded
Sensor quality	Distortion, continuity of signal
Difference between set speed and ACC adapted speed	Volume of second intermittent tone
Deviation from 1.5s THW setting	Pulse tempo of a second tone indicates THW distance; pitch of this tone dampens when THW = 1.5s to indicate steady state.
Hazardous level of the LV following situation (a combined output of TTC^{-1}, THW, and RR)	Pitch of tone (higher pitch indicates hazardous situations, lower pitch indicates non-hazardous situations; continuous gradual transition of pitch within the tone)
Off to Standby state	No sound to background noise (e.g., low hum)
Standby to On state	Background noise to primary tone

To account for the attentional demands of driving, the auditory interface was designed to inform drivers only when ACC's state changed. If ACC remained in a steady state (i.e., a constant following velocity), the sound streams faded out and were only audible at 6-second intervals. During these intervals, the sound gradually faded in and out in an oscillating pattern. If any of the changes in Table 7 occurred, the sound streams returned to their original volume and update rate. In this way, drivers were alerted to changes of ACC as a function of its response to the driving situation, but did not receive excessive information regarding its normal behavior. This design also served as a cue to drivers of when ACC was in its steady state, i.e., 1.5s THW distance behind a LV at a range rate equal to zero, and decreased the likelihood that they would find the auditory interface annoying with continued use. The continuous visual display was comparably designed—the polygon shape was at its minimum size and resting at the 1.5 s THW line when ACC was in steady state.

Conclusions

Abstract visual displays, such as the described continuous information display for ACC, are superior to more detailed displays such as pictorial ones for promoting prompt braking reaction times in car-following situations (Hirst & Graham, 1997). This finding complements the conclusion of Gantzer and Rockwell (1968) that supplementary visual headway information must be peripheral in highly time-critical situations to improve driver response. Hirst and Graham (1997) provided continuously available feedback concerning TTC to a LV and compared drivers' performance to discrete visual and auditory warnings in a car-following situation. Their findings showed that continuous feedback reduced brake RT more than the warnings.

To determine if continuous information interfaces attract undue driver attention, driving and secondary task performance measures were collected in a study comparing the peripheral visual display and auditory interface to discrete warnings in various situations of use of ACC; these findings are reported in Chapter V. Drivers who are able to perceive the visual information using their peripheral vision should have little or no decrement in their driving and secondary task performance as compared to drivers provided with discrete visual warnings. A performance advantage of the auditory interface as compared to the peripheral visual display is expected to the degree that the visual information requires focal visual resources. Drivers who are able to decipher and transfer the perceived information into knowledge of ACC should have higher accuracy in their mental model of ACC. As informed from the driver component analysis of the driver–ACC interaction model, the continuous feedback interfaces indicate set speed, current speed, set headway, current headway, ACC activation, if a LV is detected, and operating limits of ACC (e.g., LV lateral and longitudinal position, sensor degradation, braking capability). Consequently, these interfaces should lead drivers to develop more accurate mental models of ACC.

CHAPTER V. EMPIRICAL EVALUATION OF ENHANCED FEEDBACK

This chapter presents the findings of an experiment that assesses the costs and benefits of providing drivers with continuous visual or auditory feedback on ACC's state and behavior. A continuous information display is one means to promote appropriate reliance in the face of a dynamic context that influences the automation's capability. It is expected that providing drivers with information to increase their understanding of the quality of the ACC's outputs and its processes (e.g., its operation and limits—process and performance information) may improve implicit and explicit understanding (Seong, Bisantz, & Gattie, 2006). Trust is a form of implicit understanding that guides operators' expectations of automation behavior in situations characterized by uncertainty due to a dynamic, unpredictable domain. Explicit understanding is an operator's knowledge of system purpose and form, its functioning and associated state structure, i.e., mental model.

The displays in this experiment are intended as peripheral displays—those that support continual awareness of the automation's state and behavior while tasks primary to driving—lane keeping and hazard detection—are performed (see Previc, 1998; Horrey & Wickens, 2004; Watson & Sanderson, 2007; Wickens, 2002). The presentation of information in a form consistent with representation-aiding principles to convey automation state and behavior is important to determine the extent to which drivers are able to use continuous visual and auditory displays in a variety of hazardous and normal driving situations without distraction.

The aims of this experiment are to (1) evaluate the design of the continuous feedback displays, and to (2) validate the driver response predictions of the driver–ACC interaction model in Chapter III. In addressing the first aim, the effect of continuous information on driver interaction with ACC, and the effort and distraction associated with continuous information are considered. It is hypothesized that feedback about the behavior of ACC will help drivers calibrate their understanding of its performance, thus affecting their reliance. Specifically, drivers provided with a continuous interface are expected to rely on ACC more appropriately, responding more quickly to failure situations than drivers provided with discrete warnings. There is an expected tradeoff to improved reliance with use of continuous feedback in terms of a decrement to driving or secondary performance as compared to discrete warnings. In addressing the second aim, the role of implicit (trust) and explicit (mental model) knowledge in driver–ACC interaction is considered. It is expected that drivers provided with continuous interfaces will have more accurate, complete mental models and more calibrated trust than those provided with discrete warnings. Drivers provided with an auditory continuous interface are expected to have less precise mental models than those provided with a visual continuous interface. Consistent with the driver–ACC interaction model's predicted response strategies, it is hypothesized that drivers with more accurate mental models (i.e., greater explicit understanding) will be more proactive, initiating responses before precipitating events.

Method

Experimental design

A 2 x 2 x 3 x 2 x 4 repeated-measures factorial design with two between-subjects factors (modality and display) and three within-subjects factors (block, trial type, and event type) was adopted for this experiment. The modality (visual; auditory) and display (discrete; continuous) factors define the four interface types drivers interacted with in use of ACC: visual discrete, visual continuous, auditory discrete, and auditory continuous; there were 12 drivers in each of these conditions. The block factor refers to the three blocks of eight trials presented to drivers. For each block, two levels of trial type (non-failure; failure), and four levels of event type (braking exceedence; sensor degradation; lateral detection range exceedence; setting exceedence; abbreviated as braking, sensing, lateral, and setting, respectively) defined the eight trials, of which each event type was presented as both a failure trial and a non-failure trial. Thus, trial type and event type were factorially crossed and nested within block. In total, the experimental session consisted of 24 trials—three replications of each event type.

Participants

Forty-eight native English speakers (27 F, 21 M) between the ages of 25 and 40 (M = 30.1; SD = 4.53) with an active driver's license participated in this experiment. Drivers were screened for visual acuity, color perception, and depth perception. Additionally, drivers were required to have hearing ability within normal ranges (i.e., they were questioned on any irreversible hearing loss). They were screened based on their driving experience (i.e., drivers drove at least three times per week and had driven for at least five years), and cruise control (CC) and ACC experience (i.e., only individuals who regularly interacted with CC but had *not* interacted with ACC were recruited). Drivers were recruited as volunteers and paid $15 per hour, with an additional bonus of up to $5 depending on secondary task performance. Penalties of up to $5 were imposed for inappropriately relying on ACC, calculated based on a standard deviation of THW from the set 1.5 s THW, and if any collisions occurred. Average participation time was three hours.

Apparatus

Data were collected at 60 Hz using a fixed-base driving simulator with a 50-degree field of view, full instrumentation with functional gauges, a force-feedback steering wheel, and a surround-sound audio system. The fully-textured graphics were delivered at a 60-Hz frame rate at 1024 x 768 resolution. Throughout each drive, rain was simulated on the forward screen, visible as falling raindrops superimposed on the driving environment. This rain was audible through the surround-sound speakers. Windshield wipers were not used. A 7-inch head-down display with a 640 x 480 pixel screen displayed the visual discrete warnings and the visual continuous information interface. This display was mounted on the dash of the car, approximately eight degrees horizontally and 11 degrees vertically from the driver's line of sight. Powered-PC speakers were positioned at the front of the vehicle equal distance left and right of the driver to deliver the auditory interface information.

Adaptive cruise control

Drivers used Adaptive Cruise Control (ACC) to maintain a 1.5 s THW to a lead vehicle. The ACC system operated when the driver's vehicle traveled between 20 mph (32 km/h) and 85 mph (137 km/h). If no vehicle was detected in front of the driver's vehicle, ACC operated like a conventional cruise control system, maintaining the driver's set speed (fixed to 55 mph, i.e., 89 km/h, for this study). If a slower moving vehicle was in front of the driver's vehicle, ACC adjusted vehicle speed to maintain a set THW (fixed to 1.5 s for this study), using a maximum of 20% of the vehicle's braking power, or 0.2 g. ACC is a detection system that uses radar to sense objects. Moving vehicles beyond 80 m (262 ft), the longitudinal range of the radar, were not detected. Further, stationary objects were not recognized by ACC. Drivers pressed an "On" button located on the steering wheel to initialize ACC, and a "Set speed" button to engage ACC at the set velocity. To disengage the system, drivers could either press an "Off" button located on the steering wheel or depress the brake pedal. The controls, functions, and limitations of this ACC system were modeled after a 2004 Mercedes-Benz E-Class Distronic ACC system.

Displays

Throughout each drive, drivers interacted with one of four interfaces. Drivers were provided with a description of the purpose (i.e., the intent of the automation) of ACC (to maintain a set speed and keep a set distance (THW) from moving objects in front of it; for use at high speeds on highways; intended as a convenience system and not as a collision warning system) during training.

According to ISO standards for minimum feedback information provided to drivers, in each display condition, drivers were informed of ACC's activation state (on/off) and set speed (ISO/PWI 15622, 2007). In the visual display conditions, the display screen color turned white if drivers pressed the 'On' button, and black if they pressed the 'Off' button. In the auditory conditions, a different tone sounded when drivers' pressed the 'On' button as compared to the 'Off' button. Drivers were instructed of the set speed but were not provided with a visual or auditory indicator because it was a fixed requirement for the duration of the study.

Discrete warnings. In the discrete warning conditions, warnings were delivered when the ACC system reached its operating limits, per current system standards (ISO/PWI 15622, 2007). The auditory warning consisted of a single warning tone (890 Hz) of a 1-second duration at 64 dB (Hirst & Graham, 1997). This warning sound matched the sound used in the auditory continuous interface condition for hazardous driving situations. The visual warning was a yellow triangle, visually identical to the shape used in the visual continuous interface to indicate hazardous driving situations, delivered for a 1-second duration.

Continuous information interfaces. For the continuous interface conditions, continuous information corresponding to the situational context was provided on ACC's process and performance. Purpose information, while indicated to drivers in a written description, could be inferred from the variables used in the continuous interfaces—those required to maintain headway. The visual and auditory interfaces described in Chapter IV were used in this study. Appendix A describes in detail the experimental implementation of the interfaces.

Driving environment

The driving environment included 4-lane urban and freeway roads with a jersey barrier separating opposite lanes of traffic, shoulders on each side of the roadway, and periodic curves (one 45^{o} curve every minute; 90^{o} curves used in failure situations). Drivers encountered oncoming traffic at a rate of three to five cars per minute; this moderate level of traffic was also present in the passing lane. In each drive, there was a continuous light fog (at a distance of 1300 m) to help reduce simulator sickness. Mild rain was present in each drive. Drivers were informed that billboards were located on either side of the road at intervals of ~200 m.

Driving tasks

Driving consists of lane keeping, speed and distance maintenance, and attending to relevant objects and signs (Brookhuis, van Winsum, Heijer, & Duynstee, 1999). Each of these tasks was represented in this experiment as drivers had to maintain lateral control in curved and straight road sections, monitor speed and distance to lead vehicles, and attend to billboards located along the road.

In each drive, drivers followed a lead vehicle (LV) that varied its speed according to a sum of two sine waves (amplitude, frequency, and phase for these sine waves were 7, 0.3, and 5, and 5, 0.2, and 0, respectively), producing a seemingly random pattern. ACC's set speed was 55 mph but the LV traveled at or below 55 mph according to the sinusoidal velocity pattern, induced the ACC system to adapt its following velocity to maintain a 1.5-second headway to the LV for the duration of each drive. The experimental drives were designed to be sufficiently demanding: using the ACC to manage the speed and headway exceeded the demands of engaging and disengaging the system (Kirlik, 1993).

Throughout each trial, drivers engaged in a secondary task. A series of roadside billboards had the side of a dice (dots arranged from 1 to 6) painted on them. Drivers were required to indicate when they observed two consecutive dice that were identical (task adapted from Terry, Charlton, & Perrone, 2008). Dice images were overlaid onto the billboards, which were located every ~200 meters (excluding the first 200 m of each trial when drivers were setting their cruise speed using ACC). The billboards were placed both on the right and left-hand sides of the roadway. Drivers were instructed to press a button on the steering wheel that corresponded to the side of the roadway where the billboard with the consecutive identical dice was located. The two response buttons, one on each side of the steering wheel, were appropriately placed and labeled ("LEFT' and "RIGHT") to reflect the left and right-hand sides of the roadway.

The purpose of the secondary task was to introduce visual and cognitive distraction. Performance degradation on a secondary task is a means to estimate spare capacity and primary task workload (e.g., Bahrick, Noble, & Fitts, 1954; Brown & Poulton, 1961; Zeitlin, 1995). Driver performance on this task is a measure of the level of attentional capacity available to drivers, i.e. the level of interference imposed on the driving task. This task demanded both ambient and focal visual resources. Drivers had to scan the left and right sides of the driving environment to locate the billboards, requiring ambient vision in terms of its function of spatial orientation. Focal vision, which is involved in high-acuity visual searches and object recognition (Horrey, Wickens, & Consalus, 2006; Leibowitz & Post, 1982), was required for drivers to search each billboard image to find the dice (billboard-to-dice ratio - 1:40); the dice were randomly placed on each 8 x 19 ft. billboard. The billboard images were photos of actual on-road billboards that were selected based on criteria of being primarily textual and containing only object imagery (i.e., no human faces or body parts); this criterion was applied to reduce differences in saliency among the billboards. Each billboard within a trial contained a unique image.

There were 18 billboards per 3-minute trial: six billboards were signal billboards (i.e., required a button response once detected) and 12 billboards were noise billboards (i.e., did not require a button response once detected). The billboards with overlaid dice images were distributed throughout the driving environment so that drivers experienced approximately two detection events per minute for a total of six detection events per trial.

Procedure

Upon arrival, drivers completed a 3-minute screening for visual acuity, color perception, and depth perception using an Optec Vision Tester. If a driver's visual parameters did not fall within normal ranges s/he was compensated $15 and the study concluded. Following this procedure, drivers completed an informed consent form, and an interpersonal trust questionnaire, and then drove a short, 3-minute drive to acclimate them to the driving simulator controls and environment. Training on the interface that accompanied ACC followed.

For all interface conditions, drivers were informed of how to engage and disengage the ACC system, its purpose, and of its functional definition. As part of the functional description, drivers were informed of the ACC's maximum braking power of 20% or 0.2 g, and of its radar operational boundaries. In the visual continuous interface condition, drivers were instructed that the shape conveyed speed and distance information, and operational state of the ACC. In the auditory continuous interface condition, drivers were instructed that the auditory signals conveyed speed and distance information to a lead vehicle as well as operational state of the ACC. For the warning interface conditions, drivers were informed that the visual or auditory warning, respective to the modality condition, informed them of when the ACC system limits were exceeded. Each driver was randomly assigned to an interface condition.

In addition to the training on the interface condition, drivers were briefly shown the cost of not relying on the ACC via a 1-minute training drive in which they maintained a set 1.5s headway to a lead vehicle without use of the ACC; the error term of their headway as compared to the set headway was continuously displayed on the forward driving scene. Drivers next read a definition of trust in automation and were informed of the anchor points of the subjective trust scale (as in Lee & Moray, 1994) to promote a more consistent trust response amongst drivers. During this training session, drivers were informed of the monetary compensation bonus and penalty.

Drivers next drove a 6-minute control drive to introduce them to the ACC, allowing them to become familiar with the ACC system, i.e., the controls used to engage and disengage the system, and the 1.5 s THW it maintained. Drivers then drove a second, 6-minute control drive with the task of detecting the dice images on the billboards. No ACC failures occurred in either control drive. The control drives were intended to increase drivers' trust in the function and response of the system. It is important that operators experienced reliable automation initially to provide them an opportunity to observe how the ACC worked and, as a consequence, to develop their trust in and understanding of the automation.

Following the control drives, drivers drove 12 trial-based experimental drives. These drives were composed of two, 3-minute trials. Half of the total 24 trials had an ACC failure. The order of the failure and non-failure trials were counterbalanced, grouped according to four possible pairings: 1) failure–non-failure; 2) non-failure–failure; 3) failure–failure; and 4) non-failure–non-failure. Such pairings were included to reduce drivers' ability to predict when a failure would occur. Non-failure trials are defined as those in which there was a change in condition but no precipitating event. Failure trials are defined as those in which there was both a change in condition and a precipitating event. (These trial definitions are consistent with the model description in Chapter III.) A trial was stopped if a driver collided with the lead vehicle. If a collision occurred during the first of two grouped trials, i.e., the first half of an individual drive, the drive was re-started at the beginning of the second trial. An intersection with a stoplight served as the mid-point of each drive, separating a single drive into the two trials. The end of the second trial within drives also ended with a stoplight intersection.

Before each practice, control, and experimental drive, drivers were instructed to maintain a 1.5 s THW to a lead vehicle for the duration of the drive using ACC. This instruction was followed with the qualifier that they should rely on ACC *when it could handle the driving situation*. They were instructed to monitor the ACC as part of the car-following task to ensure that it properly maintained the set following distance (1.5 s), operated within its limits, and safely responded to driving situations. Instructions also stated that if they felt that ACC might not operate properly (i.e., within its limits), as informed from the feedback interface, they should disengage it, and re-engage ACC once they felt comfortable using it again. Drivers were also instructed to drive safely, to remain in their lane, to stay aware of the vehicles ahead, and to avoid unnecessary braking. Drivers were further asked to detect the dice images while driving.

At the end of each trial, drivers completed a brief trust rating (while stopped at the stoplight). This trust rating was administered on an in-vehicle touch-screen; drivers responded to the single trust question by pressing one of the on-screen buttons that were ordered along a continuous scale; the on-screen questionnaire disappeared following their button press to indicate that their response had been registered. Prior to and following the set of control drives, and after every 4th drive, drivers completed a mental model questionnaire and a subjective trust questionnaire. Grouping drives into 4-drive blocks served a two-fold purpose: 1) it factored in break periods for drivers to reduce fatigue for the required 72 minutes of driving, and 2) it provided sufficient driving time to introduce both a non-failure and failure trial for each of the four event types (discussed in detail below), each of which instantiates a meaningfully different operational characteristic of the ACC system. Essentially, in each block of drives, drivers were provided sufficient driving experience to populate their mental model of the full function of the ACC system. Following the final experimental drive, drivers were debriefed and compensated (see Appendix B for the payment structure). Figure 30 provides an overview of the experimental procedure.

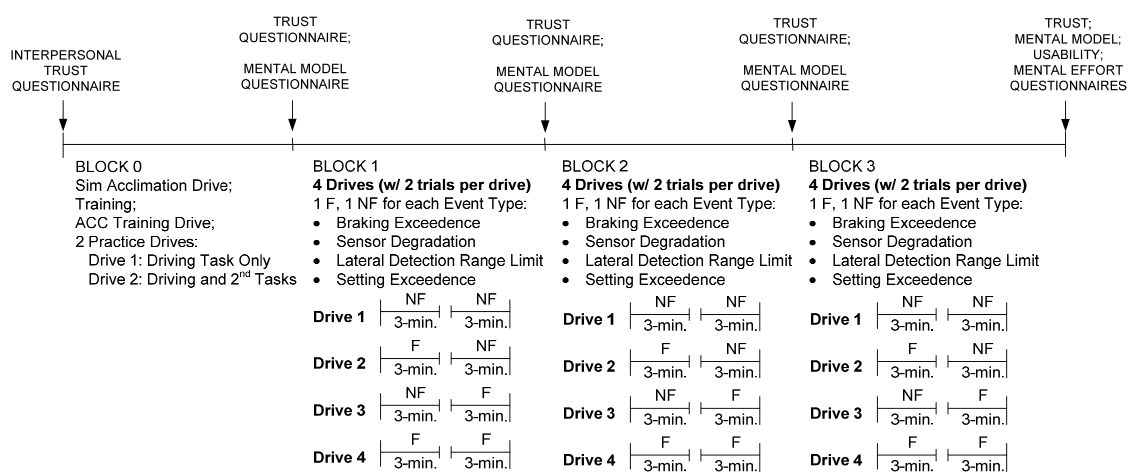

Figure 30. Experimental procedure and drive design. There were eight trials per block, as indicated with the 3-minute segments. NF and F refer to the non-failure and failure trial types, respectively. The four event types were braking exceedence, sensor degradation, lateral detection range limit, and setting exceedence. For each block of drives, there was a NF and a F trial for each event type.

Trial types

The non-failure trials were designed with the same situational factors as the failure trials in which the difference between these trial types was the presence of a precipitating event, which occurred only in failure trials. In terms of display implications, in the non-failure trials, the display transitioned to but did not exceed limit boundaries, while in the failure trials the display transitioned to and crossed limit boundaries. Transitioning to limit boundaries in the non-failure trials allowed for analysis of driver response in the period following a change in condition but prior to a precipitating event (refer to Figure 13 from Chapter III). A response to disengage the ACC was only necessary in failure trials following the failure point. In all failure trials, if drivers did not respond to the failure, they would collide with the LV. In this design, driver response (i.e., brake press or "Off" button press) was a behavioral indicator of mental model accuracy; drivers who were aware of the limits of ACC and its proximity to those limits were predicted to disengage ACC prior to the failure point, and in the non-failure trials.

Regardless of failure occurrence, each 3-minute trial followed this sequence: randomly placed 30–60 seconds into a trial, a change of condition occurred that 35-seconds later resulted in a near-failure or actual failure, dependent on the trial type; see "Change Condition Period" in Figure 31. The initial 30–60 seconds provided a period of normal ACC operation, during which drivers had sufficient time to accelerate to the set speed and to engage ACC. After the event/failure occurred, the driving conditions returned to steady state. The total time elapsed from the change in condition to the return to steady state was 2-minutes, labeled "Event Period" in Figure 31. The period following the end of change in condition provided drivers time to recover from an ACC failure (if one occurred) and to re-engage the system.

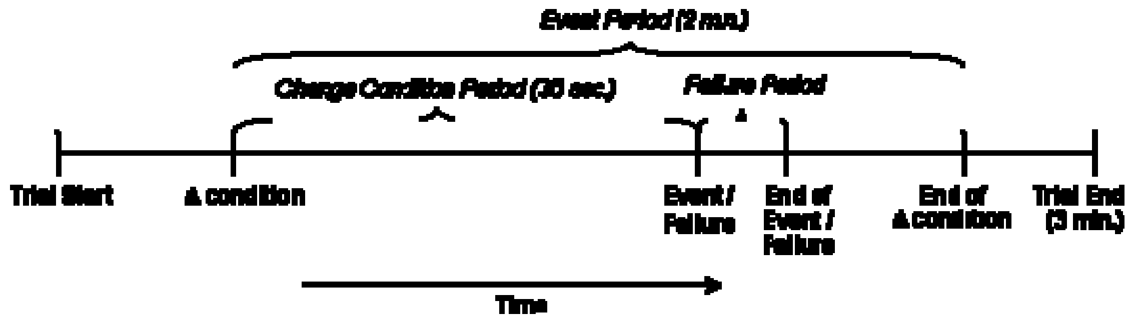

Figure 31. Trial timeline.

Event types

The 24 trials (12 non-failure; 12 failure) introduced situational factors and vehicle dynamics that are reported in the literature as problematic to drivers in use of ACC (Hoedemaeker, 2000; Nilsson, 1995; Rudin-Brown & Parker, 2004; Stanton et al., 1997; Zheng & McDonald, 2005). These scenarios were grouped into four categories: 1) braking limits, 2) sensing limits (i.e., degraded sensors in heavy rain), 3) detection range limits (i.e., lateral detection range limits in curves), and 4) setting limits (i.e., set velocity deviant from LV velocity until induced following speed drops below operating limit).

For each of these four scenario categories, a representative event type was created; the model findings (from Chapter III) informed the selection of parameter settings. Each event type occurred once as a failure trial and once as a non-failure trial within a block of drives; the order of the event types within a block were randomized.

The events were replicated in each of the three blocks, for a total of three non-failure and three failure trials of each event type.

For all event types, the change condition period lasted 35 ± 1.6 seconds, and the event period lasted two minutes. Due to the event-specific dynamics required to induce failures, the failure periods were necessarily different amongst event types. For instance, the braking exceedence event type required a large deceleration by the LV in a short amount of time to induce ACC to exceed its deceleration capabilities. In contrast, the LV needed to gradually decelerate in the setting exceedence event type to stay within the ACC's deceleration capability while at the same time causing the driver vehicle's following velocity to drop below 20 mph—ACC's lower functional velocity limit. For braking exceedence, sensor degradation, lateral detection range exceedence, and setting exceedence event types, the failure periods (i.e., length of time ACC's operational limits were exceeded) were 5.53 s, 30.3 s, 8.52 s, and 11.05 s in duration, respectively. In the non-failure trials, this period of time represented the time during which the same event was initiated as in the failure trial but to a reduced extent—the ACC's limits were reached but not exceeded. For braking exceedence, sensor degradation, lateral detection range exceedence, and setting exceedence event types, the failure period during non-failure trials lasted 5.4 s, 21.8 s, 9.71 s, and 16.08 s, respectively.

Baseline conditions for all event types were as follows: varied velocity of a LV according to a sinusoidal pattern, constant light rain, two 45^{o}-curves per minute, and periodic signed speed limit changes. These baseline conditions normalized the probability of any particular event type occurring so that drivers had to rely on their mental model of the ACC's operational capabilities rather than on situational cues to alert them to changes in the appropriateness of using ACC. Further, the events were designed to gradually approach ACC's limits so that drivers were responsive based on the information provided through the feedback interface and in turn their mental model of ACC's capabilities rather than on overt situational cues.

The scenario details and ACC's associated response for the four event types were as follows:

1) *Braking exceedence*. For this event type, at the start of the change in condition, the LV initiated more frequent, more intense velocity fluctuations in response to an increase in surrounding traffic. For the event, the LV decelerated at a rate that induced the ACC to respond with a system brake slightly less than 0.2 g. For the failure, the LV decelerated at a rate that maximized the 0.2 g brake response of the ACC. Following the event/failure, the magnitude and frequency of the LV velocity decreased over time in tandem with a decrease in the rate of traffic. At the end of the 2-minute period, the LV velocity normalized at 50 mph. In response to the braking exceedence (> 0.2 g required deceleration to maintain a 1.5s THW to the LV), ACC would maximize at a 0.2 g deceleration for one second; after 1-second of required maximum deceleration, it would transition to standby mode, releasing all brake pressure.
2) *Sensor degradation*. In this condition, at the start of the change in condition, the rain increased gradually and the level of fog drew closer, reaching its maximum rain level and closest fog distance at the event/failure. The rain level was 20% higher and the fog level 100 m closer for the failure than for the event. Following the event/failure, the rain level decreased over time and the fog distance increased, returning to baseline

condition at the end of the 2-minute period. In response to a degraded, non-functional sensor, and consequently unable to detect the presence of a LV, ACC would accelerate to 55 mph.

3) *Lateral detection range exceedence*. In this event type, at the start of the change in condition, the roadway curved 90^{o}. After 400 m, the roadway again curved 90^{o}. During this second 90^{o}-curve, the LV moved off-center of the lane at the apex of the curve towards the inner part of the curved roadway. In the failure, the LV offset was 0.5 m greater than in the event, thus moving the LV slightly outside of the lane. Following the event/ failure the LV corrected its offset gradually, returning to a centered roadway position by the end of the 2-minute period. In situations in which the LV moved outside of ACC's lateral detection range, ACC would accelerate to 55 mph as it was unable to detect the presence of the LV.
4) *Setting exceedence*. For this event type, the LV began a gradual deceleration to 30 mph at the change in condition in response to a signed slower speed section of urban roadway. The LV initiated a deceleration to 20 mph (the minimum functional speed of the ACC) for the event. In the failure, the LV initiated a gradual deceleration to 15 mph. Following the event/failure, the LV accelerated to 30 mph, maintaining this speed for the duration of the slower speed section, returning to 50 mph at the end of the 2-minute period when the signed speed limits were posted. In response to a LV decelerating below its minimal functional speed of 20 mph, ACC would transition to standby, releasing all brake pressure.

The response of ACC to the event types is consistent with current ACC system design. Specifically, according to ISO standards, the average deceleration capability is not to exceed 2.0 m/s^2 (0.2 g), nor should there be a sudden brake force release in the case of an automatic deactivation of the ACC system. When ACC is active (set), the vehicle speed should be controlled automatically to maintain a clearance to a detected forward vehicle, or to maintain the set speed, whichever speed is lower (i.e., if the lead vehicle is not detected, the ACC will function to maintain set speed). The minimum set speed should be greater than or equal to 7 m/s (16 mph), and if the vehicle's speed drops below this minimum velocity the ACC system may drop from active state to standby state (ISO/PWI 15622, 2007).

Interface implications. The four described event types induced interface changes that were designed to surpass drivers' perceptual boundaries. The continuous visual/auditory changes were calibrated to exceed two perceptual levels during the change in condition period, and to exceed another level to signal the failure point. The magnitude of the changes for each level adhere to Stevens' power law (which describes the relationship between the magnitude of a physical stimulus and its perceived intensity) to ensure driver perception (Stevens, 1957). For example, in referring to the visual changes of the visual continuous display that occurred for each event type as shown in Figure 32, the length of the black bar, which signaled the difference in set speed and ACC's adapted speed, doubled for each level change. In terms of the auditory interface's equivalent cue: loudness of the interval beep doubled with each level change, i.e., the sound intensity of the beep increased 10-dB for each level (Stevens, 1957).

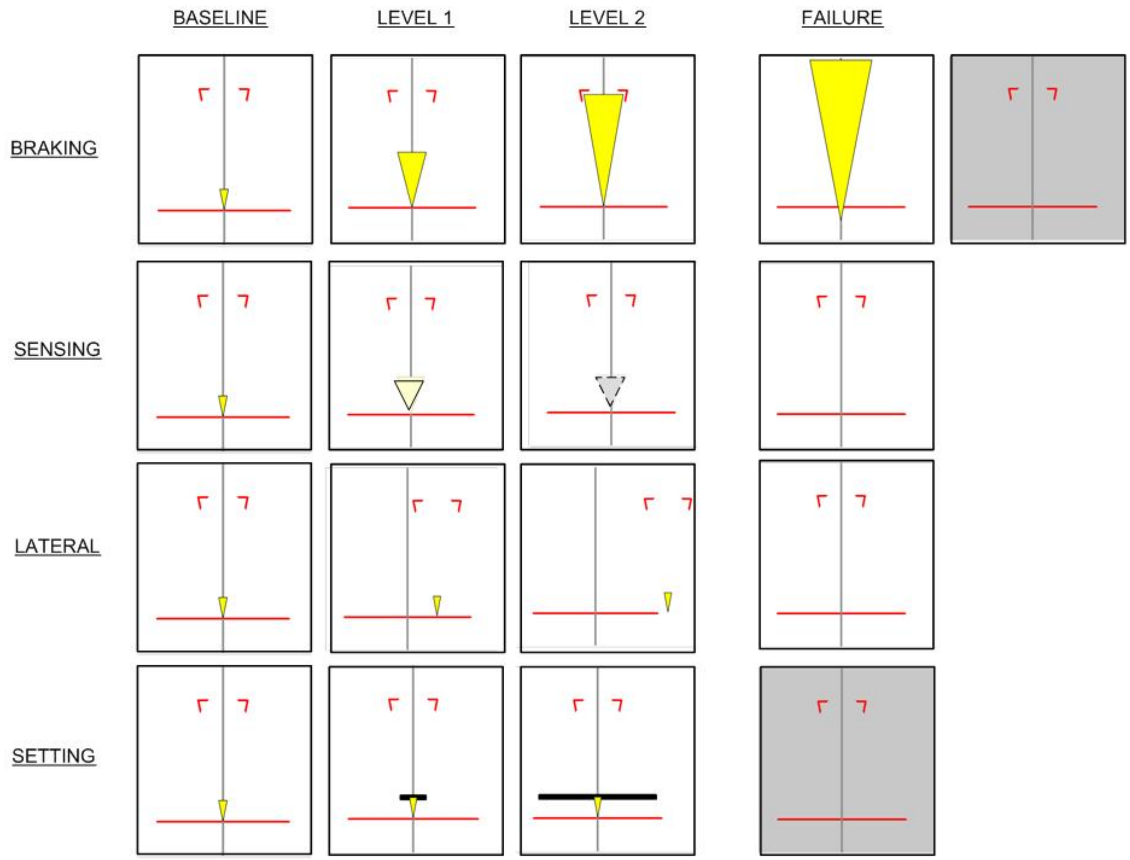

Figure 32. Visual continuous display implications by event type.

At failure point, for the braking event type, the yellow hazard shape continued to display on screen for 1-second and the warning tone continued to sound for 1-second before ACC transitioned to standby in the visual and auditory continuous interface conditions, respectively. For the visual and auditory discrete warning conditions, the hazardous shape and the hazardous tone, respectively, were delivered for 1-second. At failure point for the sensing and setting event types, the shape disappeared from the screen in the visual continuous interface condition, and the sound streams were no longer audible in the auditory continuous interface condition. For the discrete warnings in these event types, no alerts were delivered per ISO standards, which do not require drivers to be informed of when a LV is or is not detected (ISO/PWI 15622, 2007). At failure point for the setting event type, ACC immediately transitioned to standby mode, thus the shape disappeared and the background shifted from white to gray in the visual continuous interface condition, while in the auditory continuous interface condition, the sound changed to the standby tone. In the discrete warning conditions, the setting event type failure point was indicated with the hazard shape and the warning tone for the visual and auditory conditions, respectively.

Dependent variables

Data were collected to assess the costs and benefits of continuous information. The dependent measures collected are shown in Table 8, grouped according to their high-level constructs.

Table 8. Experimental Analysis Design

CONSTRUCT	DEPENDENT VARIABLE	DEPENDENT MEASURE
Driver-ACC Interaction	Driver Response Relative to Event Boundaries	RT to Event/Failure THW/TTC at Response Frequency of Responses Prior to Event/Failure
	Reliance	Time to Re-Engage ACC Following Failure THW/TTC at Point Re-Engaged Amount of Time ACC Engaged
Trust	Subjective Trust	System Trust Questionnaire Ratings Interval Trust Questionnaire Ratings
Mental Model	Accuracy	Scored Questionnaire Ratings
Visual and Cognitive Distraction	Driving Task Performance	Steering Velocity Time-to-Line Crossing Lane Exceedences
	Secondary Task Performance	Signal RT Sensitivity; Response Bias
Interface Design Quality	Perceived Benefit of Interface	Usability Questionnaire Rating Mental Effort Questionnaire Rating

Results

The analyses presented here are those data collected from Blocks 1-3 for each interface condition. Block 0 served as practice to allow drivers to become acquainted using ACC and its associated feedback interface. Data were analyzed using the mixed model procedure in SAS 9.2. The analysis of variance (ANOVAs) included modality and display as between-subjects factors; trial type and event type were included as repeated measures factors nested within block. Based on (AIC) fit statistics, an autoregressive covariance structure was applied to account for time dependence between repeated measures. A level of $\alpha = .05$ was adopted to test for significance of effects; only significant effects are reported unless non-significance is notable. When applicable, marginally significant results are discussed; these are defined as a α-value between 0.051 and 0.1. Post-hoc comparisons were evaluated using student's t-tests. The figures show standard error (SE) bars of ± 1 SE for each mean.

Measures collected within trials were analyzed according to the trial timeline from Figure 31. There are three meaningful periods within a trial: (1) from the change in condition start to the end of the change in condition, i.e., Event Period; (2) from the change in condition start to the start of the event/failure, i.e., Change Condition (CC) Period; and (3) from the event/failure start to the event/failure end, i.e., Failure Period. Data analyses presented in this section will refer to these periods. Due to these differences in failure period between event types, results are summarized according to event type for trial-specific analyses.

The results are organized according to the dependent variables from Table 8. Dependent measures for driver response relative to event boundaries, and for reliance indicate the effect of continuous information on driver interaction with ACC. Dependent measures of trust and mental model accuracy, and an analysis of their influence on driver response are reported to determine the role of implicit and explicit knowledge on driver–ACC interaction. Dependent measures for driving and secondary task performance indicate effort and distraction consequences of continuous information. Finally, measures of the perceived benefit of the interfaces are included to assess the design quality of the continuous interfaces.

Effect of continuous information on driver interaction with ACC

This section reports results for driver response to event boundaries and for reliance.

Driver response relative to event boundaries

In the non-failure and failure trials, drivers experienced a change in condition followed by either an event or failure, respectively. Drivers were instructed to monitor ACC and to disengage it if they felt that the ACC would not operate within its limits. In the non-failure trials, because ACC reached its limits but did not cross them and therefore remained engaged and functional, only a proportion of drivers responded to the event and initiated either a brake response or an 'Off' button response. In failure trials, the situation dynamics necessitated a response to avoid collision, therefore on all but two instances when collisions occurred and excluding those cases in which drivers did not have ACC engaged when the failure occurred, there was a reaction time to the failure for each trial. Based on these response differences, non-failure trials were analyzed separately from failure trials. Reaction time (RT) was calculated from the start of the event/failure to a brake response greater than 0.05 (above noise level) or to an 'Off' button press, whichever occurred first. RTs that occurred prior to the event/failure were negative values. Outlier change-in-condition RTs (< -6 s) were identified and examined—those that were a true response to the change in condition were re-coded as a -1 to prevent an artificially deflated mean and unrepresentative standard error.

RT to event/failure. For failure trials, drivers responded faster to failures with use of the continuous interfaces (M = 4.0, SE = 0.173) as compared to the discrete warnings (M = 4.5, SE = 0.175), $F(1, 192) = 3.99$, $p = .047$; this display effect is dependent on event type, $F(3, 376) = 2.96$, $p = .032$ (see Figure 33). Reaction times were significantly different between event types, $F(3, 376) = 45.95$, $p < .0001$. Sensing RTs in particular were longer than the other three event types (M = 6.45, SE = 0.232; braking: M = 2.94, SE = 0.239; lateral: M = 3.4, SE = 0.241; setting: M = 4.2, SE = 0.247). Post-hoc t-tests indicated that the RTs for braking, sensing, and lateral failures were significantly different between display conditions, $t(83) = 3.42$, $p = 0.001$, $t(140) = 1.98$, $p = 0.05$, and $t(129) = 2.04$, $p = 0.044$, respectively. Setting failure RTs did not significantly differ between display conditions, $t(83) = -1.24$, $p = 0.217$. The main effect of modality approached significance, $F(1, 192) = 3.06$, $p = .082$, in which auditory responses were faster than visual responses (auditory: M = 4.03, SE = .173; visual: M = 4.47, SE = .176).

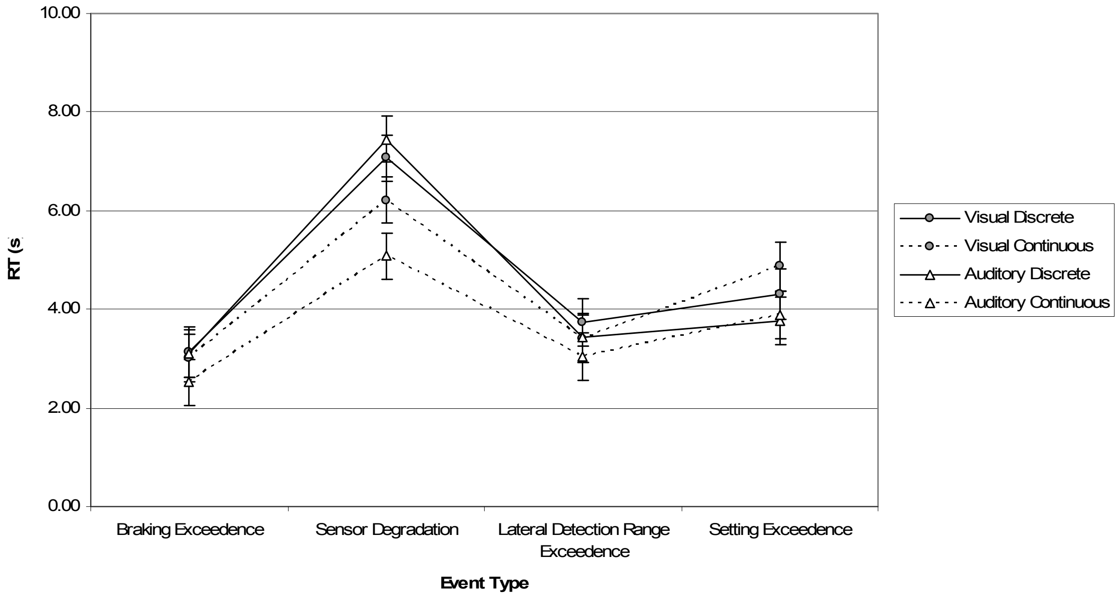

Figure 33. Driver RT to ACC failures in failure trials by event type for each interface condition.

The 500 ms reaction time benefit afforded by continuous displays as compared to discrete displays is practically significant. To provide context, display interventions discussed in collision warning literature report RT benefits on the order of 100-200 ms. Graham (1999) compared auditory icons that conveyed information about system events (e.g., tire skid, horn) to those that emitted only a single tone for use as emergency warnings; the meaningful warning sounds produced faster reaction times on the order of 70-120 ms compared to the non-informative auditory tone. Scott and Gray (2008) considered how the effectiveness of rear-end collision warnings depended on sensory modalities: tactile, auditory, visual, and no warning as a baseline. They reported brake RTs were ~100 ms faster between each condition ordered from fastest (tactile) to slowest (no warning: e.g., 0.9s, 0.8s, 0.7s, 0.6s for tactile, auditory, visual, no warning, respectively). An additional half-second to respond to an automation failure is considerable.

For non-failure trials, the paucity of the RTs made it infeasible to conduct an ANOVA. A count of the number of RTs by event type for each display condition, however, was consistent with the observed benefit of continuous over discrete displays found in the failure trials (see Table 9).

Table 9. Driver Responses to Non-Failure Events

Frequency of Responses	#
Braking Exceedence *	
Discrete display	39
Continuous display	52
Sensor Degradation	
Discrete display	1
Continuous display	1
Lateral Detection Range Exceedence	
Discrete display	0
Continuous display	1
Setting Exceedence *	
Discrete display	8
Continuous display	19
TOTAL	
Discrete display	48
Continuous display	73

* Indicates $p < .05$

In particular, braking and setting event types resulted in an increased number of responses in non-failure trials for the continuous display conditions compared to the discrete display conditions, $\lambda(1) = 6.26$, $p = .012$; $\lambda(1) = 7.97$, $p = .005$. In the braking event type, the mean values for these RTs are consistent with the faster reaction times for continuous displays observed in the failure trials: continuous: M = 3.18, SE = 0.198; discrete: M = 3.96, SE = 0.24 (SEs are reported from a one-way ANOVA of braking RTs for display).

THW/TTC at response. Reporting time headway (THW) and time-to-collision (TTC) at failure response indicates the severity of the driving situation when drivers disengaged ACC. Such measures also allow for framing driver RTs according to response thresholds (as detailed in Chapter III). In particular, a 3-second to 4-second TTC represents the boundary below which drivers unintentionally find themselves in a dangerous situation; above this boundary they are more likely to remain in control (Hirst & Graham, 1997; Horst, 1984; Maretzke & Jacob, 1992).

For THW, drivers responded at larger (i.e., safer) distances with use of the auditory interfaces compared to the visual interfaces, $F(1, 138) = 8.44$, $p < .01$, and with use of the continuous interfaces compared to the discrete warnings, $F(1, 138) = 24.64$, $p < .0001$ (see Figure 34). Primarily based on the dynamics of the event types, drivers responded at varying time distances for the different events, $F(3, 364) = 468.6$, $p < .0001$ (braking: M = 1.24, SE = 0.018; sensing: M = 0.868, SE = 0.017; lateral: M = 0.97, SE = 0.018; setting: M = 1.68, SE = 0.018). Interestingly, the longer RTs for the sensor degradation event type had the consequence of short time headways (< 1 s), indicating that drivers either were unaware for longer that ACC's sensor were not functioning or simply that they waited to determine if a response was required. Drivers were responsive to setting exceedences, initiating a response at a safe distance from the LV.

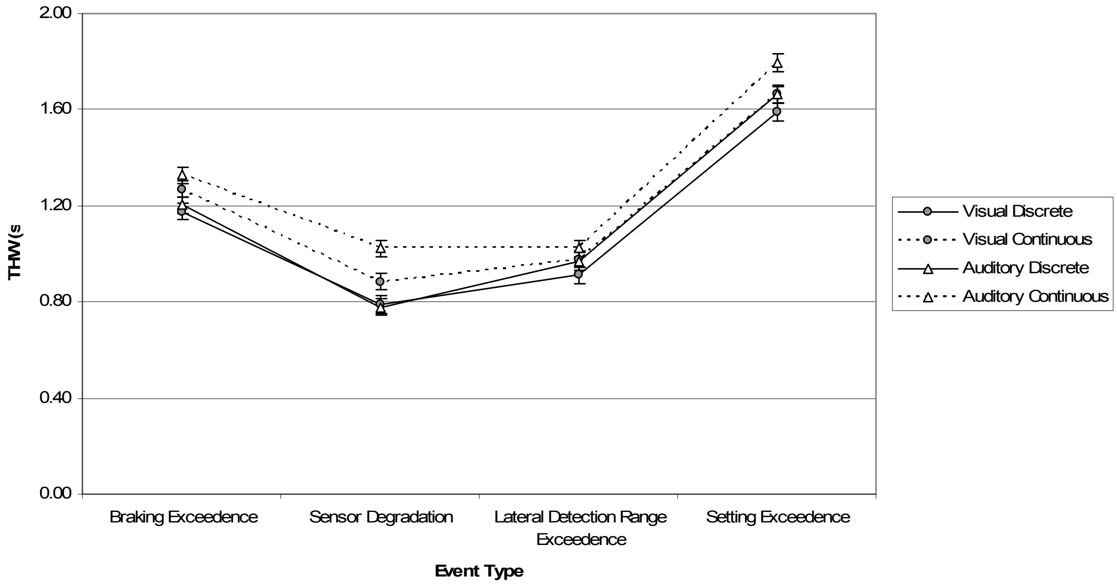

Figure 34. Time headway (THW) at failure response by event type for each interface condition. THW is reported in seconds.

For TTC at brake response, the main effects of modality, $F(1, 137) = 13.67$, $p < .001$, display $F(1, 137) = 12.82$, $p < .001$, and event type $F(3, 355) = 53.90$, $p < .0001$, are discussed according to their interaction with event type (modality x event type: $F(3, 355) = 4.29$, $p = .005$; display x event type: $F(3, 355) = 4.82$, $p = .003$). The larger (i.e., safer) TTCs for auditory over visual modalities are particularly prominent for setting failures. The continuous interfaces offered a clear advantage over the discrete ones for sensing failures, though across failure types the auditory continuous interface in particular afforded the safest response (see Figure 35).

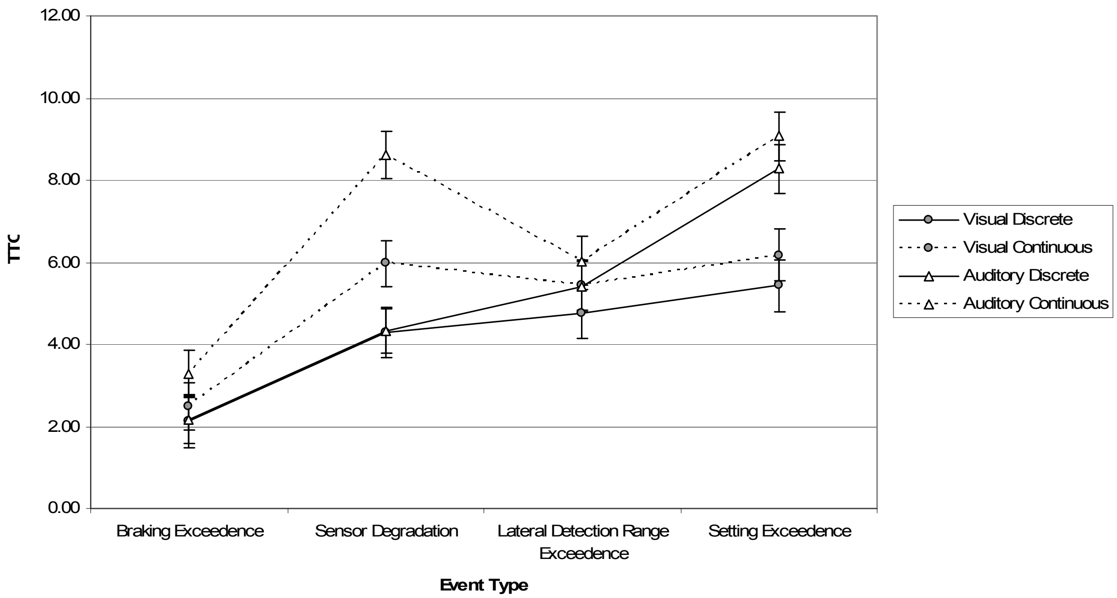

Figure 35. Time-to-collision (TTC) at failure response by event type for each interface condition. TTC is reported in seconds.

Drivers responded above the 4-second TTC threshold for the sensing, lateral, and setting failures (sensing: M = 5.8; lateral: M = 5.41; setting: M = 7.24). For the braking failure, all mean responses were below the 4-second threshold, though when compared to a 3-second TTC threshold, only the auditory continuous interface condition resulted in a mean TTC at response above three seconds (visual discrete: M = 2.11; visual continuous: M = 2.47; auditory discrete: M = 2.17; auditory continuous: M = 3.28). When compared to the RT results, the pattern of TTC at response is consistent across event type: faster RTs led to larger TTC values.

Frequency of responses prior to the event/failure point. Driver responses in the change condition period precede the failures or near-failures of ACC and indicate informed mental models and/or conservative, responsive driving behavior. The number of these proactive responses provides a measure of driver responsiveness to the task of monitoring ACC and of assessing its appropriateness of use. A count of the number of RTs in the change condition (CC) period by event type further supports the continuous-over-discrete display benefit seen in the RT and THW/TTC at RT data. This benefit is evident in both failure ($\lambda(1) = 12.65$, $p < .001$) and non-failure ($\lambda(1) = 13.69$, $p < .001$) trials (see Table 10). In failure trials, the continuous displays resulted in more frequent CC RTs for sensing and setting failures, $\lambda(1) = 6.26$, $p = .012$; $\lambda(1) = 3.83$, $p = .05$, respectively, as compared to the discrete displays. In non-failure trials, there were more CC RTs for braking and setting event types, $\lambda(1) = 6.26$, $p = .012$; $\lambda(1) = 7.97$, $p = .005$, respectively, in continuous display conditions than in the discrete display conditions.

Table 10. Driver Responses to Events/Failures in Change Condition Periods

Frequency of Responses	*# (In Failure Trials)*	*# (In Non-Failure Trials)*
Braking Exceedence **		
Discrete display	0	0
Continuous display	2	6
Sensor Degradation *		
Discrete display	0	0
Continuous display	6	0
Lateral Detection Range Exceedence		
Discrete display	0	0
Continuous display	1	0
Setting Exceedence * **		
Discrete display	1	1
Continuous display	6	10
TOTAL * **		
Discrete display	1	1
Continuous display	15	16

* Indicates $p \leq .05$ for Failure Trials; ** Indicates $p < .05$ for Non-Failure Trials

Reliance

Reliance on ACC was measured in three ways: 1) amount of time that elapsed following an ACC failure until drivers re-engaged ACC, 2) THW/TTC at the point drivers re-engaged ACC, and 3) amount of time ACC was engaged during the trials. ‘Engaged’ refers to when ACC was on *and* set; standby mode and off were coded as ‘not engaged’.

Time to re-engage ACC following failure. Following a brake/’off’ button response to the ACC failure in the failure trials, drivers re-engaged ACC at the point they felt comfortable using the system again. Across modality and display interface conditions, there were no significant differences in the amount of time elapsed until drivers re-engaged ACC. RTs differed as a function of event type, however, due primarily to the differences in failure times, $F(3, 329) = 39.63$, $p < .0001$ (braking: M = 22.21, SE = 1.7; sensing: M = 31.15, SE = 1.73; lateral: M = 27.13, SE = 1.75; setting: M = 42.84, SE = 1.65).

THW/TTC at point re-engaged. For THW and TTC values at the point drivers re-engaged ACC, there were no significant differences for interface conditions. A significant effect of event type for THW and TTC indicates that drivers adopted longer THWs following braking and setting failures (THW: $F(3, 339) = 2.98$, $p = .032$; braking: M = 2.55, SE = 0.146; sensing: M = 1.67, SE = 0.149; lateral: M = 1.5, SE = 0.151; setting: M = 2.6, SE = 0.141) but at faster closing speeds (TTC: $F(3, 311) = 15.65$, $p < .0001$; braking: M = 16.16, SE = 0.431; sensing: M = 17.72, SE = 0.44; lateral: M = 17.58, SE = 0.446; setting: M = 17.21, SE = 0.418). TTC at point re-engaged also increased significantly over time (block: $F(2, 217) = 3.23$, $p = .041$), indicating a trend to safer driving.

Amount of time ACC engaged. There were no significant differences in the amount of time ACC was engaged for interface conditions in either failure periods or in the change condition periods preceding and following the failure period. A main effect of event type for these periods reflects the differences in failure times for event types (failure period: $F(3, 398) = 314.36$, $p < .0001$; change condition periods preceding and following failure period within the event period: $F(3, 397) = 41.59$, $p < .0001$).

Role of implicit (trust) and explicit (mental model) knowledge

To assess the effect of interface condition on drivers' implicit and explicit understanding, subjective measures of trust and of their mental model of ACC were collected. Trust and mental model questionnaire data were converted to a 0–1 scale (0: low–1: high) using simple normalization to allow for ready interpretation across measures.

Subjective trust

The Interpersonal Trust questionnaire that drivers filled out at the beginning of the experiment provided a baseline measure of drivers' tendency to trust (Rotter, 1991). The multi-question trust rating administered at the end of each block (system trust) probed drivers' general attitudes and affective responses in use of ACC and its associated feedback interface (adapted from Lee & Moray, 1994), while the single-question trust rating administered at the end of each trial (interval trust) measured trial-specific variances in trust related to moment-to-moment interaction with ACC. Essentially, drivers were questioned on their system-level and mode-level trust (Lee & See, 2004). For the system trust questionnaire, there were eight Likert-scale questions. Seven of the eight questions were related to drivers' trust in the vehicle control automation; the eighth question asked drivers about their confidence in their ability to drive manually. For each questionnaire, the trust-related questions were averaged and subtracted from the single self-confidence rating. Both the averaged trust rating, and the trust rating qualified with self-confidence are reported in this section.

System trust ratings. In analyzing the system trust results, interpersonal trust was included as a covariate to account for differences in drivers' system trust ratings based on their baseline trust. From the ANOVAs, interpersonal trust was significant as a covariate factor for the trust results ($F(1, 46) = 7.69$, $p < .01$) but not for the T-SC results ($F(1, 46) = 3.02$, $p = .09$). Although interpersonal trust (IT) ratings were not significantly different between modality and display conditions, when included as a covariate, the significance of the modality x display interaction effect present for both trust and for trust minus self-confidence (T-SC) results increased (trust w/o IT covariate: $F(1, 46) = 2.29$, $p = .14$; trust w/ IT covariate: $F(1, 46) = 3.42$, $p = .071$; T-SC w/o IT covariate: $F(1, 46) = 8.51$, $p < .01$; T-SC w/ IT covariate: $F(1, 46) = 9.70$, $p < .01$). In visual form, trust in continuous feedback was higher than in discrete warnings, but in auditory form, trust in discrete warnings was higher than in continuous feedback (see Figure 36).

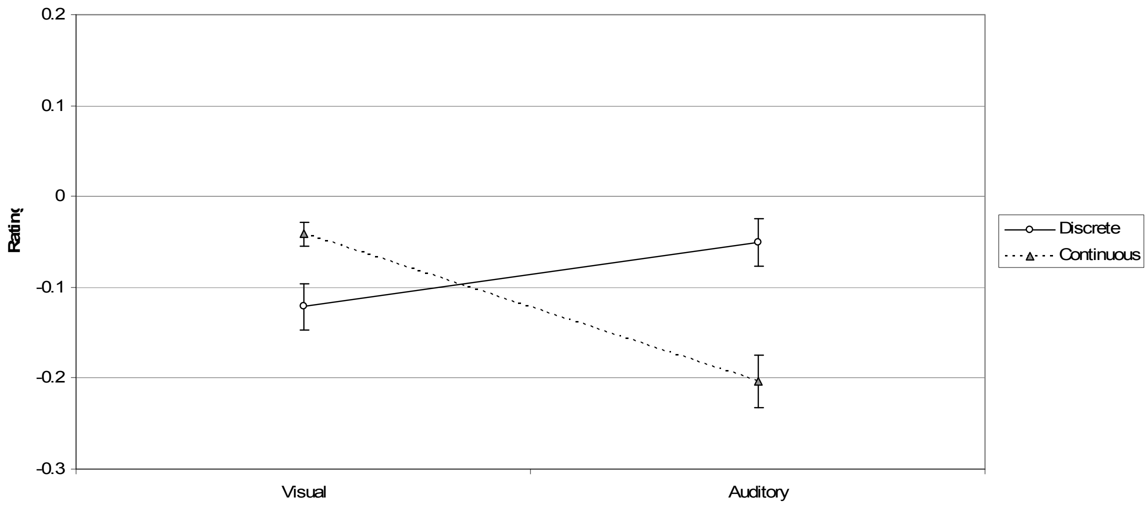

Figure 36. Trust minus self-confidence scores by modality and display conditions for the System Trust questionnaire.

These results indicate that the continuous information made drivers more confident in their ability to drive without ACC and less trusting of ACC when it was presented in auditory form. Considering that ACC exceeded its limits in half of the trials, lower trust is more appropriate. Interval trust results, reported next, indicate if the lower trust scores for continuous auditory feedback are calibrated to ACC capability.

Interval trust ratings. For the trust ratings collected at the end of each trial, there were significant main effects of modality ($F(1, 109) = 7.54$, $p < .01$) and of display ($F(1, 109) = 10.62$, $p < .01$). Auditory interfaces resulted in higher trust (M = 0.799, SE = 0.014) than visual interfaces (M = 0.744, SE = 0.014). Discrete warnings resulted in higher trust (M = 0.8, SE = 0.014) than continuous interfaces (M = 0.739, SE = 0.014). Predictably, non-failure trials resulted in higher trust than failure trials, $F(1, 864) = 39.29$, $p < .0001$ (non-failure: M = 0.8, SE = 0.011; failure: M = 0.74, SE = 0.011), and there were significant differences in trust by event type, $F(3, 892) = 5.25$, $p < .01$ (braking: M = 0.772, SE = 0.011; sensing: M = 0.754, SE = 0.011; lateral: M = 0.777, SE = 0.011;

setting: M = 0.783, SE = 0.011). Display type interacted with event type: trust was lower for continuous displays than for discrete displays for braking and setting event types, $F(3, 892) = 2.74$, $p = .042$ (braking: $t(158) = 2.95$, $p = .004$; setting: $t(158) = 2.67$, $p = .008$). Event type also interacted with trial type: trust was lower for failure trials than for non-failure trials in sensing and lateral event types, $F(3, 906) = 21.08$, $p < .0001$ (sensing: $t(265) = 6.11$, $p < .0001$; lateral: $t(281) = 4.40$, $p < .0001$; see Figure 37).

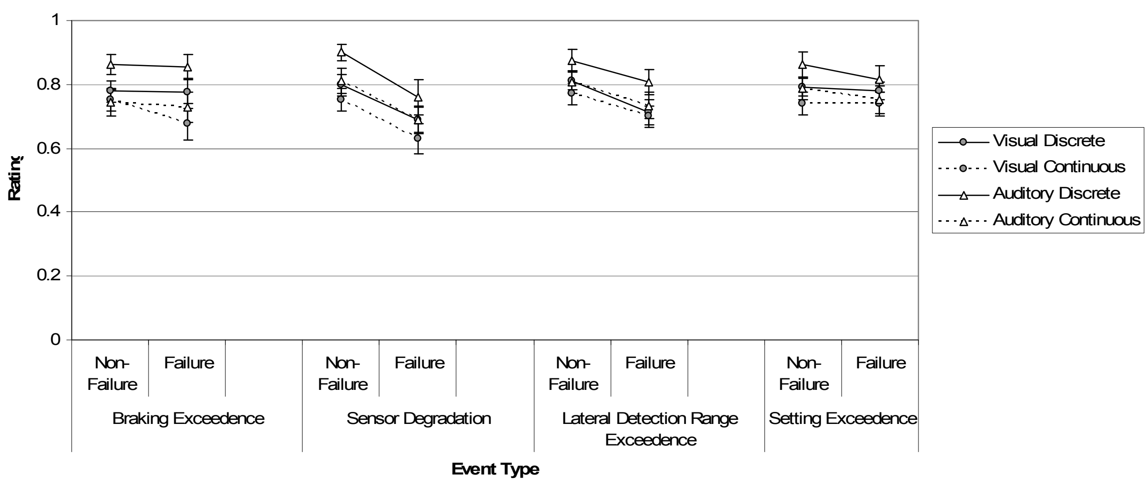

Figure 37. Interval trust ratings by event type for non-failure and failure trials by interface condition.

The appropriateness of these trust results depends on how well trust matches the true capabilities of ACC. Specifically, a person's trust is calibrated if it corresponds to the automation's capabilities (Lee & See, 2004). In this experiment, ACC's capability can be defined in a number of ways:

1) Percent of time ACC was functional within a trial, i.e., event period excluding the failure period (see values in column entitled "ACC Capability 1" in Table 11)

2) Percent of time ACC was appropriate to use within a trial, i.e., event period excluding the failure and change condition periods (see values in column entitled “ACC Capability 2” in Table 11)
3) Percent of trials that ACC was fully functional (see values in column entitled “ACC Capability 3” in Table 11)

To explicitly compare driver trust to automation capability, a subjective measure of perceived reliability of ACC would allow for subtraction from the ACC capability calculations (Kantowitz, Hanowski, & Kantowitz, 1997; Wickens et al., 2000). In this study, however, drivers were not asked to provide a rating of perceived reliability. An indirect means to calculate perceived reliability is through the amount drivers used ACC (Kantowitz et al., 1997; Merlo, Wickens, & Yeh, 1999; Parasuraman, Mouloua, & Molloy, 1996). Reliance amounts, according to the periods specified in the definition of ACC capability, however, did not reveal differences by interface condition. Interval trust ratings compared to ACC capability indicate relative differences; these differences provide a crude metric of trust calibration. The column in Table 11 entitled “Driver Trust (DT)” lists the means from the interval trust ANOVA for non-failure and failure trials by event type x display type. These mean values are subtracted from the ACC capability calculations (see columns entitled “ACC 1/2/3 - DT” in Table 11) to indicate trust calibration, in which the trust ratings are assumed to represent drivers’ reliability rating. If calculated based on non-failure periods within trials, discrete display conditions afford more calibrated trust than the discrete display conditions. If calculated based on appropriate periods of use, or on percent of trials during which ACC is fully functional, the continuous display conditions afford more calibrated trust than the discrete display conditions (see the framed mean difference averages in Table 11). This exercise demonstrates the importance of defining an automation system's "capability" as this definition determines how trust ratings are interpreted.

Table 11. Calculations of Trust Calibration According to ACC Capability

APPROPRIATE TRUST	*Driver Trust (DT)*	*ACC Capability 1 (≠ F periods)*	*ACC 1 - DT*	*ACC Capability 2 (≠ F + CC periods)*	*ACC 2 - DT*	*ACC Capability 3 (≠ failure trials)*	*ACC 3 - DT*
Non-Failure Trials							
Discrete display							
Braking	0.82	1.00	0.18	0.74	0.08	0.5	0.32
Sensing	0.85	1.00	0.15	0.71	0.13	0.5	0.35
Lateral	0.84	1.00	0.16	0.71	0.14	0.5	0.34
Setting	0.83	1.00	0.17	0.71	0.12	0.5	0.33
			0.17		**0.12**		**0.34**
Continuous display							
Braking	0.75	1.00	0.25	0.74	0.01	0.5	0.25
Sensing	0.78	1.00	0.22	0.71	0.07	0.5	0.28
Lateral	0.79	1.00	0.21	0.71	0.08	0.5	0.29
Setting	0.76	1.00	0.24	0.71	0.05	0.5	0.26
			0.23		**0.05**		**0.27**
Failure Trials							
Discrete display							
Braking	0.82	0.95	0.14	0.69	0.13	0.5	0.32
Sensing	0.72	0.75	0.02	0.46	0.26	0.5	0.22
Lateral	0.76	0.93	0.17	0.64	0.12	0.5	0.26
Setting	0.80	0.91	0.11	0.62	0.18	0.5	0.30
			0.11		**0.17**		**0.27**
Continuous display							
Braking	0.70	0.95	0.25	0.69	0.01	0.5	0.20
Sensing	0.66	0.75	0.09	0.46	0.20	0.5	0.16
Lateral	0.72	0.93	0.21	0.64	0.08	0.5	0.22
Setting	0.75	0.91	0.16	0.62	0.13	0.5	0.25
			0.18		**0.10**		**0.21**

F refers to failure, CC to change condition.

Given the limitations in this study, as discussed above, of directly comparing automation capability and trust, another way of analyzing trust calibration is to determine if trust changes in the same direction and in proportion to changes in automation capability (Lee & See, 2004: 55). At a basic functional level, automation either is or is not operating properly; thus, at any given moment, its capability is either 100% or 0%.

Trust calibration, then, should reflect automation's moment-to-moment shift in capability. The interval trust ratings were collected at a rate intended to capture moment-to-moment trust changes but the 3-minute intervals between ratings still introduce some calculation error.

At the level collected, calibrated trust would result in trust ratings that were significantly higher in non-failure trials than in failure trials. In a comparison of discrete warnings and continuous information interfaces, if drivers in the continuous interface conditions were more calibrated in their trust, they should have had a larger difference between trust ratings for non-failure and failure trials compared to drivers in the discrete warning conditions, i.e., a significant display type x trial type interaction for the full-factor ANOVA reported above. This interaction term did not indicate significance, $F(1, 864) = 0.03$, $p = .859$. When non-failure and failure trials are analyzed separately, however, there are significant display type differences. In the non-failure trials, drivers had higher trust ratings for discrete warnings (M = 0.835; SE = 0.018) than for continuous interfaces (M = 0.771; SE = 0.018), $F(1, 65) = 6.12$, $p = .016$. In the failure trials, drivers had lower trust ratings for continuous interfaces (M = 0.707; SE = 0.019) than for discrete warnings (M = 0.774; SE = 0.019), $F(1, 75) = 6.10$, $p = .016$. Drivers using the continuous interfaces may have had increased awareness of ACC's limitations and therefore a tendency to distrust it, resulting in the observed lower trust ratings across all trial types as compared to drivers provided with discrete warnings.

If drivers' trust in the continuous interface conditions was a function of increased knowledge of how ACC functioned and its limitations, their mental model accuracy scores should be higher than those in the discrete warning conditions. The mental model accuracy scores are reported next.

Mental model accuracy

Drivers filled out the same mental model questionnaire at the end of each block of drives to detect differences in their understanding of ACC as a function of their interaction with it over time (i.e., experience). The questionnaire was designed to test their knowledge of the purpose, process, and performance of ACC; the mental model questionnaire, as developed for this study, is included in Appendix C. The first section contained four multiple-choice questions that asked drivers about the basic operation of ACC, i.e., its purpose. The second section included 11 multiple-choice questions that asked about situations and conditions of use of ACC, i.e., its operational response in specific situations, including those pertaining to the event types used in the experiment; this section assessed drivers' process understanding of ACC. The final section of the questionnaire contained four Likert-scale questions: two asked drivers about their perceived understanding of ACC, namely if they thought their understanding was correct and complete, and two asked about ACC's perceived performance. Space was provided at the end of the questionnaire for drivers to describe particulars about their interaction with ACC, e.g., any confusing states or features of ACC.

For the multiple-choice questions, more than one of the choices was often correct (of this possibility drivers were informed of in the questionnaire's instructions). The following coding scheme was adopted to calculate each question's accuracy: a "0" was assigned to each correct statement within a question that was *not* selected; a "1" was assigned to each correct statement that was selected; a "-0.25" was assigned to each incorrect statement that was selected. These values were averaged for each question. This particular coding scheme penalized drivers more for incorrect mental models than for incomplete mental models. The "-0.25" value was assigned to incorrectly selected statements so that in calculating accuracy scores, per question, drivers with incorrect mental models were differentiated from those with impoverished (i.e., correct but incomplete) mental models.

Questionnaire ratings. Purpose accuracy ratings did not significantly differ across independent variables. For the process questions, those that pertained to event types included in the experiment were analyzed separately. The other process questions were summarized and were defined as advanced process knowledge as drivers did not experience the full range of scenarios to answer these questions; these questions were designed to test if drivers could extrapolate their understanding of ACC as informed from the particular feedback interface to other situations of ACC use. For the advanced process questions, drivers did not significantly differ across interface type in their ratings. For process questions specific to the event types, however, drivers did differ in their understanding. While the ANOVA for drivers' knowledge of ACC's braking limits indicated a non-significant effect of display type, $F(1, 46) = 2.02$, $p = .162$, a look at the data in Figure 38 shows an important modality x display type difference that was not captured by the ANOVA. In particular, drivers in the auditory continuous interface condition had higher accuracy scores than those in the auditory discrete condition, $t(70) = 3.35$, $p = .001$, though for the visual discrete-continuous comparison, there were non-significant differences in accuracy scores, $t(70) = 0.3$, $p = .763$.

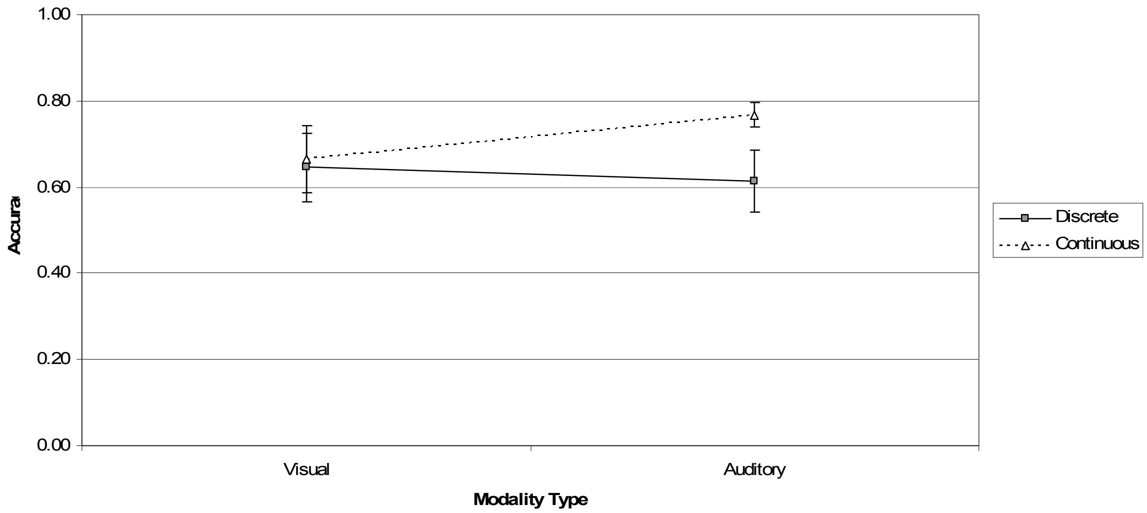

Figure 38. Mental model accuracy for braking limits question - process knowledge of ACC - by modality and display type.

ANOVA results did not indicate significant differences in drivers' knowledge for sensing and lateral limit questions across interface conditions. There were significant differences for the setting limit question: continuous displays afforded higher mental model accuracy than discrete displays, $F(1, 45) = 5.07$, $p = .029$. Across time, there were differences in the effect of modality of the feedback interface on mental model accuracy, $F(2, 85) = 4.32$, $p = .016$ (see Figure 39), that appear to resolve by Block 3.

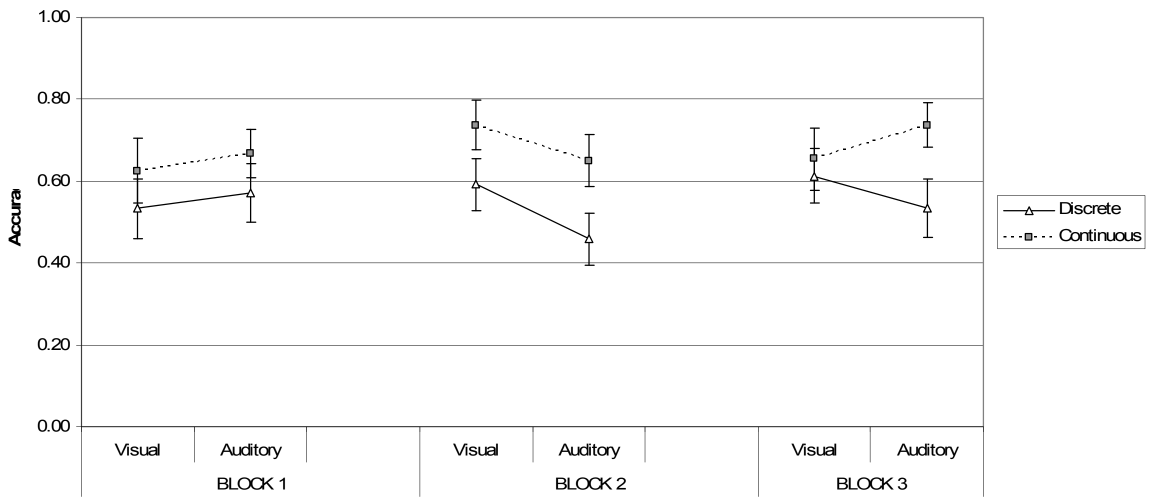

Figure 39. Mental model accuracy for setting limits question - process knowledge of ACC - by modality and display type. Accuracy ratings are shown over time (i.e., Blocks 1, 2, 3).

For drivers' perceived performance ratings of ACC, they differed by modality type, $F(1, 44) = 4.18$, $p = .047$, and across time, $F(2, 86) = 14.92$, $p < .0001$ (see Figure 40). Specifically, drivers in the auditory interface conditions perceived ACC's performance, in terms of its predictability and understandability, as higher than drivers in the visual interface conditions. Across time, drivers' perceived ratings of ACC's performance increased, indicating their added comfort in using the automation with additional experience.

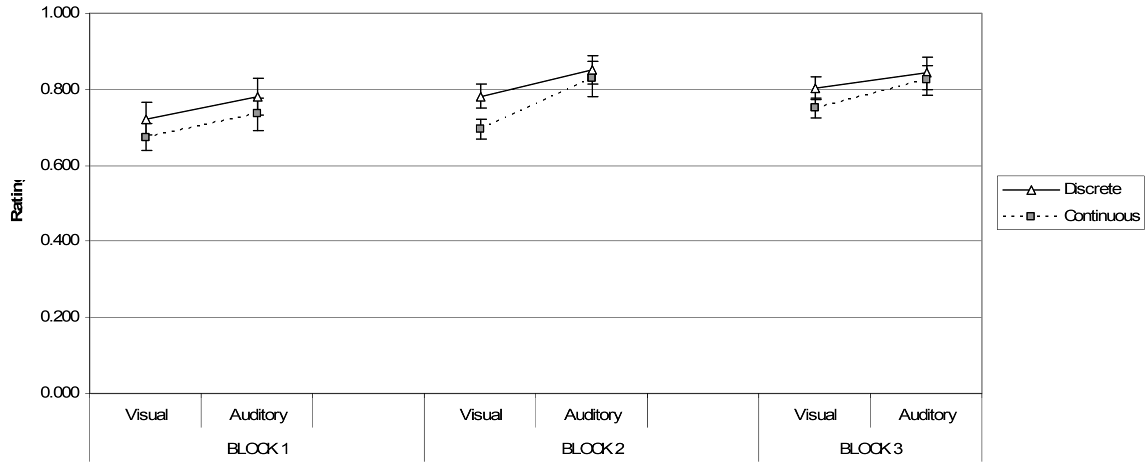

Figure 40. Mental model ratings for subjective performance of ACC by modality and display type. Ratings are shown over time (i.e., Blocks 1, 2, 3).

Influence of trust and mental model accuracy on driver response

According to the driver–ACC interaction model described in Chapter III, a driver with a more accurate mental model (i.e., explicit understanding) should recognize the driving conditions that make ACC inappropriate to use and disengage ACC at or prior to precipitating events. Responses following precipitating events are more likely in response to the deteriorating driving conditions than to an informed awareness of ACC's state and behavior. To test these model predictions, and the role of trust and mental model accuracy in determining driver response, the following analyses were conducted: 1) regressions of interval trust ratings and mental model accuracy scores on driver RTs, and 2) ANOVAs to analyze trust and mental model accuracy differences between driver–ACC interaction groups.

Regression analyses. Only RTs from failure trials were used to run the regression analyses because of the disparity of RTs in non-failure trials. Also, per block, there were only one set of mental model accuracy scores (four scores per administered questionnaire: one accuracy ratings for each event type) to pertain to either the failure trial or the non-failure trial RTs. For every trial there was an associated interval trust rating—those pertaining to the failure trials were used. There were 12 trust scores, mental model accuracy scores, and failure RTs per driver, representing the three blocks with four event types per block. Data were averaged across blocks for each event type, resulting in four data points per driver.

For the first regression analysis, trust, display type, modality type, and event type were included as predictor variables. The overall model indicated marginal significance, $F(4, 186) = 2.30$, $p = .061$. Only 5% of the total variance of failure RTs was explained by this regression model ($R^2 = 0.047$). Adding mental model accuracy to the regression model reduced the overall model significance, $F(5, 185) = 1.87$, $p = .10$, and did not add increased predictive power of failure RT ($R^2 = 0.048$).

Correlation analyses for each event type confirm the non-predictive power of trust and mental model accuracy for failure RT. Separate Pearson product-moment correlations calculated for each event type indicated that trust was not significantly correlated with failure RT. The pattern of the data for braking, sensing, lateral, and setting trials indicated a wide spread in trust ratings associated with failure reaction times. Mental model accuracy was also not significantly correlated with failure RT; the pattern of these data for the event types again indicated a wide spread in mental model accuracy scores associated with failure reaction times. Grouped by IVs, driver RTs did not conform to predicted categories from the driver–ACC interaction model. Re-grouping RT data according to the event boundaries, however, confirms predicted effects.

ANOVAs for driver–ACC interaction model groups. For failure and non-failure trials, respectively, RTs were grouped according to those initiated prior to the precipitating event (i.e., proactive responses) and those initiated after this event (i.e., reactive responses). In both trial types, the same 10 drivers initiated the proactive responses. These 10 drivers were coded as 'proactive responders'. The other 38 drivers were coded as 'reactive responders'. Of the 10 proactive responders, nine were from the continuous interface conditions.

For the same reasons listed as in the correlation analyses, only failure trial data were analyzed. A three-way ANOVA, with model group (proactive, reactive), event type, and block as factors, was conducted. Dependent variables were mental model accuracy scores, and trust ratings. A separate ANOVA was performed for each dependent variable. For mental model accuracy, drivers in the proactive response group had significantly higher scores than drivers in the reactive response group, $F(1, 178) = 5.6$, $p = .019$ (proactive: M = 0.746, SE = 0.032; reactive: M = 0.662, SE = 0.016). Accuracy scores also significantly differed across event type, $F(3, 408) = 4.88$, $p = .002$, as seen in Figure 41.

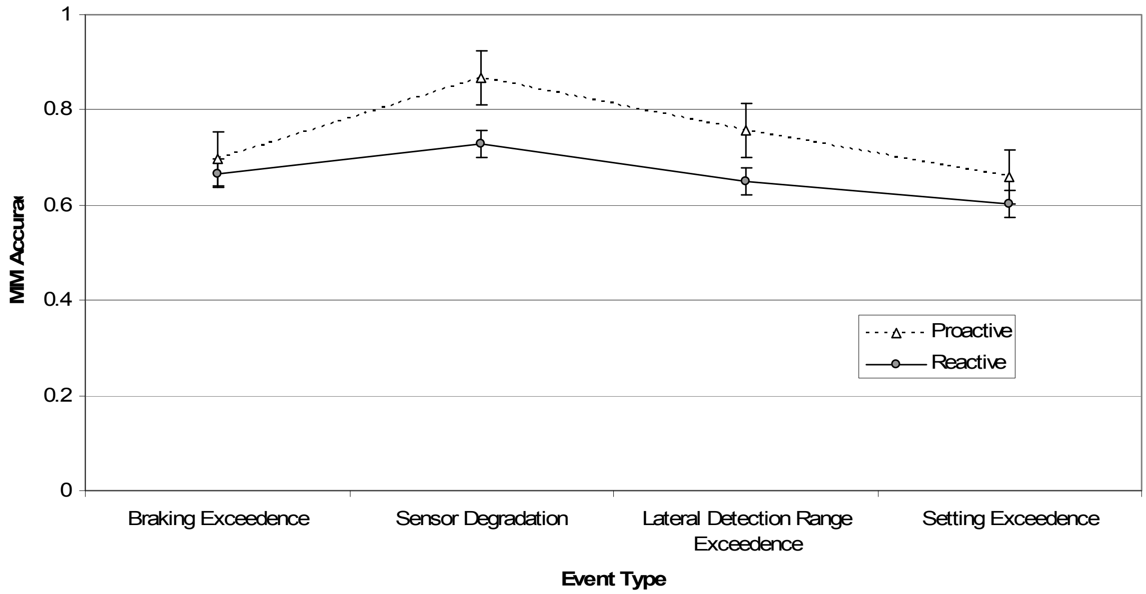

Figure 41. Mental model accuracy for driver–ACC interaction model groups by event type. 'Proactive' are those drivers who initiated responses prior to the precipitating event—in the change condition period; 'Reactive' are those drivers who initiated responses after the precipitating event—in the failure period.

For trust, drivers in the proactive response group had significantly lower ratings than drivers in the reactive response group as a function of event type and block, $F(6, 460) = 2.15$, $p = .047$. As derived from Figure 42 (a plot of the ANOVA means and standard errors for the 3-way interaction), this lower trust for proactive responders was specific to braking failures in the first block of drives.

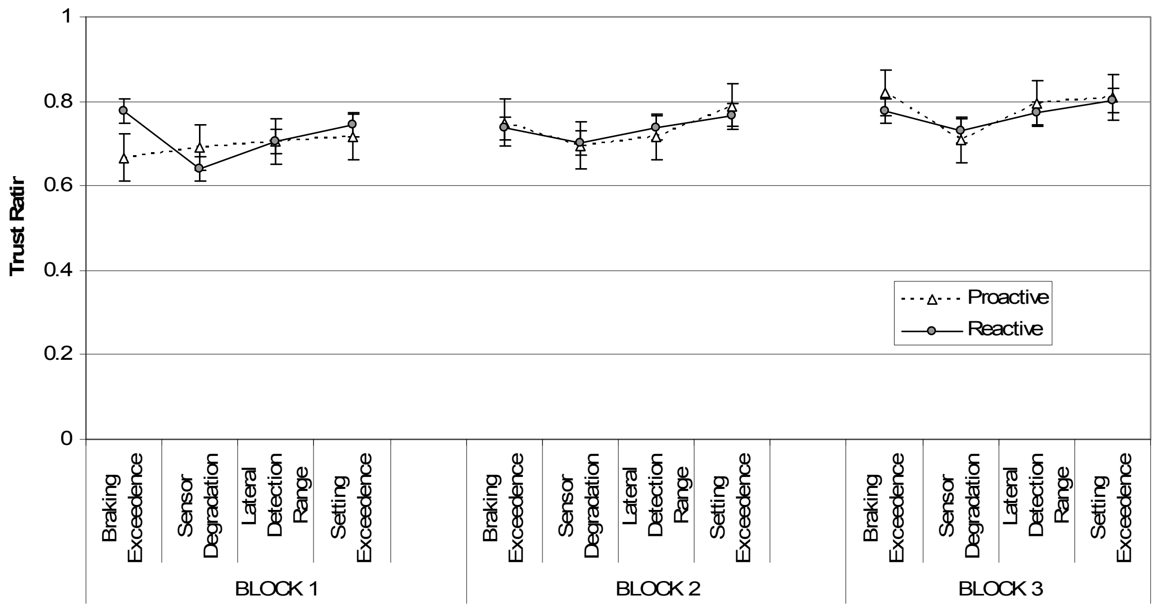

Figure 42. Trust ratings for driver–ACC interaction model groups by event type and block. 'Proactive' are those drivers who initiated responses prior to the precipitating event; 'Reactive' are those drivers who initiated responses after the precipitating event.

Effort and distraction consequences of continuous information

To evaluate the visual and cognitive costs to providing drivers with continuous feedback information on ACC's state and behavior, measures for driving task performance and for secondary task performance were collected. Decrements in driving and secondary task performance are expected if the provided continuous information induced visual/cognitive distraction.

Driving task performance

Driving task performance was evaluated with measures of steering velocity, time-to-line crossing, and lane exceedences. Steering velocity characterizes steering behavior and was defined as change in steering wheel angle over 330-ms increments (Peters, Kloeppel, & Alicandri, 1999; Skipper, Wierwille, & Hardee, 1984). This time window served as a high-pass filter to correct for roadway curvature (i.e., slow steering wheel angle changes that were characteristic of curves were filtered out with this 330-ms time constant). Time-to-line crossing is the ratio between the lateral position and the rate of change of the lateral position (van Winsum, Brookhuis, & de Waard, 2000). The same 330-ms time window was used to calculate rate of change of lateral position. A lane exceedence occurred if any part of the driver's vehicle exceeded lane boundaries, crossing over into either the shoulder or the passing lane. Driving task performance measures are reported for the failure trials; both non-failure periods within the failure trials and the failure periods were analyzed.

Steering velocity. A lower steering velocity indicated more controlled driving behavior. There were no significant main effects or interaction effects for display type. Predictably, steering velocity significantly differed for event type in the non-failure periods of the failure trials, $F(3, 390) = 240.44$, $p < .0001$. Drivers appeared to have less erratic steering behavior in setting exceedence event trials as compared to the other event type trials (see Figure 43). A modality x event type interaction, $F(3, 390) = 3.05$, $p = .029$, is driven by the larger steering velocity for visual interfaces during the braking exceedence event trials, $t(134) = 1.91$, $p = .058$. The result of visual interfaces increasing steering velocity is consistent with expected effects for a visually demanding interface, whereby driver's attention is drawn away from the roadway to the in-vehicle display. Interestingly, this visual demand is evident only in the braking exceedence event trials, potentially due to more salient display changes for this event type as compared to those of the other event types.

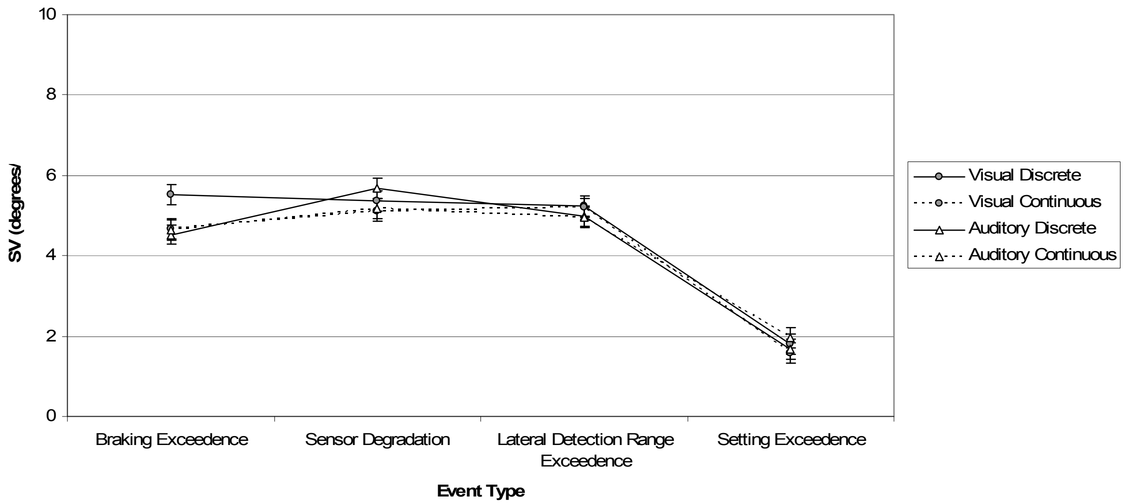

Figure 43. Steering velocity (SV) in degrees/second during non-failure periods within the failure trials by event type per interface condition.

For the duration of the failure period, steering velocity was affected by display and by modality, $F(1, 159) = 7.78$, $p = .006$, and $F(1, 159) = 4.03$, $p = .046$, respectively. These main effects, in which steering velocity was higher for visual than for auditory interfaces, and higher for discrete than for continuous interfaces, are best interpreted within their interaction effects. As seen in Figure 44, steering velocity also differed by event type, $F(3, 377) = 43.3$, $p < .0001$. A modality x event type interaction reflected the higher steering velocity for visual interfaces in braking exceedence trials, $F(3, 377) = 3.42$, $p = .018$. A modality x display interaction indicates a higher steering velocity for visual discrete warnings than for the other interface types, $F(1, 159) = 8.38$, $p = .004$. A display x event type interaction points to the particularly large difference in steering velocity for braking exceedence trials between discrete and continuous displays, $F(3, 377) = 3.07$, $p = .028$. Finally, the three-way interaction effect for modality, display, and event type indicates that visual discrete warnings resulted in significantly higher steering velocity in failure periods for braking exceedence trials as compared to the other interface types within this same period, $F(3, 377) = 4.56$, $p = .004$.

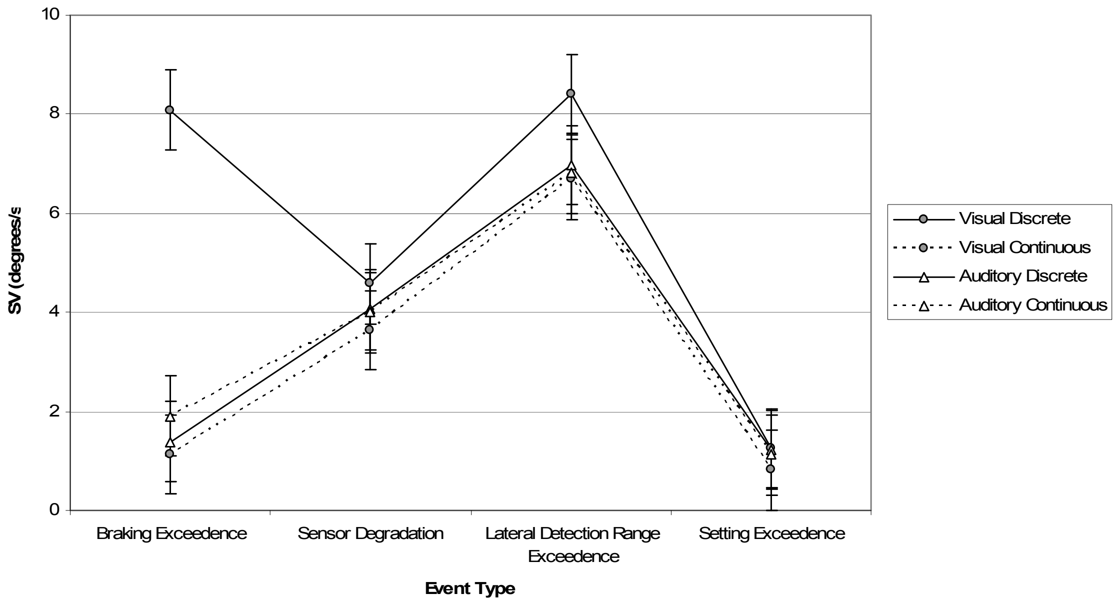

Figure 44. Steering velocity (SV) in degrees/second during failure periods by event type per interface condition.

Time-to-line crossing. Another metric of driving control is time-to-line (TLC) crossing. The higher the TLC value the more time there is available for a driver until the moment at which any part of the vehicle reaches one of the lane boundaries (Godthelp, Milgram, & Blaauw, 1984). The main effect of event type is consistent with the steering velocity results for non-failure periods within failure trials, $F(3, 407) = 270.16$, $p < .0001$, in which the setting exceedence trials resulted in better driving control (see Figure 45). A modality x display interaction for the non-failure periods also conforms to the steering velocity findings, indicating that visual discrete warnings induced poorer lateral control as compared to the other interface types, $F(1, 99) = 6.39$, $p = .013$ (visual discrete: M =

15.962, SE = 0.02; visual continuous: M = 16.524, SE = 0.02; auditory discrete: M = 16.826, SE = 0.02; auditory continuous: M = 16.373, SE = 0.02).

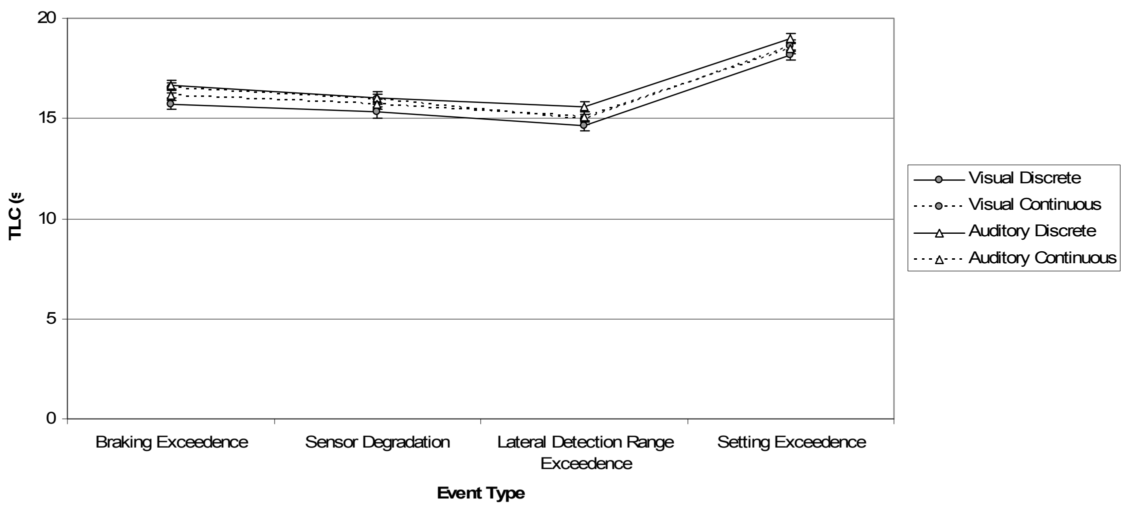

Figure 45. Time-to-line crossing (TLC) in seconds during non-failure periods within the failure trials by event type per interface condition.

During the failure periods, the effects observed in the non-failure periods of the failure trials were magnified. A marginally significant effect of lower TLC values for discrete displays compared to continuous displays, $F(1, 167) = 3.14$, $p = .078$, is compelling in the context of its interaction with modality, in which visual discrete warnings induced poorer lateral control as compared to the other interface types, $F(1, 167) = 5.01$, $p = .027$. As evident in Figure 46, TLC values significantly differed by event type during the failure periods, $F(3, 395) = 441.32$, $p < .0001$. The TLC values for lateral detection range exceedence event types are appropriately lower than the other event types, indicating that drivers were responsive to the lateral movements of the LV during the failure periods, likely in an effort to re-position the LV within the ACC's detection range.

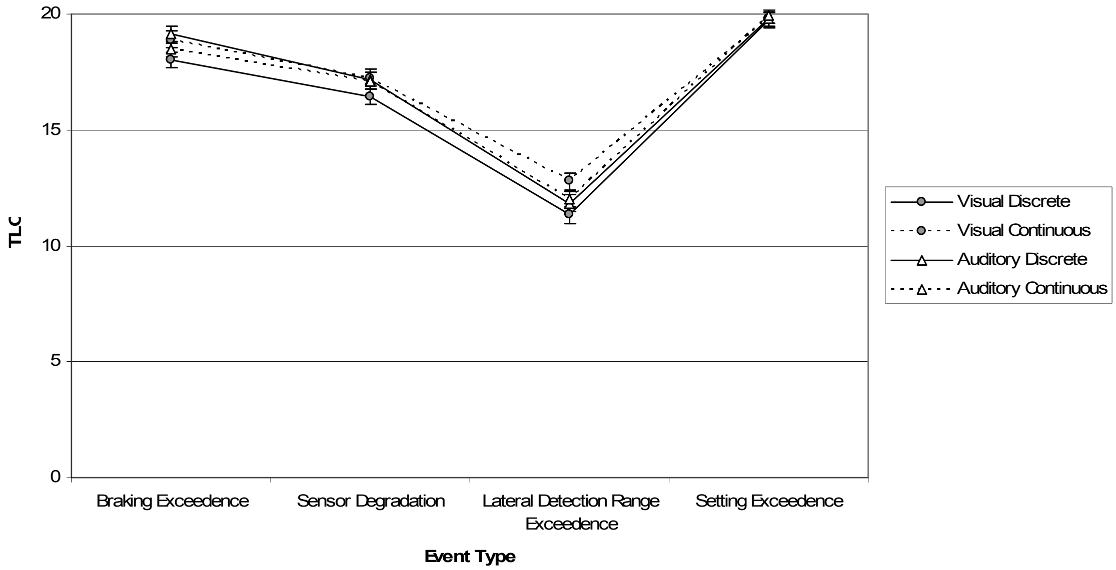

Figure 46. Time-to-line crossing (TLC) in seconds during failure periods by event type per interface condition.

Lane exceedences. Lane exceedences indicate loss of driving control. Table 12 presents the number of times drivers crossed lane boundaries by display type and event type for both non-failure periods and failure periods during failure trials. The frequency of lane exceedences did not significantly differ between display types for non-failure periods, $\lambda(1) = 0.0721$, $p = .788$. Drivers did cross lane boundaries more frequently, however, with use of discrete displays compared to continuous displays during failure periods, $\lambda(1) = 6.042$, $p = .014$.

Table 12. Lane Exceedences

Frequency of Lane Exceedences	# *(NF)*	# *(F)*
Braking Exceedence		
Discrete display	2	4
Continuous display	2	0
Sensor Degradation		
Discrete display	3	1
Continuous display	4	0
Lateral Detection Range Exceedence		
Discrete display	2	2
Continuous display	1	0
Setting Exceedence		
Discrete display	0	0
Continuous display	1	0
TOTAL		
Discrete display	7	* 6
Continuous display	8	0

* Indicates p < .05

F refers to failure periods; *NF* refers to non-failure periods

Together, the driving task performance results do not indicate that the continuous feedback undermined driving performance. If anything, these results showed that visual discrete warnings were distracting for drivers. An analysis of the secondary task performance data reveals whether or not drivers using the continuous interfaces shed the secondary task in order to preserve their driving performance.

Secondary task performance

Secondary task performance was evaluated with measures of signal reaction time (RT), sensitivity, and bias. Signal RT is the amount of time that elapsed from a signal billboard (i.e., one that displayed the same dice image consecutive to the previous billboard's dice image) and a driver's button press on the steering wheel. This button press had to occur on the same side of the steering wheel as that of the location of the billboard. Sensitivity, d', reflects how good an operator is at the signal detection task, and is higher if there are more correct responses and fewer detection errors. Response bias, β, indicates the bias of the operator to respond "yes" (or affirm a signal) versus "no" (to affirm the lack of a signal; Green & Swets, 1988; Wickens, 1992). Simply, response bias is the probability that the operator will respond "yes". An operator's expectation that a signal will be seen, and higher value in the costs or benefits of either detecting or not detecting signals both lead to increases in the probability of an operator responding "yes". The consequences of an increasing shift in beta are both more hits and more false alarms; therefore, a lower beta is characteristic of a more conservative operator (fewer hits but fewer false alarms) while a higher beta is characteristic of a riskier operator (more hits but more false alarms). The non-failure trials revealed the same pattern of effects as the failure trials and are therefore not reported.

Signal RT. In direct refutation of the theory that drivers shed the secondary task to preserve the primary driving task, drivers who used the continuous displays responded faster to the signal billboards than drivers who used the discrete displays, $F(1, 92) = 3.87$, $p = .05$. Table 13 lists the means and standard errors for this main effect and for the significant effect of event type, $F(3, 408) = 8.24$, $p < .0001$.

Sensitivity and response bias. Measures of sensitivity and response bias did not indicate significant differences for interface conditions. For sensitivity, the significant effect of block, $F(2, 222) = 8.45$, $p < .001$, showed that drivers performed the secondary task better over time, i.e., more correct responses and fewer errors (Block 1: M = 2.25, SE = 0.044; Block 2: M = 2.49, SE = 0.044; Block 3: M = 2.45, SE = 0.044). A significant main effect of event type for both sensitivity and response bias, $F(3, 375) = 24.5$, $p < .0001$ and $F(3, 382) = 9.57$, $p < .0001$, respectively, indicated a tradeoff of lower sensitivity and increased riskiness with faster RTs; there is no evidence that this tradeoff effect depends on display type (see Table 13).

Table 13. Secondary Task Means and Standard Errors for Signal RT, Sensitivity, and Response Bias

	Signal RT		Sensitivity		Response Bias	
Secondary Task Summary Data	*Mean*	*SE*	*Mean*	*SE*	*Mean*	*SE*
Discrete display	0.537	0.079	2.356	0.037	1.012	0.023
Continuous display	0.318	0.079	2.44	0.037	1.031	0.023
Braking Exceedence	0.367	0.07	2.419	0.045	1.108	0.03
Sensor Degradation	0.573	0.07	2.478	0.045	0.959	0.03
Lateral Detection Range Limit	0.517	0.07	2.588	0.045	0.923	0.03
Setting Exceedence	0.252	0.07	2.106	0.045	1.093	0.03

Together, for drivers using the continuous interfaces, the secondary task performance results failed to show a decrement in their ability to attend to the secondary task. In fact, drivers in the continuous interface conditions performed the continuous detection task better than those in the discrete warning conditions.

Perceived benefit of interface

To determine if any observed benefits of the continuous information interfaces were offset with a general dislike and perceived added effort in use of these interfaces, drivers were administered a usability questionnaire and a mental effort questionnaire at the end of the experiment. These questionnaires directed drivers to respond based on their use of the ACC system and its associated feedback interface. The usability questionnaire prompted drivers to rate the interface on nine dimensions, as seen in Figure 47. These nine dimensions were used to calculate an overall usability rating. In addition, those dimensions related to annoyance (specifically 'pleasant-unpleasant', 'nice-annoying', 'irritating-likeable', and 'undesirable-desirable') were used to calculate an annoyance rating. The mental effort questionnaire asked drivers to rate their effort on a 0-100 scale.

My judgments of the safety system I just used are:

Useful	☐	☐	☐	☐	☐	Useless
Pleasant	☐	☐	☐	☐	☐	Unpleasant
Good	☐	☐	☐	☐	☐	Bad
Nice	☐	☐	☐	☐	☐	Annoying
Effective	☐	☐	☐	☐	☐	Superfluous
Irritating	☐	☐	☐	☐	☐	Likeable
Assisting	☐	☐	☐	☐	☐	Worthless
Undesirable	☐	☐	☐	☐	☐	Desirable
Raising Alertness	☐	☐	☐	☐	☐	Sleep-inducing

Figure 47. Usability scales within administered form.

Usability and mental effort ratings. While the usability ratings did not indicate significant differences for either display type or modality type (usability – display: $F(1, 44) = 0.00$, $p = .983$; usability - modality: $F(1, 44) = 0.01$, $p = .943$; annoyance – display:

$F(1, 44) = 0.16$, $p = .693$; annoyance – modality: $F(1, 44) = 0.04$, $p = .843$), the mental effort rating showed an interaction between these factors, $F(1, 44) = 5.27$, $p = .027$. Drivers considered the visual continuous interface to be more effortful than the visual discrete warning, but the reverse to be true for auditory interface types (see Figure 48). Taken across modality, the continuous information interfaces did not show an added or reduced amount of perceived effort as compared to the discrete warnings.

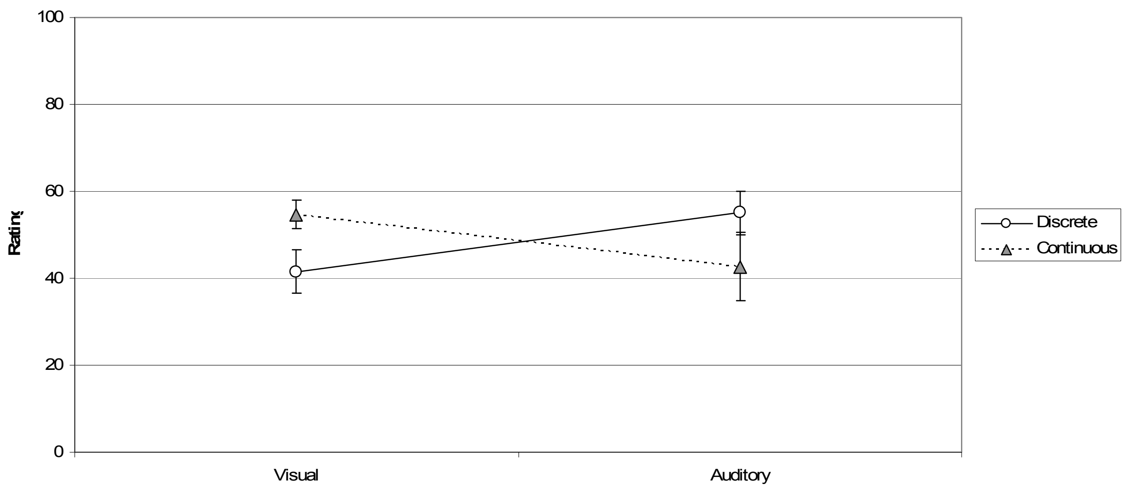

Figure 48. Mental effort ratings by modality type for display type.

Discussion and Conclusions

The results support the first hypothesis related to aim one: drivers provided with continuous feedback on ACC's state and behavior relied more appropriately on ACC in terms of their response to failure situations. The second hypothesis, however, concerning the expected tradeoff of this benefit with a resulting decrement to driving or secondary task performance, was not supported. Specific to the second aim hypotheses, as expected from the driver–ACC interaction model predictions, drivers who were proactive in responding to the precipitating event had more accurate mental models. As hypothesized, providing drivers with continuous feedback led to increased mental model accuracy as compared to discrete warnings; however, contrary to expectation, presentation of the continuous feedback in the auditory modality did not compromise this advantage.

Benefit and cost of the continuous feedback interfaces

Considered together, the results show a clear benefit of continuous interfaces over discrete warnings. Drivers responded a half-second faster with use of continuous interfaces as compared to discrete warnings in situations that induced ACC to cross its operational limits, and in normal operating conditions were more responsive to condition changes that signaled inappropriate use of ACC. The faster responses at failure point translated to larger following distances to the lead vehicle, confirming the afforded benefit of an earlier driver response. Drivers were able to process the continuous information without decrement to their lane keeping performance and steering control. Further, the comparative improved performance to that of the discrete warnings in the task of detecting billboard dice images indicates that drivers were able to use their peripheral vision to process the display information. The mental model results indicate that drivers were able to encode this perceived information into improved knowledge of ACC.

Specific to interface modality, the benefits in providing drivers with continuous feedback were slightly more prominent in auditory form compared to visual form in terms of driver response to failure and associated following distance. The inherently-alerting quality of the auditory information may have primed drivers to respond more readily. And while drivers indicated a perceived reduction in workload with use of the auditory continuous feedback, continuous feedback prompted improved driver interaction with ACC compared to discrete warnings independent of interface modality. An increase in driving or detection task demand, however, may make the differences in presentation of the continuous information more prominent.

Event-specific differences with use of continuous interfaces in drivers' response to ACC failures qualify the success of providing drivers with continuous feedback. Drivers were more responsive in braking exceedence and setting exceedence situations than in the sensor degradation and lateral detection range exceedence situations. Further, drivers were not calibrated in their trust for the sensing and lateral event types with use of continuous displays. As corroborated from their mental models scores, drivers were uncertain of ACC's behavior in these situations and did not fully understand its response.

Drivers provided with continuous feedback—as compared to those provided with discrete warnings—did not develop more accurate mental models of ACC's behavior in all event conditions as expected. The event-specific differences in mental model benefits may have been due to more effective cue mappings to ACC's braking and setting limits as compared to the cues used to inform drivers of ACC's sensor capabilities. The discrepancy between event types highlights the importance of selecting design features that are compatible with drivers' perceptual abilities as well as intuitive as to how automation characteristics are encoded. Assuming cue effectiveness in the interfaces, drivers' preconceptions of ACC may have prompted them to disregard information provided in the continuous interfaces or to interpret the information according to incorrect preconceptions. Alternatively, drivers may have used heuristics in processing the interface information that belied ACC's complexity (Todd & Gigerenzer, 2000).

In interpreting drivers' trust in ACC and its associated feedback interface, the high rate of failure trials may have artificially magnified drivers' affective response. Across conditions, drivers' trust levels were unexpectedly high ($M = 78.33$) considering the rate of failure (50% of trials). Drivers potentially recognized the artificial nature of the driving task and allowed for greater variability in ACC's performance as a result. The high rate of trust measurement may have also contributed to the inflated trust ratings. It is expected that increased exposure to ACC coupled with more realistic failure rates would induce trust levels more consistent with ACC's capability. In this study, lower trust was more appropriate—a function of the study's high ACC failure rate and in accord with an increased awareness of ACC's limitations. Importantly, continuous interfaces induced lower (more appropriate) trust across event conditions compared to discrete warnings.

Human-automation model validation

Driver responses to enhanced feedback were consistent with those of the driver–ACC interaction model. Specifically, drivers with better mental models tended to initiate responses to conditions that degraded ACC performance prior to failures. Nine out of ten of these drivers received continuous feedback. Interestingly, those drivers with less accurate mental models that responded after the precipitating events still showed a benefit with use of the continuous information, i.e., faster reaction times, suggesting that these interfaces were more informative *and* more alerting.

The just-noticeable differences of the continuous interface cues were analyzed to ensure that responses initiated prior to the failure occurrences (in the continuous interface conditions) were not simply due to cues in the interfaces that alerted drivers of the need to respond. For the visual interface, it was assumed that drivers noticed a rate of visual angle change of 0.17 degrees per second (Hoffmann & Mortimer, 1994). The visual angles for the display were computed as a function of the arctan of the average distance from the driver to the display divided by the width, height, and vertical position of the hazard polygon. For each trial per driver, the derivative of the visual angle was computed from the data and compared to the threshold of 0.17 degrees per second. For the auditory interface, it was assumed that drivers noticed a 0.5% change in pitch and a 0.5% change in volume per second (Neuhoff & McBeath, 1996). Results showed that noticeable changes in the continuous interfaces occurred within ten seconds from the start of the change condition period in all event conditions (Braking: M = 0.42; SD = 1.20; Sensing: M = 0; SD = 0; Lateral: M = 6.63; SD = 3.28; Setting: M = 1.08; SD = 1.85). The interface JND immediately preceding the precipitating event for each event condition was also calculated and compared to driver response times for those responses initiated prior to this event; all driver responses were initiated prior to this JND (mean response time difference between driver response and interface JND: M = 8.68, SD = 6.38).

This analysis of JNDs for the visual and auditory continuous interfaces showed that very slight changes in these interfaces were noticeable. The interface changes that occurred from minor variations in lead vehicle velocity during the change in condition periods, for example, were enough to exceed perceptual thresholds for detection. A driver who relied on an interface JND to prompt his/her response would have disengaged ACC at the start of the change condition periods. Drivers, instead, disengaged ACC a few seconds prior to the JND that signaled a failure event, confirming that interface JNDs were not the cause of drivers' decision to disengage it.

To test the degree to which the reaction time benefits of the continuous interfaces as compared to the discrete warnings were a result of timing differences for when each alerted drivers to respond, the following analyses were conducted: regressions of display alert time (continuous interface JNDs; discrete warning delivery time), interval trust ratings, and mental model accuracy scores on failure RTs. For the first regression analysis, display alert time, display type, modality type, event type, and block were included as predictor variables. The overall model was significant, $F(5, 455) = 7.54$, $p < .0001$. Display alert time and modality type were predictive of failure RT, $t(455) = 4.72$, $p < .0001$ and $t(455) = 2.19$, $p = .03$, respectively. Only 8% of the total variance of failure RTs was explained by this regression model, however ($R^2 = 0.077$). Adding interval trust ratings to the regression model slightly improved its predictive power ($R^2 = 0.09$; model significance: $F(6, 453) = 7.48$, $p < .0001$). Display alert time and interval trust ratings were predictive of failure RT, $t(453) = 4.81$, $p < .0001$ and $t(453) = 2.43$, $p = .015$, respectively, whereas modality type had a reduced effect in predicting failure RT, $t(453) = 1.69$, $p = .09$. Adding mental model accuracy to the regression model did not increase the overall model significance, $F(7, 452) = 6.40$, $p < .0001$, or fit, $R^2 = 0.09$. Display alert time and interval trust ratings were again predictive of failure RT, $t(452) = 4.80$, $p < .0001$ and $t(452) = 2.42$, $p = .016$, respectively, and modality type marginally so, $t(452) = 1.68$, $p = .09$; mental model accuracy, however, was not predictive of failure RT, $t(452) = 0.02$, $p = .981$. These results indicate that drivers' RTs to ACC failures were dependent on the alerting characteristics of the displays. Because of correlations between the predictors, however, these results do not provide a definitive answer for whether or not drivers initiated their responses as a function of their understanding of

ACC or of the display characteristics. Regardless of the cause, an earlier response to ACC failure, as resulted from use of continuous feedback, translates to more appropriate reliance, and in turn, improved driver safety.

Limitations

The demonstrated benefits of continuous feedback to promote more appropriate driver reliance on ACC depend on how accurately driver response in a driving simulator translates to on-road use. The low number of collisions (only two across all drivers) indicates that drivers were immersed in the driving tasks and mindful of the consequences of misuse of ACC comparable to that of on-road use.

Long-term use of ACC may diminish the differential benefits of discrete and continuous interfaces. Drivers need approximately two to three weeks of continued system use to learn the operation of ACC and situations in which its limits are exceeded (Weinberger, Winner, & Bubb, 2001). As indicated in this study, however, the accuracy of this learning has important implications for driver reliance. A study that evaluated the long-term effects of continuous feedback on driver behavior—one, for example, that examined driver response to failure events when continuous feedback is removed—would further substantiate its benefit of improved understanding of ACC.

Extensions

To further distinguish between visual and auditory benefits of continuous information, analysis of eye movement data would indicate any distracting effects of the continuous displays. These data would confirm as to whether the information in the visual display was truly peripheral.

In more thoroughly assessing the effect of trust on driver response, a comparison of interface type by gender may indicate differential benefits of continuous information. An analysis of the demographics from a survey of 132 ACC users indicated that males were more likely to over-trust ACC (Dickie & Boyle, 2009). This effect may be due to gender-specific tendencies to trust that carryover to trust in automation.

In more thoroughly assessing the effect of mental model accuracy on driver response, additional analyses of variables such as brake magnitude and duration combined with RT might indicate more specific flaws in drivers' mental models beyond a binary accurate/not-accurate classification. Ideally, driver response behaviors predict mental models variants (i.e., models that have different error states). Driver RT was too one-dimensional, however, to provide any predictive power of state-specific model accuracy.

CHAPTER VI. CONCLUSIONS

Experience with an automated system over time allows operators to learn its limits and when, in terms of overall human-machine system performance, it is appropriate to perform the task manually. This dissertation proposed that a display that provided the purpose, process, and performance of the automation would inform this learning process, and lead to accurate explicit understanding (mental models) of automation behavior that are effective in both normal and unexpected situations. Ideally, operators learn to trust the automation respective to its capabilities, able to interact with the automation to achieve maximal performance. The continuous information display builds on the assumption that operator assessment of system performance evolves over time in relation to the context and to their expertise with the automated system.

This dissertation considered a central hypothesis that continuous feedback on the state and behavior of the automation informs operators of the evolving relationship between system performance and operating limits, therefore promoting accurate mental models and calibrated trust. Three specific aims addressed this hypothesis. The first aim applied a quantitative model to define the effect of understanding on driver–ACC interaction failures and to predict driver response to feedback. The second aim presented a systematic approach to define the feedback needed to support appropriate reliance in a demanding multi-task domain such as driving. The third aim assessed the costs and benefits of presenting drivers with continuous visual and auditory feedback. Specific contributions of this dissertation include (1) a computational model of driver–ACC interaction, (2) an ecological approach to inform design of an ACC information display, and (3) a design strategy to account for environmentally-induced variability of automated systems.

The first aim demonstrated that inadequate feedback contributes to impoverished understanding of ACC's state and behavior and, in consequence, to driver-ACC interaction failures. The second aim indicated that configural, representation aiding-principled information designs are able to be tailored to consider the attentional demands present in driving. Finally, the third aim demonstrated that continuous feedback is a viable means to inform drivers of ACC's behavior.

Practically, this work has implications for the design of automation support displays. Shape properties that produce looming effects inform of situation severity and an impending need to intervene to an imperfect automation system. Information presence, however, is not a salient cue of automation's performance in demanding, multi-task domains. Particular to the continuous information interfaces, the removal of the shape from the screen for sensor failures was not a salient cue for drivers in understanding that ACC no longer detected the LV. A flashing shape, with its rate of onset correlated to reliability, may have more effectively indicated that ACC's sensors were not operating properly in rain conditions. In curves, a more prominent lateral displacement of the shape was potentially needed to indicate the lateral range limits and the LV's position within those limits. Alternatively, a shift of the background instead of the shape may provide a more salient indicator of the changes in the LV position.

To fully assess the benefit of the concurrent, continuous information displays, additional research is required to evaluate if the displays provide cues that predict failure and if the cues provided in the displays inform operators of the purpose, process, and performance of automation. There are cues in the environment that predict failure and cues in the display that predict failure. Validation of the EID-inspired displays involves identification of these cues and an analysis of the correspondence between the environment and display cues. The Lens Model is a methodology for capturing and assessing judgments in complex, uncertain domains such as the driving domain (Pritchett & Bisantz, 2006). This model is a means to determine in both normal and failure situations the information a driver seeks and uses to form judgments of automation reliance. This information informs on the validity of the cues used in the different displays, and whether the cues available conform to those that drivers use. It is also important to assess if drivers accurately identify the failure cause as a function of the cues that inform their decision to engage or disengage the automation when a failure occurs.

Additional research would include an evaluation of multi-modality continuous information displays, as well as comparisons of single-modality and multi-modality continuous information displays with discrete warnings based on different timing triggers. Following data collection for the single-modality conditions (presented in this dissertation), data was collected for the combined-modality condition using the same experimental setup. An analysis of single-modality compared to combined modality interface conditions is planned. Additional modalities such as tactile feedback are also viable forms for presenting continuous feedback to drivers. Further testing and design iterations are needed to validate the display choices. Computer-based testing of individual design features would further perfect design recommendations for presentation form and format of enhanced feedback interfaces. In terms of the computation model of driver–ACC interaction, iterative model validation with simulator-based testing is needed to further define the relationship between trust and mental models, e.g., the associative effects of implicit and explicit understanding on driver reliance.

More broadly, this research has implications for many types of control systems that interact with the environment; such systems require operators to monitor the automation and to use their judgment for when to intervene to achieve desired performance. Collision warnings systems, for example, interact with the driving environment in non-predictable ways thereby confounding driver response (Brown et al., 2001). Automated planning systems for unmanned vehicle deployment, as another example, produce route recommendations dependent on environmental constraints; these systems are prone to inadequately inform operators of the algorithm variables and of optimization functions used to produce its recommendations. Operators of these systems require clear feedback on the state of the automated system, and information displayed in a way that reveals the important relationships between variables (Seppelt, Hoffman, Lee, & Crittendon, in review). Continuous feedback that maps domain, task, and system constraints into the interface form offers a promising strategy to improve operator–automation interactions by supporting more accurate mental model development and more precisely calibrated trust.

APPENDIX A. EXPERIMENTAL IMPLEMENTATION OF AUDITORY AND VISUAL CONTINUOUS INTERFACES

Microsoft Visual Basic 6.0 was used to create the visual and auditory continuous interfaces. Dynamic variables including position, velocity, and ACC state were passed between HyperDrive and Visual Basic at a rate of 5 Hz over an internet socket. The Visual Basic 6.0 PictureBox component was used to translate these dynamic variables into continuously changing visual display features. The Windows Direct X sound libraries were used to translate the dynamic variables into continuously changing auditory features. The original sound files were created using the open source audio editing and creation tools Audacity and DSK Ethereal PadZ.

Auditory Continuous Display (Sonification)

The auditory interface used two sound streams. Sound stream one was composed of 2 different sounds, hazardous and non-hazardous. The hazardous sound was used when the driver vehicle was approaching the lead vehicle (positive range rate). The non-hazardous sound was used when the lead vehicle was pulling away from the driver vehicle (negative range rate). Sound stream two was a periodic beep. The characteristics of each of the sounds were adjusted in real-time based on the dynamic variables of the driving scenario. The algorithms for changing the sound characteristics are given below.

Volume

Stream 1

The volume of sound stream one, hazardous and non-hazardous, was set as a function of range according to the following equation:

$$V = -0.49375 * RNG - 0.5 \tag{A.1}$$

where *RNG* was the lead vehicle position minus the driver vehicle position in meters and *V* was the sound volume gain in dB. If *RNG* was greater than 80 meters, then the volume was set to -100 dB (inaudible). The volume level as a function of range is plotted in Figure A1.

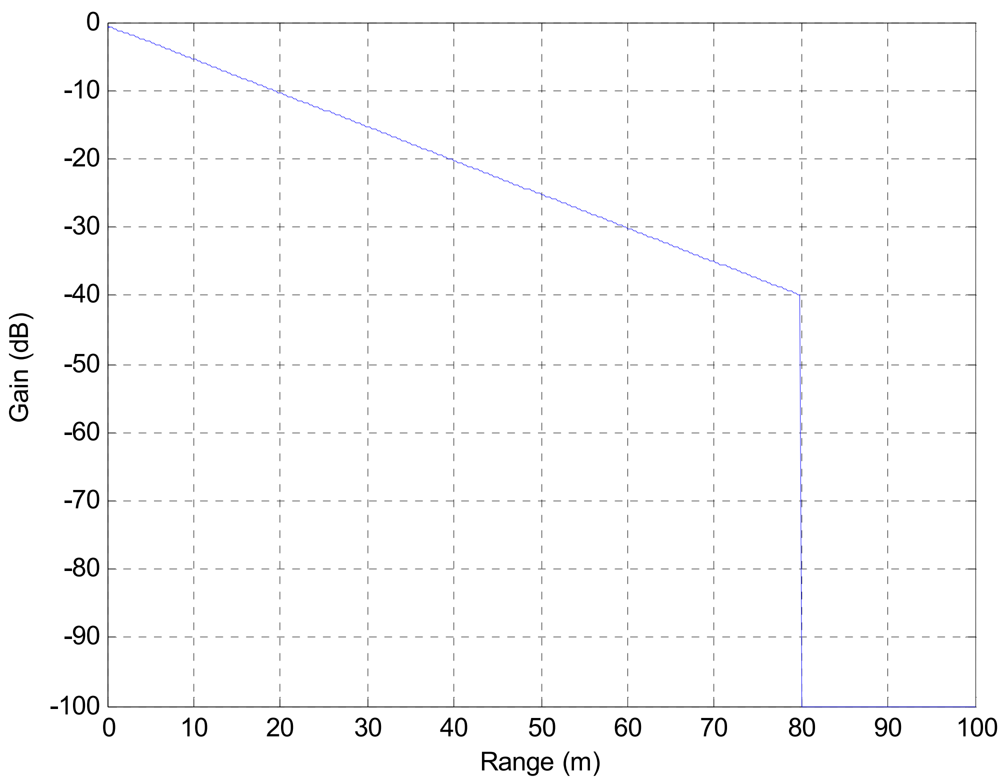

Figure A1. Volume as a function of range for sound stream 1.

A sleep state was implemented that activated when driving variables were held constant, indicating to drivers that ACC was in steady state (i.e., velocity control) and that event dynamics were unchanging. The sleep state was activated based on a general ACC error term. The ACC error term (*AccErr*) was computed using the following equation (adapted from Zheng & McDonald, 2005):

$$AccErr = 0.75 * RRT + 0.1 * (RNG - 1.5 * LVV) \tag{A.2}$$

where *RNG* was the lead vehicle position minus the driver vehicle position in meters, *RRT* was the range rate defined as the driver vehicle velocity minus the lead vehicle velocity in m/s, *LVV* was the lead vehicle velocity and *AccErr* represented ACC's error in maintaining the set headway of 1.5 s and in keeping the RRT at 0.0 m/s. If this ACC error term was maintained at 0.0 ± 0.2 for four seconds, then the auditory interface system transitioned to the sleep state. The sleep state algorithm first ramped the volume down with the following equation:

$$V = (0.013 * RNG - 0.983) * i - 0.75 * RNG + 19.15 \tag{A.3}$$

where *RNG* was the lead vehicle position minus the driver vehicle position in meters, *i* was the sample number at a 5 Hz sample rate, and *V* was the sound volume gain in dB. Then, in the sleep state, the volume changed as a function of time according to the following equation:

$$V = -0.1 * RNG - 10 * VolFade - 30 \tag{A.4}$$

where

$$VolFade = -\cos\left(\frac{2\pi(i - 50)}{15 * THW}\right) + 1, \tag{A.5}$$

RNG was the lead vehicle position minus the driver vehicle position in meters, *i* was the sample number at a 5 Hz sample rate, *THW* was the time headway between the driver and lead vehicles in seconds, and *V* was the sound volume gain in dB.

A plot of the sleep state volume algorithm is shown in Figure A2. This figure shows the volume as a function of time after sleep state is initiated given a THW of 1.5 seconds and range of 40 meters. If ACC's input variables changed, the system switched out of sleep state, and the original volume control algorithm was used. This switch signaled to drivers that event dynamics had changed to move ACC out of steady state (velocity control) into an adaptive state (following control).

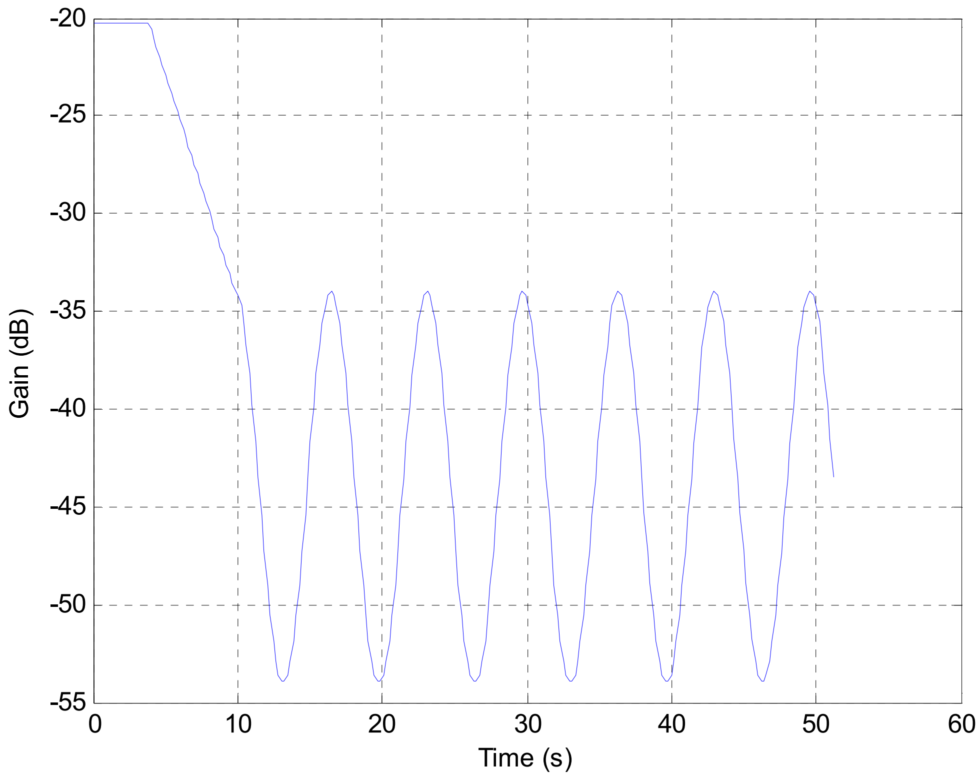

Figure A2. Sleep state volume as a function of time.

Stream 2

The volume of sound stream two was set as a function of the difference between the set speed and the driver vehicle speed according to the following equation:

$$V = \min(2 * SDF - 40, 0) \quad (A.6)$$

where *SDF* was the difference between the set speed and the driver vehicle velocity in m/s, "min" was a function that selected the minimum of two numbers to limit the maximum volume, and *V* was the sound volume gain in dB. The volume level as a function of SDF is plotted in Figure A3.

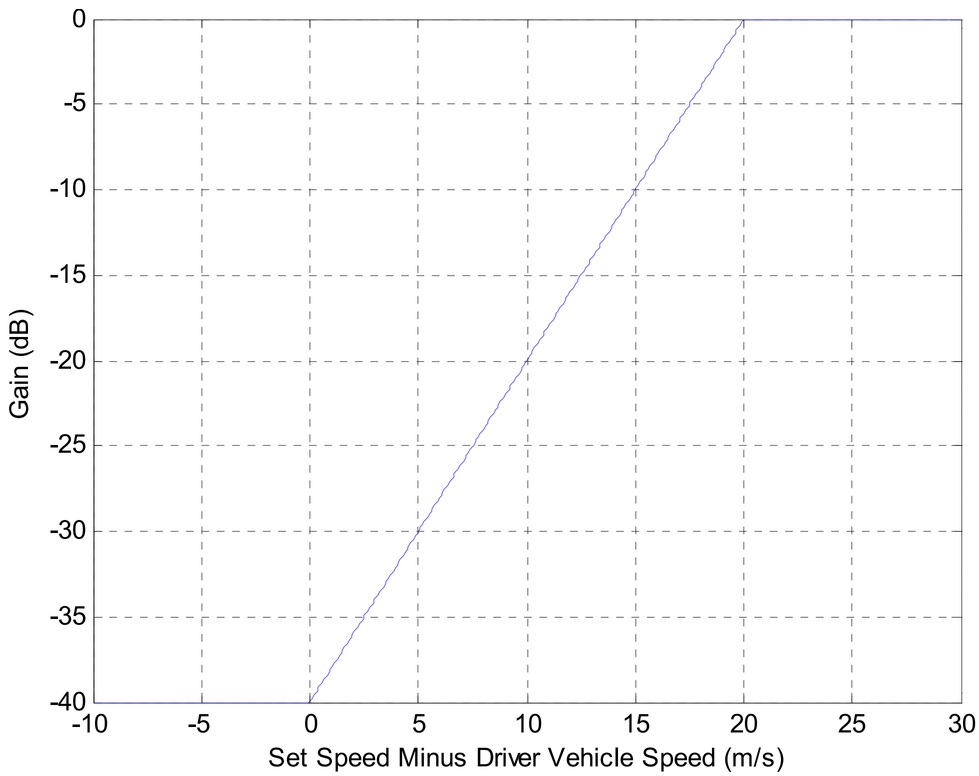

Figure A3. Volume as a function of SDF for sound stream 2.

Frequency

Stream 1

The baseline frequency spectrum of the hazardous part of sound stream one is shown in Figure A4.

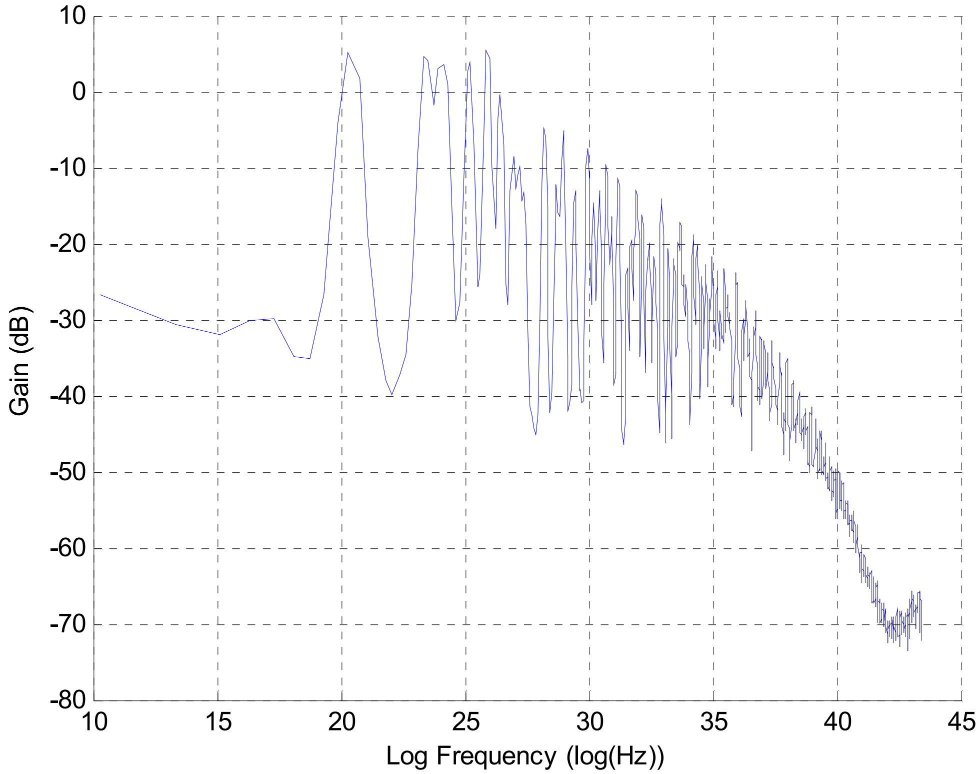

Figure A4. Hazardous wavefile spectrum.

The above spectrum was scaled in frequency according to the following algorithm:

$$
\begin{aligned}
& if\left(CAA > 0.075\right) \\
& \rightarrow Fscale = 4 \\
& elseif\left(CAA > 0.0\right) \\
& \rightarrow Fscale = 1 + 5 * CAA \\
& else \\
& \rightarrow Fscale = 1
\end{aligned}
\qquad (A.7)
$$

where *CAA* was the collision avoidance acceleration (0.5*RRT/TTC) in m/s/s, and *Fscale* was the frequency multiplier of the sound signal spectrum. The implementation of this algorithm is shown in Figure A5.

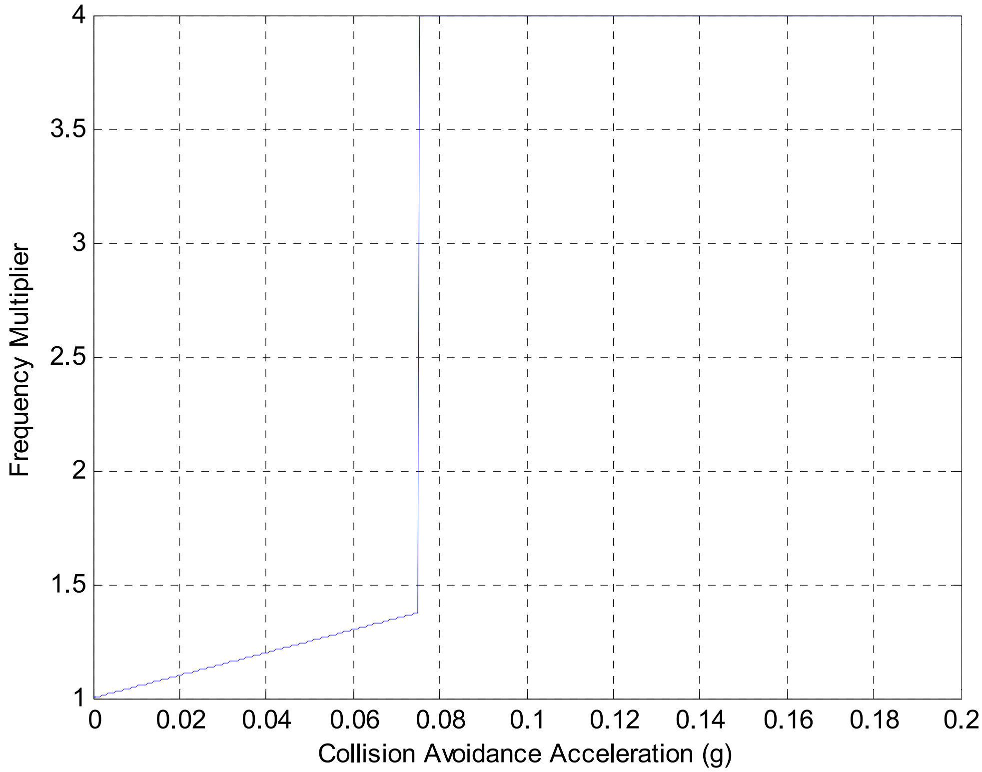

Figure A5. Frequency multiplier as a function of CAA for hazardous sound stream 1.

A discontinuity was placed in the frequency multiplier curve in Figure A5 at 0.075 g. This discontinuity in the hazardous sound stream frequency multiplier, by suddenly changing the frequency of the sound to a significantly higher pitch, signaled a warning to the driver that the ACC braking limits had been reached.

The baseline frequency spectrum of the non-hazardous part of sound stream one is shown in Figure A6.

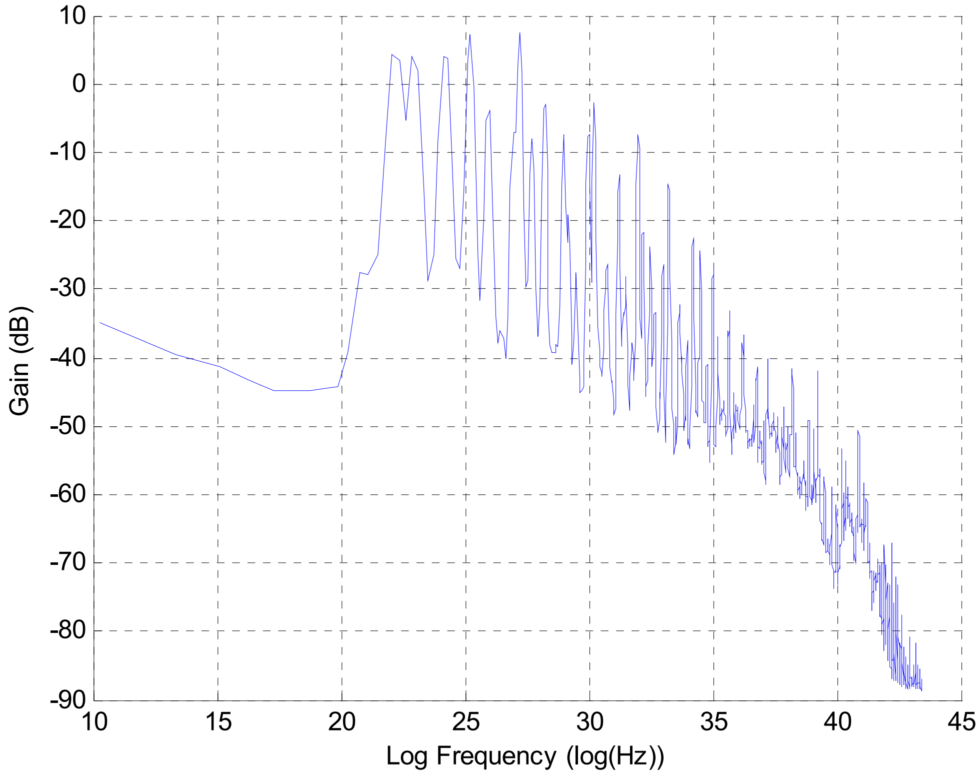

Figure A6. Non-hazardous wavefile spectrum.

The spectrum in Figure A6 was scaled in frequency according to the following equation:

$$Fscale = \frac{1}{441} RRT + 1 \tag{A.8}$$

where *RRT* was the range rate defined as the driver vehicle velocity minus the lead vehicle velocity in m/s, and *Fscale* was the frequency multiplier of the sound signal spectrum. The line that is defined by the above equation is plotted in Figure A7.

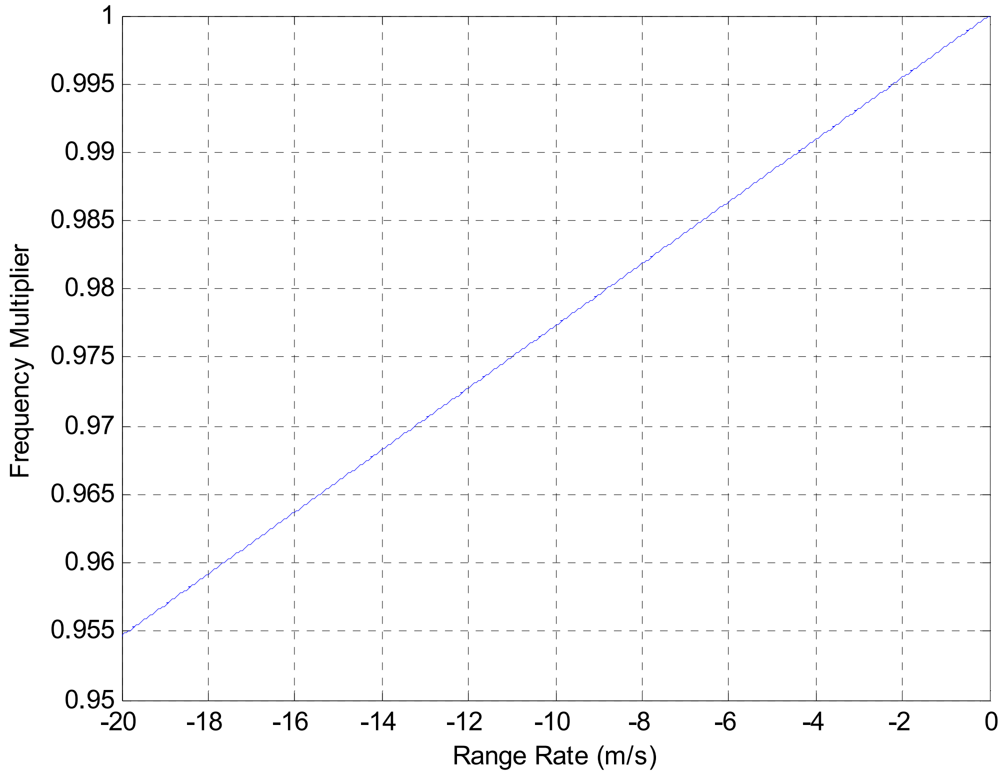

Figure A7. Frequency multiplier as a function of range rate for the non-hazardous sound stream 1.

Stream 2

Sound stream 2 was a monotone beep, centered at 335 Hz (E4). The baseline spectrum of sound stream 2 is shown in Figure A8.

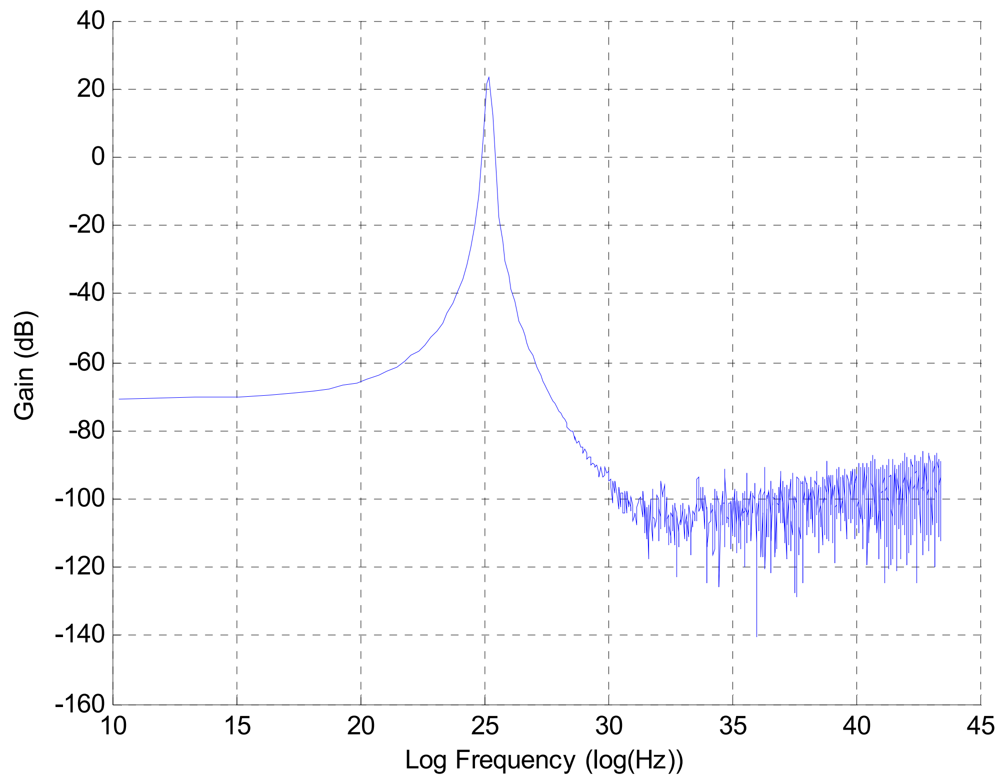

Figure A8. Sound stream 2 wavefile spectrum.

When THW was within 1.5 ± 0.4 s, the frequency spectrum of sound stream 2 was scaled down by 80%. Otherwise, the spectrum of sound stream 2 matched the spectrum shown above. The period of time between beeps for sound stream 2 was adjusted as a function of THW according to the following algorithm.

$$\begin{aligned}&if\left(THW > 0.2\right)\\&\rightarrow Interval = THW\\&else\\&\rightarrow Interval = 0.2\end{aligned} \tag{A.9}$$

where *THW* was the time headway between the lead and driver vehicles in seconds, and *Interval* was the amount of time between beeps in seconds. The implementation of this algorithm is plotted in Figure A9.

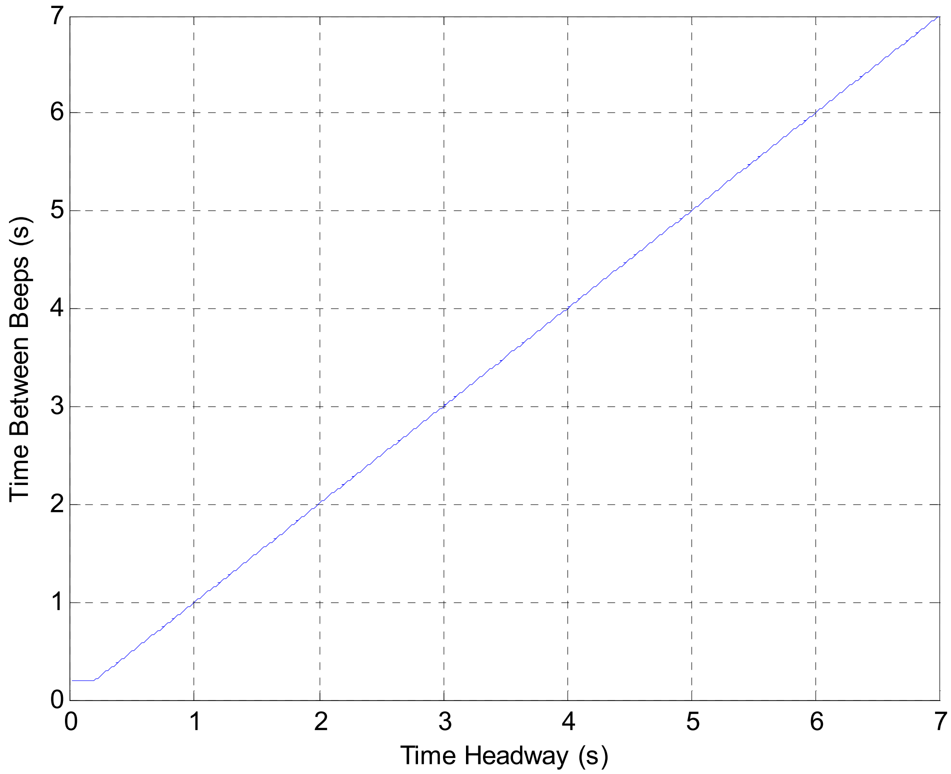

Figure A9. Time interval between beeps for sound stream 2.

Pan

The auditory interface speakers were placed in front of the driver on either side of the dashboard. The left and right balance, or pan, between the two speakers was set based on the relative lateral position between the lead vehicle and the driver vehicle. The details of this algorithm are described in the equation below.

$$
\begin{aligned}
&if\left(RLP > 1.75\right)\\
&\rightarrow V = -100\\
&elseif\left(RLP > 1.35\right)\\
&\rightarrow P = -20\\
&elseif\left(RLP > 0.9\right)\\
&\rightarrow P = -6\\
&elseif\left(RLP < -0.9\right)\\
&\rightarrow P = 6\\
&elseif\left(RLP < -1.35\right)\\
&\rightarrow P = 20\\
&elseif\left(RLP < -1.75\right)\\
&\rightarrow V = -100\\
&else\\
&\rightarrow P = 0
\end{aligned}
\tag{A.10}
$$

where *RLP* was the relative lateral position between the driver and lead vehicle in meters, *P* was the ratio in volume between the left and right speakers in dB, and *V* was the sound volume gain in dB. Both sound stream 1 and sound stream 2 abided by this pan algorithm.

Distortion

ACC sensor degradation due to rain was conveyed by adding distortion to each of the sound streams. There were two steps to creating the distortion effect:

1) The original signal was clipped at a selected amplitude. The amplitude at which clipping occurred defined how much distortion was added. Three levels of distortion were generated by clipping each sound signal at ± 0.2, ± 0.125, and ± 0.05. An example of this step is given in Figure A10. The figure on the left is the original sound signal and the figure on the right is the signal after it has been clipped. The vertical scale of both of the figures below is in arbitrary amplitude units.

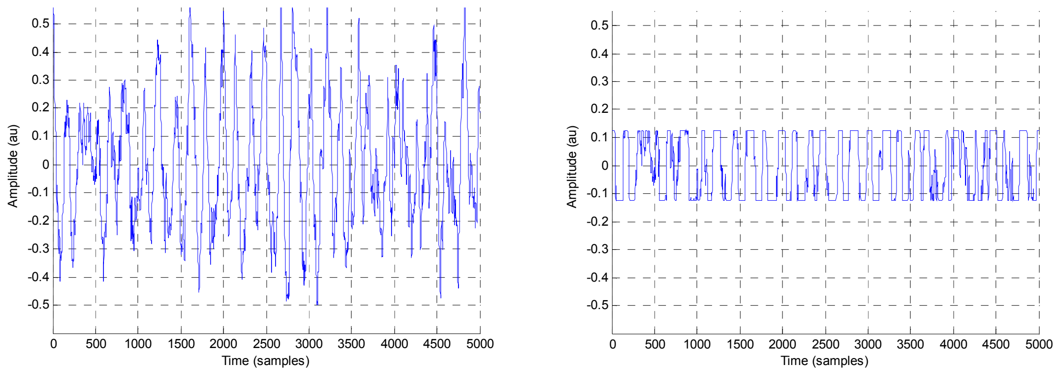

Figure A10. Example of original sound stream signal (on the left) and of the clipped signal (on the right).

2) Gain was then added to bring the clipped signal peak amplitude up to 0.25. An example of this step is illustrated in Figure A11. The figure on the left is the signal after being clipped and the figure on the right is the signal after gain has been added to bring the peak to 0.25. The vertical scale of both of the figures below is in arbitrary amplitude units.

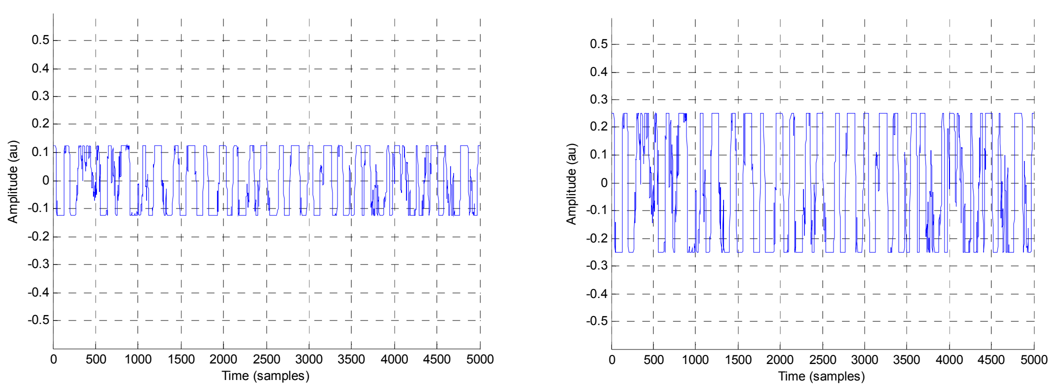

Figure A11. Example of a clipped signal (on the left) and of a gain-added clipped signal (on the right).

The three distortion levels were then mapped to three rain levels according to rain intensity, as indicated in Table A14.

Table A14. Distortion Level According to Rain Level

Rain Level	Distortion Level
Rain < 0.2	None
0.2 <= Rain < 0.4	Low
0.4 <= Rain < 0.6	Medium
Rain >= 0.6	High

Visual Continuous Display

The visual continuous display used polygons of continuously varying shape, size, color, and position to convey information about the dynamic variables of the ACC system. The algorithms for changing the characteristics of the hazard polygon are detailed in the sections below. All algorithms assumed display dimensions of 1270 pixels wide by 950 pixels tall.

Hazard polygon width

Range rate (RRT) was conveyed by changing the width of the hazard polygon. The width of the top and bottom of the polygon were changed with slightly different algorithms to cause the polygon to take a trapezoidal shape when the RRT was less than or equal to zero and a triangular shape when the RRT was greater than zero. The algorithm for changing the width of the top of the polygon as a function of RRT is listed below.

$$
\begin{aligned}
&if\left(RRT > 0\right)\\
&\rightarrow TL = -15 * RRT - 10\\
&\rightarrow TR = 15 * RRT + 10\\
&else\\
&\rightarrow TL = -10\\
&\rightarrow TR = 10
\end{aligned}
\tag{A.11}
$$

where *RRT* was the range rate defined as the driver vehicle velocity minus the lead vehicle velocity in m/s, *TL* was the horizontal coordinate of the top left corner of the polygon in pixels and *TR* was the horizontal coordinate of the top right corner of the polygon in pixels. When the range rate was less than or equal to zero, the width of the top of the polygon was held to a constant of 20 pixels, forming the top of the trapezoid. When the range rate was greater than zero, the width of the top of the polygon expanded to indicate the more significant hazard (see Figure A12).

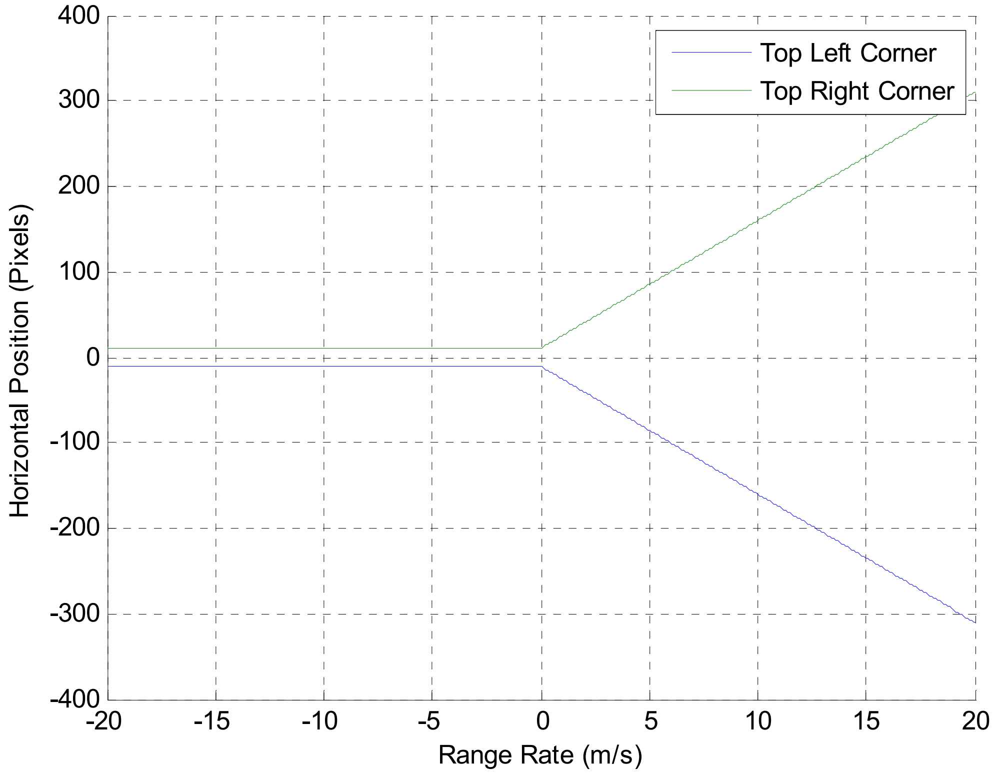

Figure A12. Horizontal position of the hazard polygon as a function of range rate, indicating how the width of the top of the polygon changed.

The algorithm for changing the width of the bottom of the polygon is listed below.

$$\begin{aligned}&if\left(RRT > 0\right)\\&\rightarrow BL = 0\\&\rightarrow BR = 0\\&else\\&\rightarrow BL = 15 * RRT\\&\rightarrow BR = -15 * RRT\end{aligned} \tag{A.12}$$

where RRT was the range rate defined as the driver vehicle velocity minus the lead vehicle velocity in m/s, BL was the horizontal coordinate of the bottom left corner of the polygon in pixels, and BR was the horizontal coordinate of the bottom right corner of the polygon in pixels. When the range rate was greater than zero, the bottom of the polygon had no width, forming the point of the triangular-shaped hazard polygon. When the range rate was less than or equal to zero, the bottom of the polygon expanded as the range rate decreased, forming the bottom of the trapezoidal-shaped hazard polygon (see Figure A13).

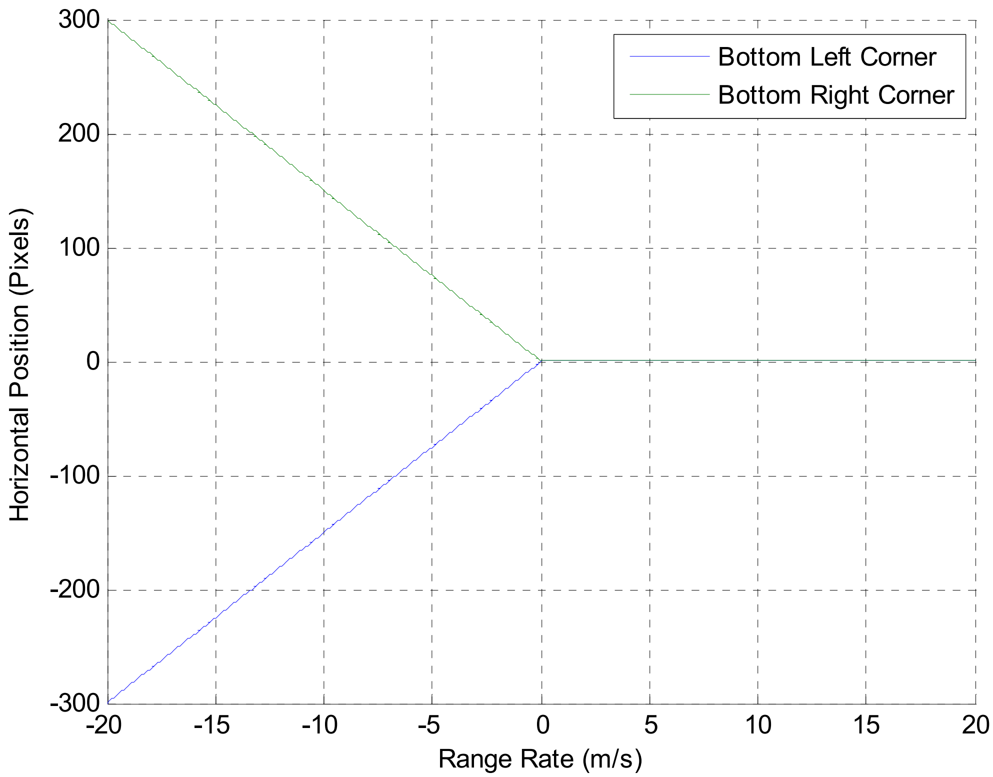

Figure A13. Horizontal position of the hazard polygon as a function of range rate, indicating how the width of the bottom of the polygon changed.

Hazard polygon height

The height of the hazard polygon was changed to convey time to collision according to the following equation:

$$H = -100 * TTC + 1092 \quad \text{(A.13)}$$

where *H* was the height of the hazard polygon in pixels, and *TTC* was the time to collision between the lead and driver vehicles in seconds. Figure A14 shows the hazard polygon height plotted over a range of TTC values. As TTC decreased, the hazard polygon height increased to convey a more significant hazard.

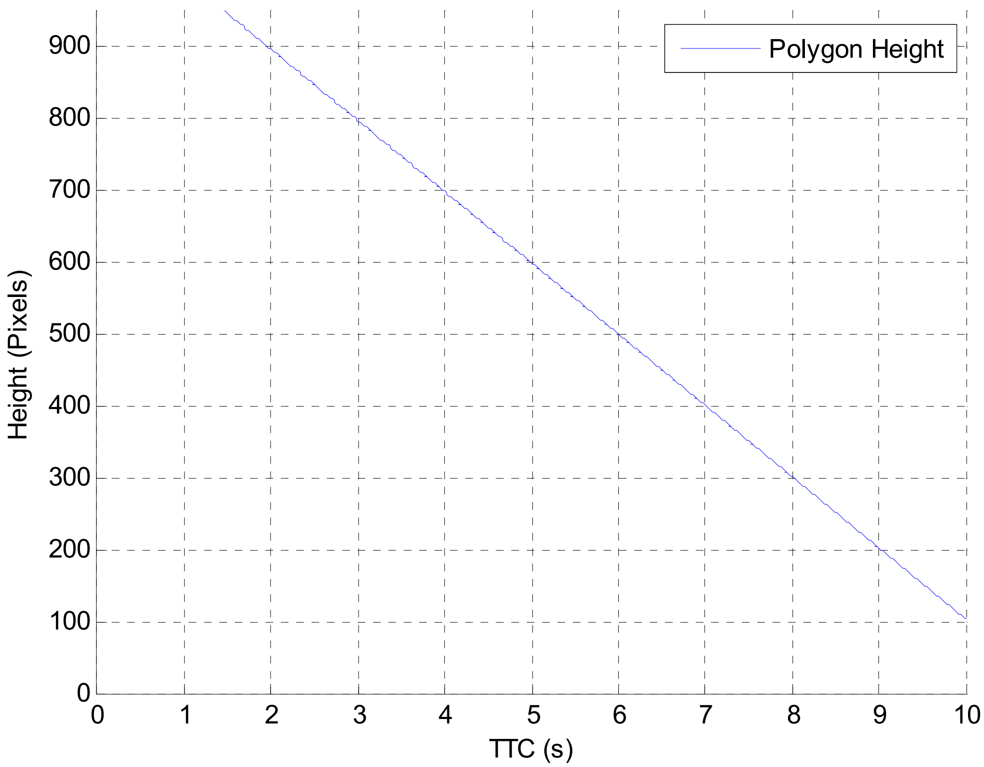

Figure A14. Hazard polygon height according to time-to-collision (TTC).

Hazard polygon vertical position

Time headway moved the hazard polygon in the vertical dimension according to the following equation:

$$VP = -50 * THW^2 + 57 \qquad \text{(A.14)}$$

where *VP* was the vertical coordinate of the bottom edge of the hazard polygon in pixels, and *THW* was the time headway between the lead and driver vehicles in seconds. To illustrate the effect of THW on the vertical position of the hazard polygon, the equation above was evaluated over a range of THW values; see Figure A15. As the THW increased, the vertical position of the hazard polygon moved vertically on the display. The vertical position was a function of the square of THW to keep the polygon closer to the middle of the display for a wider range of THW values.

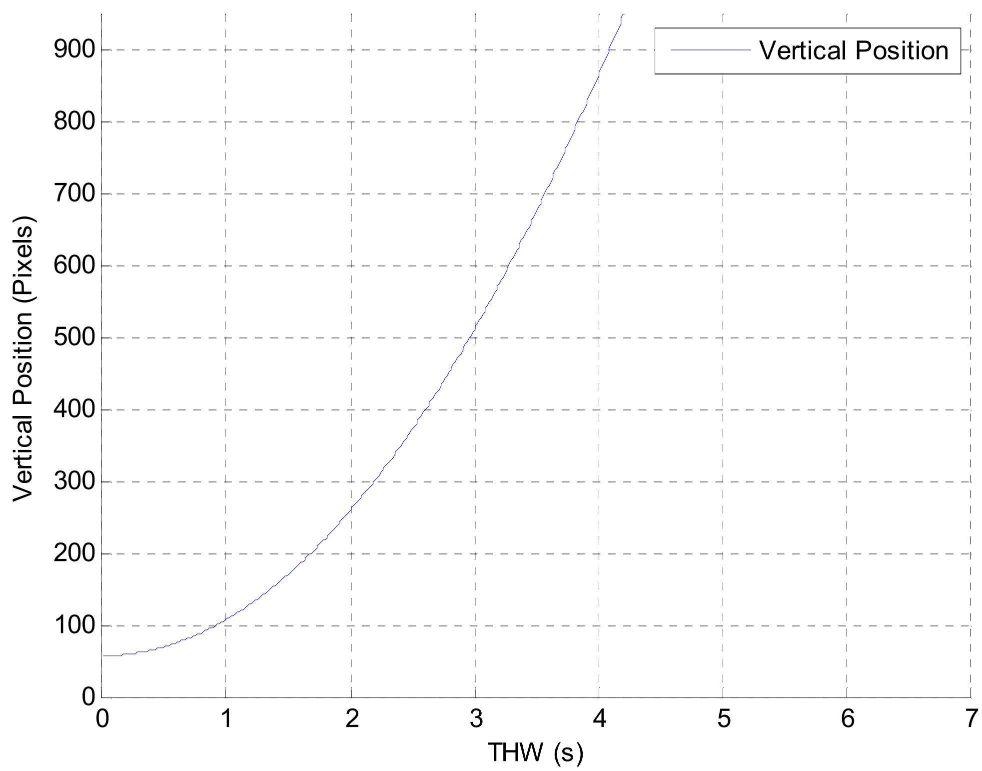

Figure A15. Vertical position of hazard polygon according to time headway (THW).

Hazard polygon horizontal position

The relative lateral position between the lead vehicle and the subject vehicle was conveyed by moving the hazard polygon in the horizontal dimension. The algorithm for moving the hazard polygon in the horizontal dimension is given in the code below.

$$\begin{aligned}
&if\left(RLP > 1.75\right)\\
&\rightarrow PLP = OffDisplay\\
&elseif\left(RLP > 1.35\right)\\
&\rightarrow PLP = -320\\
&elseif\left(RLP > 0.9\right)\\
&\rightarrow P = -96\\
&elseif\left(RLP < -0.9\right)\\
&\rightarrow PLP = 96\\
&elseif\left(RLP < -1.35\right)\\
&\rightarrow PLP = 320\\
&elseif\left(RLP < -1.75\right)\\
&\rightarrow PLP = OffDisplay\\
&else\\
&\rightarrow PLP = 0
\end{aligned} \tag{A.15}$$

where *RLP* was the relative lateral position between the driver and lead vehicle in meters, *PLP* was the polygon lateral position in pixels, and *OffDisplay* indicated a shift of the polygon off the display (no longer visible).

Hazard polygon color

ACC sensor degradation was conveyed in the visual continuous display by changing color and fill pattern of the hazard polygon. The rain levels were mapped to the various polygon characteristics, as listed in Table A15.

Table A15. Rain Level Mapped to Polygon Characteristics

Rain Level	Fill RGB	Fill Style	Line RGB	Line Width (Points)	Line Style
Rain < 0.2	255,255,0	Solid	0,0,0	3	Solid
0.2 <= Rain < 0.4	250,250,250	Solid	180,180,180	2	Solid
0.4 <= Rain < 0.6	240,240,240	Solid	220,220,220	1	Dashed
Rain >= 0.6	200,200,200	Cross-Hatched	150,150,150	1	Dashed

ACC limit lines

Three limit lines were placed on the display. The first line was a horizontal red dashed line at the vertical position corresponding to a 1.5 second THW. The second limit line was placed so that the corners of the hazard polygon crossed the line when the ACC's braking power had reached its 0.2 g limit. These reference lines remained fixed, representing the fixed braking limits of ACC, and the shape moved in relation to the fixed lines. All hazardous situations were bounded by these lines (i.e., the lines did not form a closed shape): either a horizontal or vertical movement of the shape beyond the reference lines indicated that the 0.2 g braking limit of ACC had been reached. The third limit line was a vertical line placed at the center of the display. This line provided a reference point for horizontal movements of the hazard polygon due to relative lateral position changes between the lead vehicle and driver vehicle.

Set speed minus adapted speed bar

The set speed minus adapted speed warning bar was always situated above the top line of the hazard polygon. The vertical height of the bar was always 20 pixels. The horizontal width of the bar changed as a function of the difference between the set speed and the driver vehicle speed according to the following equation:

$$W = 30 * SDF \tag{A.16}$$

where *W* was the width of the bar in pixels, and *SDF* was the set speed minus the driver vehicle velocity in m/s.

Display background color

The background color of the continuous display indicated the state of the ACC system. When the ACC system was in the "off" state, the background was black. The background color transitioned to gray when the "on/standby" state was selected. Finally, the background color was changed to white when the ACC was changed to the "set" state.

APPENDIX B. PAYMENT FOR ENHANCED FEEDBACK STUDY

Base payment was $45 ($15/hr. for three hours).

Driving Task
In the task of maintaining a 1.5 s THW to the lead vehicle, if participant had a mean THW standard deviation between:

- 0-.20: $0
- .21-.40: -$1
- .41-.60: -$2
- .61-.80: -$3
- .81-1.0: -$4
- >1.0: -$5
- Each collision reduced payment $0.50

Secondary (Billboard Detection) Task
If out of the total 144 billboard detection events, participant detected:

- > 40: $0 extra
- 40 and 60: $1 extra
- 61 and 80: $2 extra
- 81 and 100: $3 extra
- 101 and 120: $4 extra
- 121 and 144: $5 extra
- Penalty for false alarms: -$1 for every 10 incorrect button pushes

APPENDIX C. DRIVER SUPPORT SYSTEM EVALUATION ADAPTIVE CRUISE CONTROL (ACC) QUESTIONNAIRE

Date: __________ Research ID: _________ Trial: __________

Please read each question carefully and answer to your best ability.
Part I. This first set of questions asks about basic ACC operation.

1. ACC is designed to:
(*Please check each statement below that is correct. There may be more than one correct statement.*)

□ Respond to emergency braking situations and avoid collision
□ Modify vehicle speed to maintain the set 1.5 s following distance
□ Detect vehicles ahead, within sensor ranges, that move more slowly
□ Operate at low speeds (i.e., less than 20 mph)

2. ACC considers the following factors to determine its acceleration response:
(*Please check each statement below that is correct. There may be more than one correct statement.*)

□ Lateral and longitudinal position of a lead vehicle (*note*: lead vehicle is a vehicle ahead, in your lane)
□ Velocity of a lead vehicle
□ Range (i.e., distance) to a vehicle ahead
□ Street and traffic conditions
□ Driver state (e.g., distracted, alert, drowsy, etc.)
□ Positions of vehicles in the passing lane
□ Difference between the current speed and (set) cruise speed

3. ACC operates properly in the following situations (or under the following conditions):
(*Please check each statement below that is correct. There may be more than one correct statement.*)

□ In heavy fog conditions
□ On major expressways and roadways in urban environments
□ In highway construction zones
□ On straight, narrow roadways
□ In cloudy conditions with light rain
□ While in sharp curves

4. How often does ACC operate properly (e.g., operate within its limits; detect a lead vehicle that is within its detection range)?
(*Please check the percent of time below that is correct. Only one answer is correct.*)

□ 0% (Never operates properly)
□ 1 - 49%
□ 50% (Operates properly half the time)
□ 51 - 99%
□ 100% (Always operates properly)

Part II. This next set of questions asks about situations and conditions of use of the ACC system.

5. A lead vehicle, in front of your vehicle, is traveling at 45 mph. Your (set) cruise speed is 45 mph. If the lead vehicle decelerates to 38 mph, the ACC system will:
(*Please check each statement below that is correct. There may be more than one correct statement.*)

□ Transition to standby
□ Turn off
□ Decelerate your speed to the lead vehicle speed at a 1.5 s following distance
□ Maintain your current speed

5b. How confident are you in this response?

(*Note*: Not at all confident = 0; Fully confident = 6)

0 1 2 3 4 5 6

6. If a braking event by a lead vehicle requires ACC to respond with a deceleration output greater than 0.2 g, the ACC system will:
(*Please check each statement below that is correct. There may be more than one correct statement.*)

□ Transition to standby
□ Turn off
□ Initiate the required deceleration to avoid a collision
□ Initiate deceleration up to a maximum of 0.2 g

6b. How confident are you in this response?

(*Note*: Not at all confident = 0; Fully confident = 6)

0 1 2 3 4 5 6

7. If your vehicle speed drops below 20 mph in response to the lead vehicle's braking behavior, the ACC system will:
(*Please check each statement below that is correct. There may be more than one correct statement.*)

□ Transition to standby
□ Turn off
□ Initiate and maintain a 0.2 g deceleration
□ Release brake pressure (if any is actively being applied)
□ Modify vehicle speed to maintain the set 1.5 s following distance

7b. How confident are you in this response?

(*Note*: Not at all confident = 0; Fully confident = 6)

0 1 2 3 4 5 6

8. If the lead vehicle currently detected by ACC moves out of the detection range, the ACC system will:
(*Please check each statement below that is correct. There may be more than one correct statement.*)

□ Transition to standby
□ Turn off
□ Accelerate to resume the (set) cruise speed if your current speed is less than the (set) cruise speed
□ Maintain your current speed if it is equal to the (set) cruise speed
□ Accelerate your speed to the lead vehicle speed at a 1.5 s following distance
□ Do nothing

8b. How confident are you in this response?

(*Note*: Not at all confident = 0; Fully confident = 6)

0 1 2 3 4 5 6

9. If your vehicle enters a sharp curve, the ACC system will:
(*Please check each statement below that is correct. There may be more than one correct statement.*)

□ Transition to standby
□ Turn off
□ Detect the lead vehicle
□ Not detect the lead vehicle
□ Modify vehicle speed to maintain the set 1.5 s following distance, consistently
□ Accelerate your speed to the lead vehicle speed at a 1.5 s following distance

9b. How confident are you in this response?

(*Note*: Not at all confident = 0;   Fully confident = 6)

0 1 2 3 4 5 6

10. If another vehicle from the passing lane begins a lane change directly in front of your vehicle (less than 5 ft), the ACC system will:
(*Please check each statement below that is correct. There may be more than one correct statement.*)

□ Transition to standby
□ Turn off
□ Detect the lead vehicle
□ Not detect the lead vehicle
□ Modify vehicle speed to maintain the set 1.5 s following distance

10b. How confident are you in this response?

(*Note*: Not at all confident = 0;   Fully confident = 6)

0 1 2 3 4 5 6

11. Your (set) cruise speed is 45 mph. However, ACC is maintaining a speed of 40 mph to match the lead vehicle's speed of 40 mph. What will happen if the lead vehicle accelerates to 50 mph ---- 5 mph above your cruise speed? The ACC system will:
(*Please check each statement below that is correct. There may be more than one correct statement.*)

□ Transition to standby
□ Turn off
□ Accelerate your speed to the (set) cruise speed, remaining at a 1.5 s following distance
□ Accelerate your speed to the (set) cruise speed; following distance will increase beyond 1.5 s
□ Maintain your current speed

□ Accelerate your speed to the lead vehicle speed, remaining at a 1.5 s following distance

11b. How confident are you in this response?

(*Note*: Not at all confident = 0; Fully confident = 6)

0 1 2 3 4 5 6

12. Your (set) cruise speed is 45 mph. However, ACC is maintaining a speed of 40 mph to match the lead vehicle's speed of 40 mph. What will happen if you exit onto an off ramp? The ACC system will:
(*Please check each statement below that is correct. There <u>may</u> be more than one correct statement.*)

□ Transition to standby
□ Turn off
□ Accelerate back up to the (set) cruise speed – 45 mph
□ Maintain 40 mph until you press the brake pedal
□ Decelerate the vehicle

12b. How confident are you in this response?

(*Note*: Not at all confident = 0; Fully confident = 6)

0 1 2 3 4 5 6

13. If a vehicle from the passing lane begins a lane change 500 ft in front of your vehicle, the ACC system will:
(*Please check each statement below that is correct. There <u>may</u> be more than one correct statement.*)

□ Transition to standby
□ Turn off
□ Maintain your (set) cruise speed
□ Detect the lead vehicle
□ Not detect the lead vehicle
□ Modify vehicle speed to maintain the set 1.5 s following distance

13b. How confident are you in this response?

(*Note*: Not at all confident = 0; Fully confident = 6)

0 1 2 3 4 5 6

14. Your vehicle is traveling at 45 mph. If a vehicle in the passing lane slows down to 35 mph, the ACC system will:
(*Please check each statement below that is correct. There* <u>*may*</u> *be more than one correct statement.*)

□ Transition to standby
□ Turn off
□ Maintain your (set) cruise speed
□ Decelerate your speed to the lead vehicle speed at a 1.5 s following distance

14b. How confident are you in this response?

(*Note*: Not at all confident = 0; Fully confident = 6)

0 1 2 3 4 5 6

15. A lead vehicle, in front of your vehicle, is traveling at 40 mph. Your set speed is 45 mph. If the lead vehicle decelerates to 35 mph, the ACC system will:
(*Please check each statement below that is correct. There* <u>*may*</u> *be more than one correct statement.*)

□ Transition to standby
□ Turn off
□ Decelerate your speed to the lead vehicle speed at a 1.5 s following distance
□ Maintain your current speed
□ Maintain your (set) cruise speed

15b. How confident are you in this response?

(*Note*: Not at all confident = 0; Fully confident = 6)

0 1 2 3 4 5 6

Part III. *For the following questions, please mark an "X" on each line at the point which best describes your feeling or impression in interacting with the Driver Support System – this includes both the ACC system and its associated feedback interface.*

16. Do you think your understanding of ACC is correct?

(*Note*: Not at all correct = 0; Fully correct = 6)

0 1 2 3 4 5 6

17. Do you think your understanding of ACC is complete?

(*Note*: Not at all complete = 0; Fully complete = 6)

0 1 2 3 4 5 6

18. Were you ever surprised by the ACC's behavior?

(*Note*: Never = 0; Always = 6)

0 1 2 3 4 5 6

If so, please describe below.

19. Were there states and/or features of the ACC that you did not understand?

(*Note*: Never = 0; Always = 6)

0 1 2 3 4 5 6

If so, please describe below.

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