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Title

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Foreword

Vehicle technology is progressing to a point where the role and responsibility of drivers is beginning to evolve. Advanced driver assistance systems and other automation can control many of the driving tasks, including vehicle speed, headway, and lane position, and the capabilities of such systems continue to grow. In light of these changes, drivers need to understand new vehicle technology in order to ensure safe and appropriate use. Drivers' so-called mental models of vehicle technology have become an important topic among researchers and other industry stakeholders in recent years.

This report seeks to develop new ways of characterizing and visualizing driver interactions with automated systems while mapping potential error types to different aspects of drivers' mental models. The resulting technique and visualization approaches should give researchers new tools as they consider the role and impact of new technology on driver safety and performance.

This report is an outcome of a cooperative research program between the AAA Foundation for Traffic Safety and the SAFER-SIM University Transportation Center.

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About the Sponsors

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SAFER-SIM comprises a multidisciplinary, synergistic team of researchers in human factors, engineering, computer science, and psychology who will use innovative simulation approaches ranging from microsimulation to human-in-the-loop simulation to promote safety. SAFER-SIM sponsors research, facilitates outreach activities in STEM areas, and aids workforce development efforts in transportation safety.

The universities comprising SAFER-SIM study how road users, roadway infrastructure, and new vehicle technologies interact and interface with each other using microsimulation and state-of-the-art driving, bicycling, and pedestrian simulators.

Abstract

Advanced vehicle technologies are increasingly more accessible and available in vehicles. These current and future systems, despite promising added safety, convenience, and efficiency to drivers and road users, have an inherently higher level of complexity than the driving systems that most drivers are used to operating. In order to maximize the promised benefits, drivers will need to have a good understanding of these systems—referred to as mental models—in order to use them safely and appropriately. Previous research has identified drivers' gaps in knowledge of advanced vehicle technologies. Beyond users' knowledge of a system, understanding and defining a user's mental model is critical for many aspects of advanced vehicle technologies, including the design of, training for, and use of these systems. However, characterizing a driver's mental model is still a significant challenge. Moreover, these gaps and challenges will only be further accentuated with more complexity in vehicle automation, especially with higher levels of automation.

This research was conducted to better elucidate advanced vehicle technologies from a user control perspective, to examine driver interaction with such complex systems, and to characterize driver mental models in this context. This is achieved through: (i) a review of the current state and complexities of one advanced vehicle technology—Adaptive Cruise Control (ACC)—and its associated documentation, (ii) a review and synthesis of existing literature on mental models and error-making, (iii) the development of a task analysis for driver-automation interactions, and (iv) the building of a framework to help examine user interactions with complex systems to identify sources and probabilities of error commission. This document also reports on an examination of the limitations of various ACC systems in the current market in the context of manufacturer's reporting of such limitations.

Table of Contents

Introduction

Advanced vehicle technologies are increasingly more accessible and available in late model vehicles, with the promise of even more advanced systems, including automated driving systems (ADS), in future vehicle generations. These current and future systems, despite promising added safety, convenience, and efficiency to drivers and road users, are inherently complex. The complexity of these sophisticated systems and combinations of systems have the potential to fundamentally change the way drivers operate. As these systems take on more of the driving responsibilities, drivers may relegate more control to these systems resulting in potentially negative consequences. The potential manifestation of these negative consequences will depend on the driver's knowledge and understanding of these systems. A driver's knowledge and understanding of a system can be termed as the driver's mental model of the system.

The quality of a driver's mental model plays an important role in the safe, efficient, and appropriate use of these systems. A driver's mental model will define one's understanding of the capabilities and limitations of a system, and as a consequence, will allow for identification and appropriate management of the current mode of operation of these advanced vehicle technologies. A low-quality mental model, be it incomplete or inaccurate, can have significant consequences on a driver's expectations of a system, on reliance and use, and can also impact trust and acceptance of the system. Previous research has identified drivers' gaps in knowledge of advanced vehicle technologies (e.g., McDonald et al., 2018) but defining and characterizing a driver's mental model is still a significant challenge. Moreover, these gaps and challenges will only be further accentuated with more complexity in vehicle automation, especially with higher levels of automation.

One way to understand drivers' use of these systems is by examining how errors in their understanding may impact their interactions with such systems, and the subsequent impacts on safety and performance. To do so, a critical early step may be to develop a taxonomy of the potential types and categories of such errors. For example, errors in mental models can be due to misunderstandings of how a system operates, what is the system function, and what are the limitations. Also, different classes of errors (errors of commission vs. omission; skill vs. rule vs. knowledge; etc.) may have varying levels of impact. For example, a misunderstanding of the system's operational design domain (ODD) might lead users to engage the system in situations that it is not equipped to handle. In contrast, poor feedback from the system can lead to mode confusion, where the driver is unaware of the current state and who is responsible for what driving activities—whether driver or vehicle. Furthermore, different classes of vehicle functions may be impacted differentially. Thus, a comprehensive examination of the types of errors and corresponding potential impact on driver interactions with advanced vehicle technologies can form the important basis for future work related to drivers' mental models. It can help define critical assessment of the quality of mental models and can help identify evaluation scenarios that can be used in the empirical study of mental models and performance outcomes.

This research was conducted to facilitate a better understanding of advanced vehicle technologies from a user-control perspective, to examine driver interaction with such complex systems, and to help better characterize driver mental models. While the goal of the research is related broadly to advanced vehicle technologies, for the actual research implementation and approach a narrower focus was made on Advanced Driver Assistance

Systems (ADAS), specifically Adaptive Cruise Control (ACC). The approach and framework however remain relevant to a broader definition of advanced vehicle technologies and can be adapted and generalized to other ADAS and ADS. This current work thus extends the prior literature with a specific focus on users' mental models and the operation of advanced vehicle systems and proposes a process and framework for identifying operator-based errors in the use of such systems.

The rest of this report documents the research conducted towards these objectives, including: (i) a review of the current state and complexities of one advanced vehicle technology (ACC) and associated documentation, (ii) a review and synthesis of existing literature on mental models and error-making, (iii) the development of a task analysis for driver–ADAS interactions, and (iv) the building of a framework to help examine user interactions with complex systems to identify sources and probabilities of error commission. This document also reports on an examination of the limitations of various ACC systems in the current market in the context of manufacturer's reporting of such limitations.

Background

In recent years, major automobile manufacturers have released vehicles with advanced technologies as either standard or optional features. These technologies include systems categorized as ADAS, Driver Support Features (DSF), or active driver assistance systems (e.g., SAE, 2018). The availability of these systems was previously limited to higher-end vehicles and thus to a smaller population; however, lately the general driving population has been rapidly exposed to these systems with the rapid deployment and increased consumer awareness. Drivers are exposed to DSF given their easy availability and accessibility in the mass-market fleet (Milakis et al., 2017; HLDI, 2017). Current important components of DSF include systems that are capable of assisting the driver in maintaining longitudinal control (ACC, traffic jam assist, etc.) and lateral control (lane keeping assist, steering assist, etc.), with the goal of enhancing driver performance and contributing towards improving the overall safety and harmony of the roadway ecosystem (Bengler et al., 2014; Lang et al., 2014; Friedrich, 2016; Fisher et al., 2020). Despite the promise of convenience and assistance, these systems continue to rely on the human for monitoring and supervisory tasks. These requirements may result in various negative consequences, including drivers getting "out-of-the-driving-loop," developing negative behavioral adaptation, and encountering mode confusion, among others (Stanton & Marsden, 1996; Kaber & Endsley, 1997; Rudin-Brown & Parker, 2004; Fisher et al., 2020). All these can ultimately manifest as driver errors leading to crashes or conflicts.

There are many sources for driver error in human–machine interactions, including through inappropriate decision making due to rule-based or knowledge-based errors, or due to users' misconceptions about the systems, a consequence of gaps in users' mental models (Sarter & Woods, 1995; Norman, 2013; Endsley, 2015; Victor et al., 2018). Driver error thus plays a critical role in motor vehicle crashes, especially when considering safety critical systems. In widely cited research, drivers have been assigned as the *critical reason* in 94% of crashes (where the critical reason is characterized as the last event in the crash causal chain; Singh, 2015). Furthermore, among these, it has been estimated that recognition errors accounted for 41% of the crashes, while decision errors and performance errors accounted 33% and 11% of the crashes, respectively (Singh, 2015). This underlines the importance of understanding the different types of errors and the mechanisms behind those, especially in the context of advanced vehicle technologies. Foundational research has examined such operator errors broadly, including errors during the driving task (Stanton & Salmon, 2009).

The following subsections briefly review the literature on human errors and classification, mental models and drivers' use of vehicle systems, and the use of task analysis in deconstructing complex tasks to identify user errors.

Errors

Various classifications of human errors have been proposed over the years with three being largely prevalent in literature: Reason's slips, lapses, mistakes, and violations (Reason, 1990); Rasmussen's skill, rule, and knowledge errors (Rasmussen, 1988); and Stanton and Salmon's psychological mechanism–based errors (Stanton & Salmon, 2009). Reason's taxonomy classified errors in terms of slips (attentional failure), lapses (memory failure), mistakes (intention failure), and violations. *Slips* occur when the goal of a task is correct, but the task itself (the action) is performed incorrectly due to proximal controls or other factors (e.g., switching on the windshield wipers instead of turn signals). *Lapses* are generally reserved for memory failures (e.g., driving without fastening the seatbelt even though the intent was present). *Mistakes* occur when the goal, plan, or the task/action is incorrect (e.g., using gas pedal to disengage ACC). *Violations* refer to behaviors that deviate from accepted standards and procedures (e.g., deliberately going over the speed limit). It has been stated that slips and lapses are largely due to inattention while mistakes are due to the application of a bad procedure or misapplication of a procedure (Reason, 1990).

On the other hand, Rasmussen classified errors on the basis of behaviors related to skill, experience, and familiarity with a scenario. Skill-based behaviors arise from expertise at a particular task, where the task becomes routine and can be performed with minimal conscious attention. Skill-based behaviors could be as trivial as "turning or handling the steering wheel to maintain lane position," which does not require conscious decision making and is fairly routine during a driving task. Rule-based behaviors generally occur when a new, but familiar situation arises, but there are known rules or guidelines to perform tasks relevant to that situation. Rules could also be behaviors or actions that are learned through previous experiences that apply a context- or situation-based response, such as, "if the car is not switched on, then turn the key or press the 'start' button." Knowledge-based behaviors become relevant when unfamiliar situations occur, where the application of skills and rules may not apply. In these situations, the user may need to undertake several decision-making and problem-solving techniques and then modify them based on whether the outcome was successful or not. For example, on a slippery road where the vehicle loses traction, the routine handling of the steering wheel or rules regarding lane keeping may be deemed unsafe to the driver, and they may need to employ a response action plan in order to properly maneuver the vehicle to safety. Driving is a task that requires all three of these behaviors: it is a fairly routine task based on the skill of the driver (skill-based), it requires attention and situational awareness in unfamiliar situations (knowledge-based), and requires responses and appropriate actions to unfamiliar situations based on memory (rule-based) (Rasmussen, 1988). Consequently, the types of errors that drivers commit can be described within the aspects of these three behaviors. Reason's and Rasmussen's classifications have a common ground: It could be said that slips and lapses occur at a skill-based level, while mistakes occur at rule-based and knowledge-based levels.

Stanton and Salmon included the underlying psychological mechanisms in their taxonomy of driver errors (Stanton & Salmon, 2009). They stated that errors can be classified as action errors, cognitive and decision-making errors, observation errors, information and retrieval errors, and violations. Each of these error types will also have several unique error modes related to them to represent the exact nature of the error made by the user or the probable cause for that error. For example, a user may have made a cognitive and decision-making error due to a perceptual failure (failed to look at the right spot to detect objects in trajectory) or due to a wrong assumption (assumed the given trajectory was not set for colliding with another object). Similarly, a user may have made an action error due to them performing the action at a wrong time (driver turned on their blinkers too late when changing lanes) or due to failure to act to a particular situation (failed to check their side mirrors when changing lanes). Stanton and Salmon's taxonomy is especially helpful when considering the wide variety of errors that can occur while operating a vehicle. This usually requires continuous observation of the surroundings and vehicle functions; retrieving information from these observations; and processing this information to make decisions, plan the right sequence of actions, and then execute them. The prediction and identification of human error is achieved through the use of formal human error identification (HEI) techniques using a taxonomy to identify errors that could potentially occur during task performance.

Mismatches or inaccuracies in a drivers' mental model of a system can result in errors while operating the system. Errors may occur for several reasons, the most common reason being the complexity of the task and procedures that require the user to maintain attention over a prolonged duration of time and have specialized skills to perform several tasks in the correct sequence (Norman, 2013). Operator performance and error are related; errors are categorized from the quality of the performance (Woods et al., 1994). To understand the operator errors while using DSF, it is important to understand the different types of errors that may occur while performing the tasks required to optimally use the system.

Mental Models

Driver support features in vehicles are designed for the user (driver) to be in the loop of the operations (Parasuraman & Riley, 1997). That is, drivers need to be aware of not only what is going on in the driving environment, but also aware of the status and conditions of the DSF itself. A driver's awareness and knowledge about such a system is dictated by the accuracy and completeness of their mental model about the system. To examine driver understanding and use of systems, it is important to examine the decision-based and trust-based actions undertaken by the driver. It is in these actions that errors may arise, influenced to a large extent by the characteristics of the user's mental models and especially the gaps in said models (Endsley, 2015; Victor et al., 2018; Seppelt & Victor, 2020). Mental models have been defined as "the rich and elaborate structure which reflects the user's understanding about the system's contents, its functionality and the concept and logic behind the functionality" (Carroll & Olson, 1987). It has also been defined as "a representation of the typical causal interconnections involving actions and environmental factors that influence a system's functioning" (Durso & Gronlund, 1999).

To understand how a mental model is first constructed and then updated, it is helpful to understand the concept of situation models. While mental models may represent a user's overall generic knowledge about the system, the situation model represents the user's knowledge and comprehension of the system's current state in a dynamic environment (Endsley, 2000). A situation model may include not only knowledge about various parameters or values of a system's continuous functions (e.g., minimum speed required to activate cruise control, the level of the fuel gauge, etc.), but also knowledge about the dynamics of the system (e.g., trajectory of the vehicle, safe following distance from a lead vehicle, etc.), which is developed by experiencing various situations over time. Stokes et al. (1997) had expert and novice pilots listen to radio communications and build a mental picture about the described situations, and then select the best representation of situations from a set of diagrams. They found that experts were better than their novice counterparts at matching the correct diagram to the descriptions. Hence, it was concluded that "experts are better able to make practical use of situational schemata to impose form on sensory data in real time" (Stokes et al., 1997). Another example can be derived from a study by Paull and Glencross (1997) that compared a baseball batter's ability to anticipate the direction of a pitch. Expert batters were able to identify visual cues and make quicker and more accurate predictions due to the experience and knowledge developed over time. A mental model can manifest several situation models, which are formed in different ways as a result of environmental input (bottom-up) and top-down knowledge structures. Misinterpretation of a particular situation can result in incorrect or inaccurate mental models. Experiencing a situation can help update and potentially improve the mental model. Situation models and mental models thus go hand-in-hand and encountering more situations helps to construct and to update appropriate mental and situation models (Durso et al., 2017). Mental models are thus continuously updating as knowledge is stored in long-term memory and is available for processing when encountering familiar scenarios (Beggiato & Krems, 2013).

The scientific literature suggests that many users of DSF are not accurately aware of the functionality and limitations of the systems. For example, in a survey conducted on 370 ACC drivers, about 72% were unaware of the system functionality and limitations (Jenness et al., 2008; see also McDonald et al., 2018). In another study, 60% of drivers reported having only read half of the owner's manual and 40% did not read it at all (Mehlenbacher et al., 2002). Drivers with no prior experience of driving with ACC did not have a suitable mental model of ACC, and this worsened if they did not read the vehicle owner's manual due to the absence of an initial pre-use knowledge-based mental model (Beggiato & Krems, 2013; Larsson, 2012). Moreover, Singer and Jenness (2020) found that the framing and emphasis of instructional material can have an impact on a user's initial mental model; information that places an emphasis on the vehicle capabilities and features can lead to overestimation of its abilities. Research shows that a user's mental model converges with the ideal mental model, with a realistic view of system functionality, over time and with experience (Beggiato & Krems, 2013). In fact, when drivers were informed (i.e., read through the owner's manual), trust and reliance on the system increase over time; however, for drivers who were unaware of potential limitations (i.e., did not read through the owner's manual), trust and reliance on the system decreased dramatically. This suggests that learning, trusting, accepting, and using DSF depends on the driver having an appropriate initial mental model (Victor et al., 2018; Beggiato et al., 2015). Although mental models are vague concepts that are hard to quantitatively characterize, identifying and classifying the errors made by operators while using a system can potentially be used to characterize users' mental models and assess accuracy or completeness.

Task Analysis

In order to understand drivers' mental models of DSF, as well as track the errors they may commit while using them, it is critical to analyze the functioning of the system based on the required tasks or sequence of tasks. Task analysis is a popular human factors method that has been used to explore users and user behavior by observing them in detail while they perform different tasks to achieve a required goal (McCormick, 1979). Several task analysis approaches such as Hierarchical Task Analysis (HTA); the Goals, Operators, Methods and Selection rules (GOMS); and ConcurTaskTrees (CTT) have been used in past research for error identification in human–machine interaction (Limbourg & Vanderdonckt, 2004). They have been used to combat omission-based errors (Reason, 2002), for identifying errors in medication administration (Lane et al., 2006), and in identifying errors in electronic circuit design (Kieras & Butler, 1997), among other applications.

Using task analysis, it is possible to describe the various states and state changes available in a DSF system, to list the tasks that each state change represents, and identify the different subtasks that contribute to these state changes. In this context, a "state" of a system can be envisioned as a specific condition of that system, characterized by a combination of functionality and system parameters. For example, a system can have an "off" state where no features are activated, or an "on and feature 1 engaged" state. A system can transition between these defined states via various inputs or actions, either user-initiated or based on system factors or external factors.

In the past, several task analysis techniques such as Systematic Human Error Reduction and Prediction Approach (SHERPA) or Task Analysis for Error Identification (TAFEI), have been used to combine the hierarchy of activities with different error taxonomies to identify error modes relevant to each task during a state change (Embrey, 1986; Baber & Stanton, 1996; Stanton & Baber, 2005). By utilizing appropriate taxonomies, it is possible to identify user errors, their causal factors, and potential remedies to avoid those errors in future operations. Identifying users' errors could also lead to improving understanding of users' mental models and identify any mismatches that may be the underlying causal factors behind those errors.

Objectives

This research was undertaken with the following two main objectives related to the examination of the role of operator errors in the characterization of mental models of vehicle systems:

- To describe advanced vehicle technologies from a human operation perspective considering system functionalities, capabilities, limitations, controls, and displays. This was undertaken by a review of the scientific and technical literature, and by creating visual descriptions for a selected range of systems using state diagram notations.
- To propose a framework for identifying and predicting operator errors when using such systems. Multiple task analysis techniques were leveraged and adapted to identify potential operator errors that may occur while using a system; these identified errors were classified based on adapted versions of existing error taxonomies.

In addition to the above primary objectives, this research also raised a secondary question related to the reporting of system limitations of vehicle makes/models. To address this question, manufacturer materials were studied and contrasted to examine the level of detail in reporting of system limitation across selected vehicle makes and models.

The subsequent sections of this report provide detailed methodology for the research that addresses the main objectives, as well as a brief description and discussion of the outcome of the above-mentioned secondary question.

Describing Advanced Vehicle Technologies

As previously mentioned, the broad goal of this research is relevant to general advanced vehicle technologies. However, the current research was conducted in the context of ADAS technology, specifically ACC. An ACC system can essentially be considered a complex system consisting of various possible modes in which it could be or, more specifically, *states*. Each state can represent a unique condition and function with regards to the overall operation of the system. For example, “ACC is engaged (with no lead vehicle present)” can be considered a unique state that functions similar to a conventional cruise control system, maintaining the vehicle at the speed value set by the operator. This state is different from a state “ACC is engaged (with lead vehicle present).” In the latter, the ACC maintains a set distance from the lead vehicle, while its speed is also maintained relative to the lead vehicle’s speed.

State Diagrams

To better describe these systems comprehensively while taking all states and conditions into consideration, and to conduct a thorough task analysis in terms of operator interactions, one approach is to characterize the complex systems as a finite state machine (i.e., a system that can be in one of a finite number of states at any given time). This lends itself to a visual characterization of systems using standard notations and diagrams used for state diagrams. Below the process is outlined and the representation of an ACC system is described using a state diagram.

A typical ACC system maintains a vehicle at a constant speed at a value set by the driver but is capable of automatically adjusting the vehicle speed to maintain a defined distance from the vehicle ahead (Jones, 2013). Similar to other DSF, ACC can only assist the driver with certain driving tasks but is not capable of driving the vehicle by itself. Drivers are expected to be in the control loop at all times. For the purposes of this illustrative example, instead of using a real-world system, a generic ACC system is considered. This generic system is based on common features found in the ACC systems of popular vehicles and is thus representative of most manufacturers’ ACC offerings. However, in order to deconstruct an ACC system into different states it is helpful to understand the system’s design and functions as described by its manufacturer, with the owner’s manual being a credible and accessible source of information. In addition to the information obtained from the vehicle owner’s manual, online videos produced by manufacturers to showcase and explain the ACC features of the vehicle can be used to understand and gather specifics of the ACC system. Other supplementary or technical information might be gleaned from online automotive forums, professional automobile mechanics, and technical experts. The generic ACC system described here was thus based on multiple manufacturers’ ACC offerings but constructed to contain the most common features across all manufacturers.

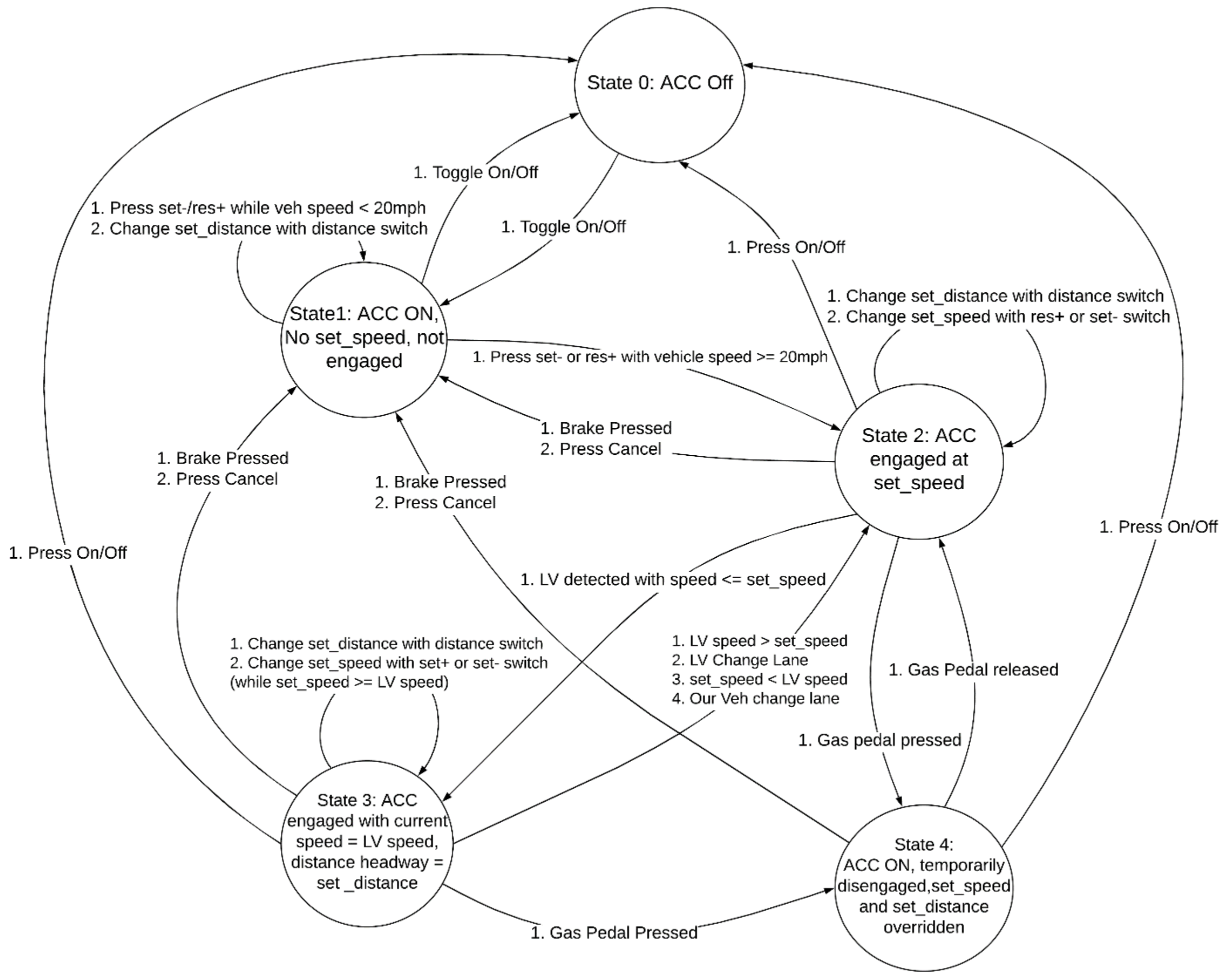

Figure 1. State diagram for a generic Adaptive Cruise Control system (Note. LV=Lead Vehicle)

This ACC system can thus be described as having five unique states:

- State 0—ACC is not switched on
- State 1—ACC is switched on but unengaged[1]
- State 2—ACC is engaged (with no lead vehicle present)
- State 3—ACC is engaged (with lead vehicle present)
- State 4—ACC is temporarily disengaged

[1] At this juncture, it is necessary to make a note about nomenclature and definitions. A typical ACC system may have two modes that characterize its operational status. For one, it might be physically unavailable (based on the ODD) or turned off. Alternatively, it might be available but not activated, or engaged. In this document the former is referred to as off (cf. on), and the latter as disengaged (cf. engaged). In manufacturer materials and other documentation such terms are often used interchangeably or in a non-standardized way.

Connectors between each state can represent the change of state, or transitions from one state to another. These elements can be visually represented in a State Diagram as illustrated in Figure 1, with States represented by circles and the transitions represented by the arrows connecting the circles.

The state diagram details each state of the ACC system, as well as the user-initiated, system-initiated, or externally initiated events, tasks, or subtasks that result in transitions between states. There is a considerable level of detail that can be included in a state diagram given the complexity of the system under consideration. In this case, the main purpose is to understand the system from an operator interaction point of view, and therefore the diagram emphasizes operator actions. It is also important to understand what other factors—external and systemic—may influence non-driver-initiated transitions between states, thus requiring the addition of such transitions in the diagram.

For consistency and accuracy, building state diagrams based only on the information and material provided about the systems as described in the vehicle owner's manuals, or from the manufacturer websites may be a best practice. Using the described approach, state diagrams were constructed to describe the ACC features of a selected set of vehicle makes and models (Ford F-150, Toyota RAV4, Volvo XC60, Honda CR-V, Subaru Outback). These vehicles were selected on the basis of popularity (based on 2018 sales figures), and to represent mass-market makes and models, as well as examples of higher-end vehicles. Appendix A contains the state diagrams for the vehicles. As can be seen from these diagrams (and from the generic diagram in Figure 1), there is a certain level of commonality across these systems. However, there are also important differences between the systems, especially in terms of the variability for the possible transitions and the actions underlying these transitions. There are also differences in the presence of intermediate states for some manufacturers, with higher-end models potentially providing more features (e.g., Volvo's Passing Assistance) that translate to additional unique states. The state diagrams are also an important visual indication of the inherent complexity of these systems. This level of complexity could increase for other systems what incorporate more features (and thus states) but still require significant user involvement to operate and transition between states (e.g., L2 systems).

Framework for Predicting and Identifying Operator Errors

An important objective of this research was to conceptualize a framework to identify errors in the use of DSF systems to help understand drivers' mental models. To do so, multiple task analysis techniques were leveraged and adapted to identify operator errors that may occur while using a system, and to classify these identified errors based on error taxonomies. This approach was informed by outcomes from the previous exercise of describing ACC systems from an operator interaction context. The state diagrams and transitions provided a comprehensive detailing of the various operator-initiated state changes in the system, along with related interactions and controls. The diagram also listed non-user-initiated transitions and helped identify what state transitions were not possible in any given system. The state diagrams and task analyses were thus used to describe operator–system interactions using transition matrices to identify state transitions and associated controls, to ultimately identify and predict potential errors that could result during these operations.

Transition Matrices

When considering state transitions, and especially since not all states can transition to every other state available in the system, it is important to keep track of transitions that are possible (or legal) given the design of a system, or not possible or not meaningful under the design constraints. Transition matrices are useful tools to do so, and can track possible, meaningful transitions and highlight transitions deemed impossible or non-meaningful (Embrey, 1986; Baber & Stanton, 1996; Stanton & Baber, 2005). The transition matrix accompanying the generic state diagram in Figure 1 offers a roadmap to further explore meaningful transitions and disregard transitions that are not possible or irrelevant (Table 1).

Table 1. Transition matrix for the states of the generic ACC system

States	0	1	2	3	4
0	×	✓	×	×	×
1	✓	✓	✓	×	×
2	✓	✓	✓	✓	✓
3	✓	✓	✓	✓	✓
4	✓	✓	✓	×	×

Note. ✓= Transition possible, × = Transition not possible

System Controls and Operator Interaction

Using the state diagram, the system functions can be visualized at different states, along with user-initiated actions or conditions required for those possible transitions listed in Table 1. ACC systems, such as the generic ACC system considered here, comprises user controls such as buttons, switches, levers, or other in-vehicle controls. These typically include: Brake Pedal, Gas Pedal, ACC On/Off Switch, Res+ Button (Resume/Increase Speed Value), Set− Button (Decrease Speed Value), Dist+/− Button (Increase/Decrease Distance from Lead Vehicle), and Cancel Button. The nomenclature, marking, design, position, form, and locations of these buttons may vary for systems of different vehicle models, but their functions remain largely similar. Operators interact with ACC systems using these controls, essentially using these operator actions or inputs as a way to change between various states of the system. Potential operator errors can manifest during these interactions or as a result of a lack of an interaction.

Tasks and Subtasks for State Transitions

State transitions can be characterized by tasks and subtasks, with *task* being the end goal of the state transition, while *subtask* is the user-initiated action or input (or system-initiated or external condition) required to undertake the task. Each state transition can be comprehensively analyzed to list the control-based errors that a user may commit while attempting to undertake the actions required for the desired transition. Table 2 shows the tasks and subtasks related to each transition for the generic ACC system.

Table 2. Tasks and subtasks for each state transition in the generic ACC system

	State Transition	Task (Transition Goal)	Subtask (User inputs)
1	0 to 1	Switch ACC On	Press ACC On/off button
2	1 to 0	Switch ACC Off when ACC is switched on	Press ACC On/Off button
3	1 to 1*	Continue driving with ACC switched on: • No change in set speed or distance • Change set speed • Change set distance	• No inputs • Press Res+ or Set− • Press Dist Switch
4	1 to 2	Engage ACC (no Lead Vehicle (LV))	Press Res+/Set− (Speed > 25 mph)
5	2 to 0	Switch ACC Off when engaged (no LV)	Press ACC On/Off button
6	2 to 1	Disengage ACC (no LV)	Press Brake or Press Cancel
7	2 to 2*	ACC engaged (no LV): • No change in set speed or distance • Change set speed • Change set distance	• No inputs • Press Res+ or Set− • Press Dist Switch
8	2 to 3	Automatic Transition—ACC engaged with LV (e.g., LV merges into driver's lane)	
9	2 to 4	Temporarily override ACC (Speed & Distance overridden; no LV)	Press Gas Pedal
10	3 to 0	Switch ACC Off when engaged (LV Present)	Press ACC On/Off button
11	3 to 1	Disengage ACC (LV present)	Press Brake or Press Cancel
12	3 to 2	Automatic Transition—ACC engages with no LV (e.g., LV exits lane/road)	
13	3 to 3*	ACC engaged (LV present): • No change in set speed or distance • Change set speed • Change set distance	• No inputs • Press Res+ or Set- • Press Dist Switch
14	3 to 4	Temporarily override ACC (Set Speed and Set Distance overridden; LV Present)	Press Gas Pedal
15	4 to 0	Switch ACC Off from the override state	Press ACC On/Off button
16	4 to 1	Disengage ACC from the override state	Press Brake or Press Cancel button
17	4 to 2	Engage ACC from the override state	Release Gas Pedal

* - No state changes take place, but parameters of the particular state may change (e.g., distance settings may change)

Error Identification and Classification

For each of these transitions, there is a possibility that the driver performs the incorrect subtask (user input) that does not contribute towards the desired transition or fails to perform the correct input, which may negatively affect the overall functioning of the system. In some cases, there is little or no consequence for these incorrect inputs, while others can result in the system transitioning to unwanted states. These incorrect inputs may be performed due to several reasons ranging from wrong assumptions, incomplete understanding of the control functions, or unintentional actions, among others. These erroneous actions can be mapped onto underlying behavioral and cognitive reasons for the error being committed.

To do this, a systematic process was designed that allowed the researchers to identify potential error actions that could be undertaken by a user, based on the above-mentioned state transitions and the actions associated with their subtasks. The process also allowed the researchers to attribute multiple potential reasons behind the commission of these errors and thus map these errors to underlying behavioral, cognitive, or other reasons. Undertaking this error prediction and identification exercise can yield a comprehensive error listing that can be further categorized according to existing taxonomies. To that end, this research adapted Stanton & Salmon's (2009) taxonomy with additional error types deemed relevant to this framework.

Table 3. Operator error taxonomy (adapted from Stanton & Salmon, 2009)

No.	**Error modes**	**Example (into the ACC perspective)**
Action Errors		
1	Fail to act	Failed to check rear view mirror
2	Wrong action - Unintentional	Pressed set speed instead of set distance
3	Mistimed Action	Brake too early or too late
4	Too much action	Stepped on the gas too much
5	Too little action	Did not press gas enough
6	Incomplete Action	Did not set enough gap between lead vehicle
7	Right action wrong location	Set the right value for distance but set it on speed instead
8	Inappropriate Action - Intentional	Speeding, Changing lanes suddenly
9	Wrong order of action in sequence	Setting speed and distance before switching on ACC
Cognitive and Decision-Making Errors		
10	Perceptual Failure	Failed to spot lead vehicle changing lanes
11	Wrong Assumption	Wrongly assume lead vehicle is changing lanes
12	Inattention	Nearly crash into lead vehicle
13	Distraction	Distracted by billboards
14	Misjudgment	Misjudged lead vehicle's speed, braking or gap
15	Looked but didn't see	Looked at the road ahead, but did not see lead vehicle signaling lane change
16	Wrong planning	Speed is set below speed limit and user accelerates temporarily disengaging ACC
Observation Errors		
17	Failed to observe	Failed to observe potholes ahead
18	Incomplete Observation	Failed to observe side mirrors when changing lanes
19	Right observation, wrong object	Failed to observe rear portion of the car
20	Mistimed Observation	Looked everywhere but too late
Information Retrieval Errors		
21	Misread Information	Misread signs
22	Misunderstood Information	Read correctly, understood wrong
23	Incomplete Information Retrieved	Saw speed limit was 65 mph, but not the lower limit
24	Wrong Information retrieved	Read a sign the wrong way

The reasoning behind why the driver may have performed the incorrect subtask could be classified under one or more error types found in the taxonomy. It is important to note that activating or using some of the controls that were required during the driving task were not considered as errors unless they contributed directly to the activation, deactivation, or transition from a state. To illustrate this exception, consider the following example: For a transition from State 0 to State 1 in Table 2, the task is to switch on ACC by performing the subtask “Press ACC On/Off button.” The driver is engaged actively in the driving task. This would mean that use of the brake pedal or the gas pedal would not be characterized as an incorrect subtask. On the other hand, pressing the“Res+” button, the “Set−” button, the “Dist+/−” button, or the “Cancel” button would be characterized as incorrect actions since at State 0 these buttons are not required for the active driving task and do not contribute towards the transition to State 1.

Table 4 illustrates a transition from State 0 to State 1, where the user could undertake the wrong action—pressing the “Res+” button—instead of correctly pressing the “ACC On/Off” button. The table describes the different reasoning for the wrong action based on an adapted Stanton & Salmon’s error taxonomy (Stanton & Salmon, 2009). Two other taxonomies, namely, Rasmussen’s taxonomy of Rule-based, Skill-based, and Knowledge-based errors, as well as Reason’s Slips, Lapses, Mistakes, and Violations could also be applied to Table 3, either as additional or standalone taxonomies (Rasmussen, 1988; Reason, 1990).

Table 4. Categorizing incorrect subtask by error types

	Why would driver perform the incorrect action	Error types based on Taxonomy
1	Driver thought Res+/Set− turns ACC on	• Inappropriate action—intentional (Action Error) • Wrong assumption (Cognitive/Decision Making Error)
2	Driver assumed speed had to be set before switching on ACC • (Knows Res+/Set− does not turn on ACC) • (Knows Res+/Set− sets the speed)	• Inappropriate action (Action Error) • Wrong order of action in sequence (Action Error) • Wrong assumption (Cognitive/Decision Making Error) • Misunderstood information (Information Retrieval Error)
3	Unintentionally pressed Res+ • (bumped it) • (Knows correct button to be pressed is ACC on/off)	• Wrong action—unintentional (Action Error) • Distraction (Cognitive/Decision Making Error) • Inattention (Cognitive/Decision Making Error)
4	Unintentionally pressed Res+ • (Thought they were pushing ACC on/off) • (Knows correct button to be pressed is ACC on/off)	• Wrong action—unintentional (Action Error) • Right action wrong location (Action Error) • Perceptual (Cognitive/Decision Making Error) • Inattention (Cognitive/Decision Making Error) • Misjudgment (Cognitive/Decision Making Error) • Misread information (Information Retrieval Error) • Misunderstood information (Information Retrieval Error) • Wrong information retrieved (Information Retrieval Error)

This approach and framework provide a structure for selecting specific user actions for various system-related functions and identifying potential erroneous actions and categories that can occur as a result of various operator-related factors. This can then form a basis for gaining a deeper understanding of the driver error types based on underlying factors or mechanisms. It can also provide a structure to empirically evaluate the error making as a potential approach for classifying an operator's mental models of a system. Finally, such a listing provides important content for training, i.e. familiarizing users with system capabilities, and testing for accuracy of drivers' understanding and knowledge of such systems.

Reporting of System Limitations across Vehicle Makes/Models

The main objectives of this research study required an in-depth understanding of manufacturers' offerings in terms of ACC Systems. The close examination of manufacturer provided material describing these systems were critical to both describing and visualizing these systems, and for the process of identifying and predicting errors in operation of these systems. In the process of examining these systems, the *reported* limitations of each system were also studied, given the importance of their role in error identification. This raised an interesting secondary question—whether there were differences in the way system limitations are reported across vehicle makes/models.

Despite the secondary nature of this question, it is an important one because although ACC systems may improve safety, they are complex systems and do have inherent limitations. These limitations are not intuitive and drivers may not understand these limitations accurately. As mentioned earlier, drivers' mental models are seeded by their knowledge and experience with systems. This in turn affects the framing of drivers' expectations, engagement, trust, and usage of these systems. Initial knowledge about these systems is thus critical to the evolution of high-quality mental models (cf. Singer & Jenness, 2020). For most users, a credible and easily available source of such information comes from manufacturers materials in the form on owner's manuals and other publications. However, previous research has shown that vehicle owners' manuals vary widely in terms of completeness and level of detail about vehicle technologies (AAA, 2019; Wright et al., 2020). Accordingly, this research team was interested in examining variability in the listing of ACC-related limitations in owners' manuals across various makes/models of vehicles with ACC.

In order to do so, the extensive review of ACC from owners' manuals, which had been undertaken for the primary objectives of this study, was leveraged. The aim of this exercise was to identify all reported limitations of ACC across several different manufacturers, and to examine how these limitations are described in different owners' manuals and whether the presentation of these system limitations is consistent and comparable across manufacturers.

Approach: Selection of Manufacturer Materials & Information Retrieval

In addition to the five vehicle models that were studied for the previous objectives, the researchers added five more makes/models of vehicles—again selected based on sales data. The ten selected manufacturers and their best-selling models for 2018 are listed in the

Table 5. Relevant vehicle owner's manuals were procured for the appropriate year for each vehicle model to examine their reporting of ACC limitations.

Table 5. Vehicle manufacturers/models studied for ACC limitations

Manufacturer	Model
Ford	F-150
Toyota	RAV4
Volvo	XC60
Honda	CR-V
Subaru	Outback
Jeep	Cherokee
Nissan	Rogue
Hyundai	Elantra
Mazda	CX-5
Mitsubishi	Outlander

ACC system limitations information was extracted from the text of the vehicle user manuals. The manuals presented this information in a non-standardized manner with significant differences in reporting style, including variability in terminology, emphasis on safety, and descriptions of scenarios and limitations, as well as variations in locations/sections in the user manuals were the limitations reported. Manuals also often reported limitations of a system in more than one way or more than one location in the manual (e.g., "system may not work properly if there is bad weather condition" and "do not use the system in poor visibility, fog, rain, snow"). This task resulted in a comprehensive list of reported limitations per vehicle model. This listing was used as the basis for two analyses: First, a comparison of the reporting of these limitations across manufacturers, and second, a categorization of limitation types from a pooled list across manufacturers.

Outcomes: Listing & Categorization of Reported System Limitations

For the first analysis, the ten ACC systems were first compared to each other to assess if any system had additional features that could prevent a fair comparison of ACC across manufacturers. This was done since ACC systems from different manufacturers could differ in some functionalities due to additional features such as automatic braking, parking assist, traffic jam assist, etc. Although most of the systems had no significantly different feature sets, for those that did (e.g., Volvo Passing Assist) the reported limitations related to the exclusive features were excluded from their list of limitations.

Then, the limitations reported for ACC by each manufacturer were tabulated by counting the number of limitations that were reported in each owner's manual. This tabulation included every instance of a limitation type that was described in a manual, as long as it was not exactly repeated (see previous example of visibility). The counts for each vehicle model are reported in Table 6.

Table 6. Count of reported limitations per manufacturer

Manufacturer	Number of Limitations
Subaru	35
Mitsubishi	26
Honda	23
Toyota	20
Hyundai	20
Volvo	19
Nissan	17
Ford	16
Jeep	16
Mazda	13

For the second analysis, these limitations were used as a basis for creating a categorization of the scenarios and events when ACC would potentially fail or come close to failing. First, the list of all limitations from Table 6 (count = 205) were pooled. At this step, even if multiple manufacturers reported a similar limitation (e.g., "ACC does not work on steep grades") these similar limitations were not combined but treated as unique instances of limitation reporting. This was done to preserve information about how the specific limitation was described or reported across manufacturers. Each of these limitations was then allocated to emergent categories based on their description. This resulted in the identification of 18 categories of ACC-specific limitations. These categories are listed in Table 7, along with the number of limitations (across all manufacturers) that constituted each category. The table also reports the number of owners' manuals that described at least one limitation from that category.

Table 7. Categorization criteria for ACC limitations across ten vehicle models

	Category	Example of limitation description	# of limitations	# manual mentions (max. 10)
1	Braking capacity	".. (system) has limits when the decelerating vehicle in front unexpectedly slows down or suddenly brakes."	8	7
2	Curves	"…may have detection issues when driving into and coming out of a bend or curve in the road."	16	10
3	Heavy cargo/vehicle modification	"Do not use the system if the vehicle is titled due to a heavy load or suspension modifications."	19	8
4	Non-standard lead vehicle shape	"Do not use the system when the vehicle ahead of you has a unique shape."	7	4
5	Off-set lead vehicle	"...may have detection issues when the vehicle is driving on a different line than the lead vehicle."	11	8
6	On-coming traffic	"...will not detect oncoming vehicles in the same lane"	7	7
7	People/animals	"Do not use on roads where there are pedestrians, cyclists."	10	9
8	Road infrastructure	"Do not use the system when driving through a narrow iron bridge."	8	6
9	Road type	"Do not use when driving in an urban or suburban environment."	13	7
10	Slow speeds	"Detection error can occur when vehicles in front are traveling at low speeds."	7	7
11	Small vehicles	"...does not brake for small vehicles, such as bikes and motorcycles."	9	8
12	Stationary vehicles/objects	"Stopped vehicles cannot be recognized by the radar."	9	8
13	Steep grades	"Do not use when driving on hilly roads"	14	8
14	Swerving	"Detection error can occur when steering wheel operation or your position in the lane is unstable."	2	2
15	Traction issues	"Do not use when driving on rainy, icy, or snow-covered roads"	13	10
16	Traffic	"Do not use when driving in heavy traffic or when traffic conditions make it difficult to drive at a constant speed."	10	9
17	Visibility/weather	"…may not work properly if there is bad weather condition."	24	9
18	Other	"...may not operate temporarily due to electrical interference"	18	8

This exercise yielded rich information about the reporting of limitations for a manufacturer and allowed for a categorization of a large set of ACC-related system limitations. The general finding was that, even after accounting for differences in some additional ACC features, the reporting of potential ACC limitations was not even or consistent across the ten manufacturers. For example, some manufacturers listed as many as thirty-five system limitations, while some listed fewer than half of that number (see Table 6). It is difficult to judge from this exercise whether this variability in reporting across manufacturers is a function of a particular manufacturer's ACC system being more robust (and hence with fewer limitations), or if it is due to a less comprehensive coverage of limitations in their respective owners' manuals. It is likely the case that some systems indeed have important safety-related limitations that are not communicated clearly or mentioned at all in the manuals. The implications and relevance of this question are further discussed in the subsequent sections.

Discussion and Future Work

The main objectives of the project were to describe advanced vehicle technologies from a human operation perspective while considering system functionalities, capabilities, limitations, controls, and displays and to propose a framework for identifying and predicting operator errors when using such systems. In this section, these tasks and related outcomes are reviewed while pointing to potential application areas and areas of future research.

Mental Models and Advanced Vehicle Technology

During human–machine interactions, humans may have gaps and misconceptions in their mental models (Sarter & Woods, 1995; Endsley, 2015). Since mental models are abstract concepts that are hard to define, it is challenging to characterize the accuracy or inaccuracy of a user's mental model. One possible way to achieve this is by observing and identifying human errors that may be occurring as a result of inaccurate or incomplete mental models. In this research, state visualizations were employed as an approach to describe the complexity of advanced vehicle technologies. A framework was proposed for task analysis and as an approach to identify driver errors when using ACC systems (generalizable to other ADAS and ADS technologies). A generic ACC system was used as an illustration for how driver errors can be identified and mapped to deficits or gaps in their mental model. Using elements from a variety of task analysis techniques and error taxonomies, potential operator errors can be identified and classified. The method has potential to be used to identify errors while using other ADAS features such as Lane Keeping Assistant systems or future higher-level Automated Driving Systems (SAE, 2018).

Advanced vehicle technologies are inherently complex, especially when compared to the vehicle functionalities that an average driver is knowledgeable about and comfortable with. It thus seems critical that a driver understands these complex systems well. Describing these systems textually may be a way to comprehensively cover all aspects of the system but may not be as easily understandable and accessible to a lay driver. The use of state diagrams to visualize system information can aid significantly in the understanding of the inner workings of the system. As a part of this effort, multiple ACC state diagrams from different manufacturers were compiled. This process helped highlight the fact that although the nomenclature and specific control/display/human–machine interface (HMI) design may differ between manufacturers or even models or years, most systems follow a generally similar construct, with similar controls and displays, and a relatively similar set of operating conditions.

Implications

While this approach will help clarify and deconstruct a system's states to a more technical audience, it also has the potential to be leveraged to describe complex systems to a less technical audience. When categorizing system limitations for ACC systems across different manufacturers, state diagrams served as a visual representation of the individual systems and inherent differences between each system could be identified easily. A state diagram can be drawn to list every unique state, along with all the tasks and subtasks required to remain in each state or transition to a different state. State diagrams thus may make for a unique visualization tool to help an individual with minimal knowledge about a system to quickly interpret and comprehend system capabilities. Although the current efforts used ACC as an exemplar, this process can be used for other ADAS features, including those that can be described as higher-level Automated Driving Systems. Future work could further explore the efficacy of using state diagrams as a meaningful and concise technique to describe complex systems for a wide audience. This has broad implications for applications in driver training and the design and content of user manuals, as well as for the design of these systems (including HMI) themselves.

The main impetus for the error identification framework was for the application in identifying errors during drivers' operation of various driver support features such as ACC. This structured approach towards error identification can form a foundational basis for examining the deeper underlying mechanisms or factors for the commission of such errors. Identifying potential errors associated with various operations (and system goals) can inform the fundamental design of the systems and controls and expectancies for the driver. This is particularly important as levels of vehicle automation change to systems that may require even lower engagement from the drivers, thus opening the door for many more types and categories of errors and increasing occasions for and probabilities of errors being committed.

This framework, and the identification of error types, also has an important application in the underlying objective of this research—to better understand and characterize drivers' mental models of advanced vehicle technologies. This approach provides a structure for empirical evaluation of these errors and their commission as an approach of measuring or classifying operators' mental models, or their level of accuracy and completeness regarding their knowledge of a system's capabilities and limitations. Mental models of a driver are currently measured using survey instruments designed to probe drivers' understanding and knowledge of capabilities. Assessing mental models by interpreting driver errors allows for novel methods to gauge mental models, possibly in real-time under experimental conditions. It is possible to further examine various systems from a human operator response viewpoint and use other frameworks such as Operator Function Modeling (Lee & Sanquist, 2000) or System-Theoretic Process Analysis (STPA; Leveson, 2012).

Another important application of this framework is in the domain of user training. Outcomes from an error identification analysis provides important content for training, i.e., familiarizing users with system capabilities, and testing for accuracy of drivers' understanding and knowledge of such systems. There is a growing recognition of the role of training and education in the safe and effective use of advanced vehicle technologies (Pradhan et al., 2019). This issue becomes relevant for licensing authorities, manufacturers, dealerships, and driver education professionals. Identifying potential operator errors during ADAS use, as well identifying underlying system limitations could help guide and focus training or educational approaches aimed at reducing or preventing such errors. The framework can further be leveraged to predict operator errors during the design of such systems. Operators rely on heuristics to process information and to make decisions. The proposed framework helps examine how various design features can elicit user errors. From a design perspective, this allows for a human-centered design approach. Errors can be mitigated by simplifying the formation of accurate mental models, and importantly, by allowing for the generation of effective heuristics that allow for the far transfer of one's understanding of an ADAS feature across manufacturers.

Related to the above discussion on training and driver education is the outcome of the analysis that was conducted on the reporting of system limitations in user manuals. By reviewing owner's manuals for different ACC systems across different manufacturers, it was possible to better understand the limitations of ACC systems and classify them into categories. A study of how these limitations were presented to users through the owners' manuals showed that the reporting of limitations is not consistent across manufacturers, with some owners' manual having a very comprehensive and detailed listing of limitations, as contrasted with others that had fewer limitations listed. It is important to note again that this variability does not necessarily indicate that a system is more or less robust and could simply be a function of the completeness or depth of a particular model's owner's manual.

These findings become especially critical when viewed in the context of recent research that indicates the vital role of how limitations are reported in owner's manuals (cf. Singer & Jenness, 2020). In their research, Singer and Jenness (2020) found that branding or reporting approaches had an impact on drivers' confidence in vehicle capabilities and therefore potentially on how drivers rely on or use the technologies, with an approach that emphasized limitations (over capabilities) potentially leading to less inflated expectancies regarding what systems can do and what situations they can handle. Their findings further underscore the importance of this current work on studying reported limitations, validating the importance of familiarizing users with all system limitations to ensure correct usage and prevent risk conditions while using ACC.

From a more practical perspective, this does raise questions about efficient ways to actually present drivers with information about system limitations and capabilities. A pragmatic and parsimonious approach may be to present drivers with a few examples of failure scenarios or malfunctioning instances and expect that this information may suffice for the drivers to extrapolate and apply towards unknown safety-critical situations. One approach towards this could constitute the use of "Quick Start Guides" or more concise publications that provide more focused information about these systems, but also refer to the owner's manual for more comprehensive information. An alternate to this approach could entail presenting the user with as much information about system limitations as possible, a strategy that may also be conducive for legal liability issues. A concern of course is that these may end up overloading the driver with too much information resulting in mode confusion or information slips. Also, worth noting that oftentimes the drivers tend to read owner's manuals immediately after purchasing their vehicles, and hence overloading a naïve driver may result in creating an incomplete or inappropriate initial mental model. Future studies could focus on answering these questions by finding optimal ways to transfer system limitation-based information to drivers (particularly new users).

From a broader perspective, the findings from this secondary question contributes to the evidence about how system-related information about complex driver assistance systems may have an impact on mental models and driving safety. Our primary research goal has been to understand how such complex systems can be described and used to identify or predict user errors. Users' operation of these systems and commission of any errors are driven by their mental models of these systems (Beggiato & Krems, 2015), and it is important to be able to gauge how accurate or complete a user's mental model may be. However, it is also important to understand how these mental models may be formed and how they may evolve over time given initial knowledge seeding, exposure to the technologies, and any experiences with system limitations. Of these, the former has been shown to be important in how drivers develop their expectations of these systems (AAA, 2019; Abraham et al., 2017; Nees, 2018). Initial knowledge seeding can be greatly influenced by vehicle owner's manuals or from similar manufacturer material. How this knowledge is reported has an impact on drivers' expectation, and by extension shapes their mental models of these systems. In addition to reporting approaches, the content of the information seems similarly critical. Along these lines, the outcomes of the secondary questions show inconsistency in reporting of system limitations, potentially affecting drivers' expectations and use of these systems, and their impact on driving safety. Future work could expand the analyses to include more manufacturers and a broader range of ADAS types. Experimental evaluation of the impact of inconsistencies in reporting system limitations could be carried out (e.g., see Singer & Jenness, 2020) leading to recommendations and guides for best practices in reporting of system limitations and capabilities.

Conclusions

This research was undertaken to examine the role of driver errors in helping characterize their mental models of a complex vehicle technology. The research aimed to describe complex systems from a human operator perspective, and to lay out a structured framework using task analysis and error identification methods to identify and categorize potential driver errors.

Complex advanced vehicle systems were represented using diagrams that visually represented these systems as unique states and transitions between states, using standard notation for state diagrams. These diagrams were used as the basis for task analyses that were comprised of identifying and listing operator-related inputs or actions that were relevant to state changes, i.e., undertaking of system function tasks. A structured process was then proposed for identifying operator-initiated errors for each level of operator inputs and classifying these errors into error types based underlying mechanisms based on an error taxonomy.

This research also involved an in-depth examination of the *reported limitations* of ACC systems in manufacturer prepared materials (owner's manuals) in order to understand variability between manufacturers in consistency of such reporting. It was found that there was considerable variability between manufacturers in the reporting of ACC limitations, although this may not be indicative of the actual capabilities or robustness of said systems.

This report discusses the implications of this research in relation to the broad underlying goals of understanding drivers' mental models in the context of driver safety, and how the outcomes from this research can be used to inform or catalyze future work to better understand how to potentially measure drivers' mental models, how to better educate or train drivers regarding systems capabilities and limitations, and the implications for driver safety and the benefits of advanced vehicle technologies.

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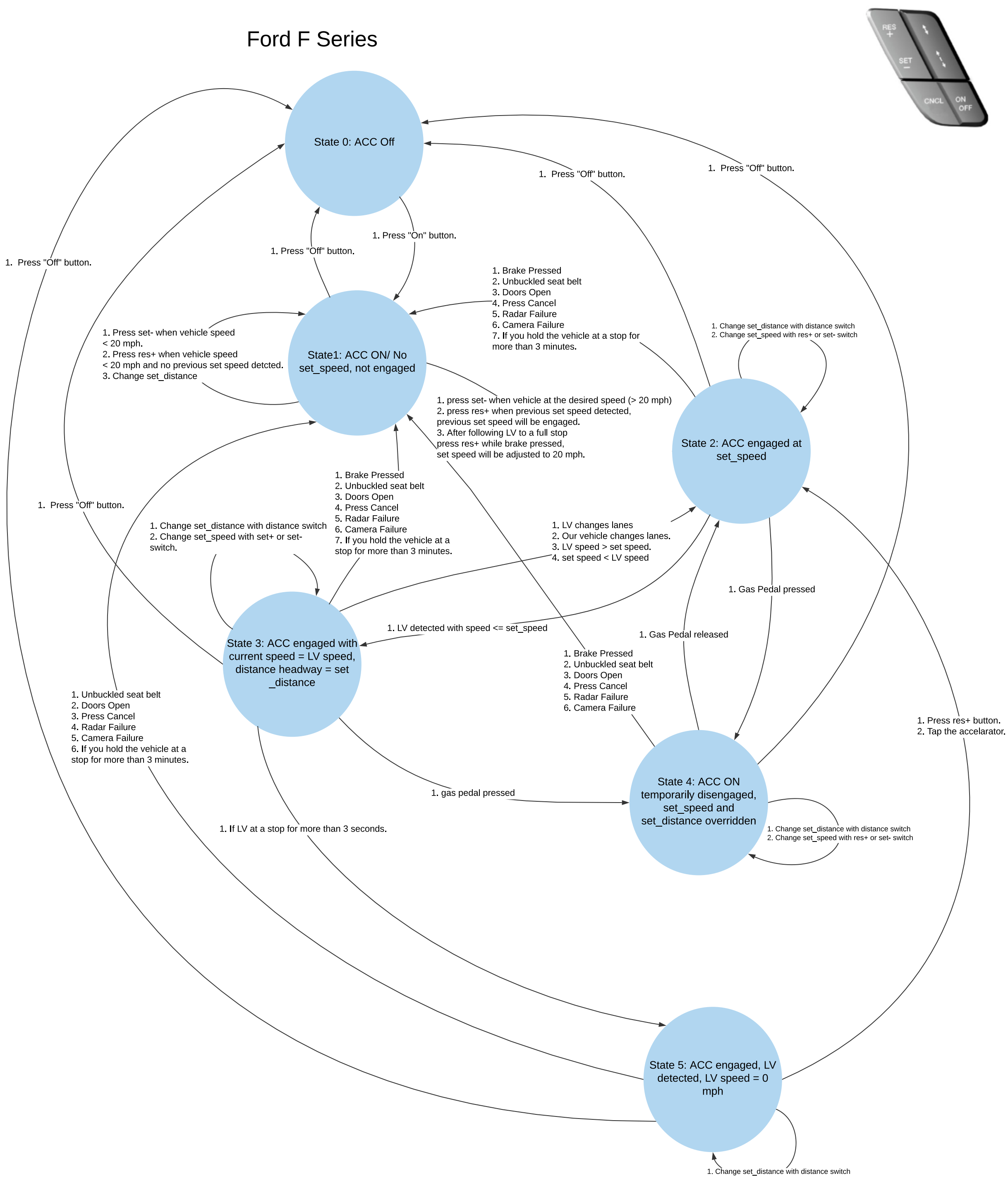
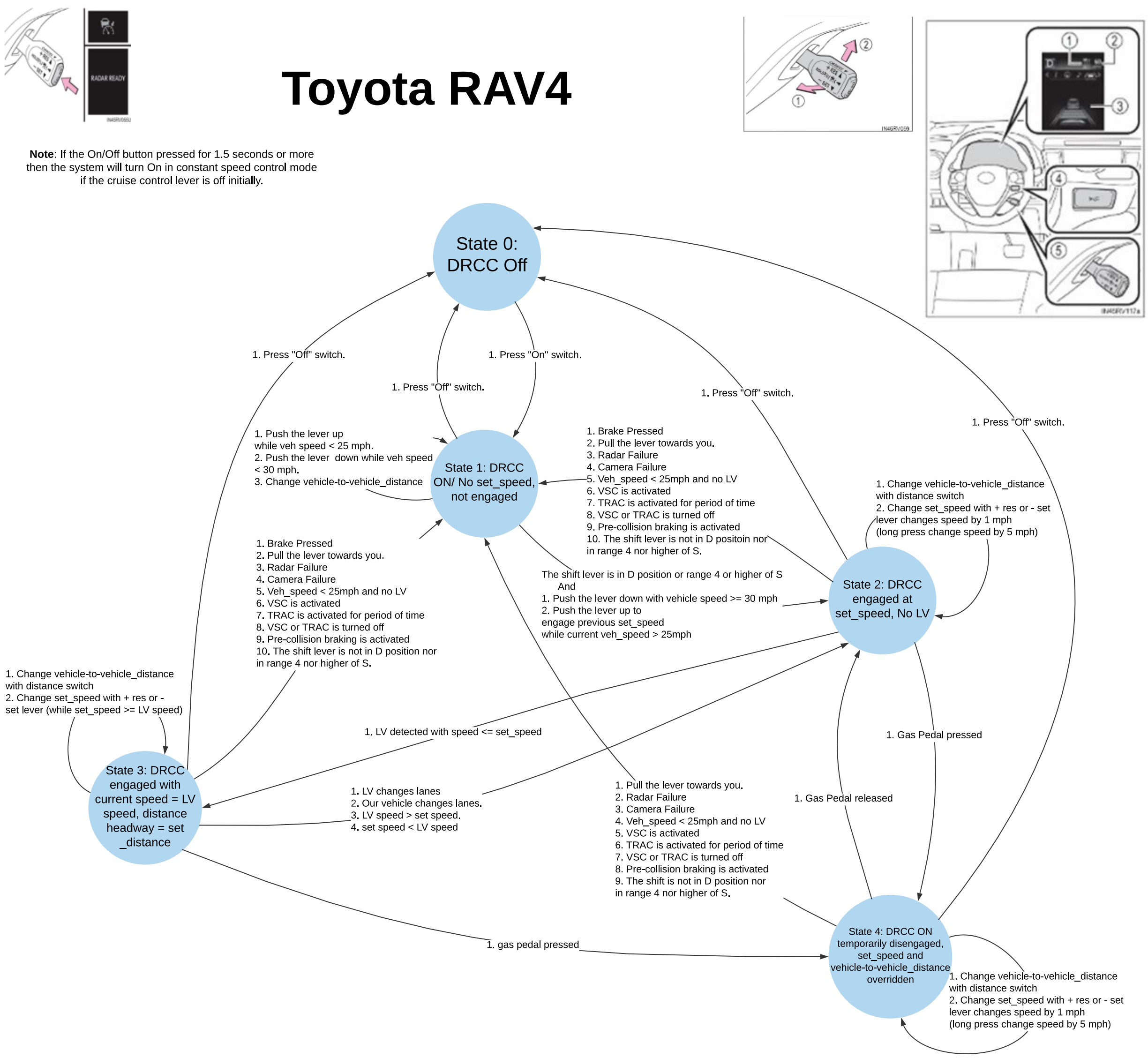
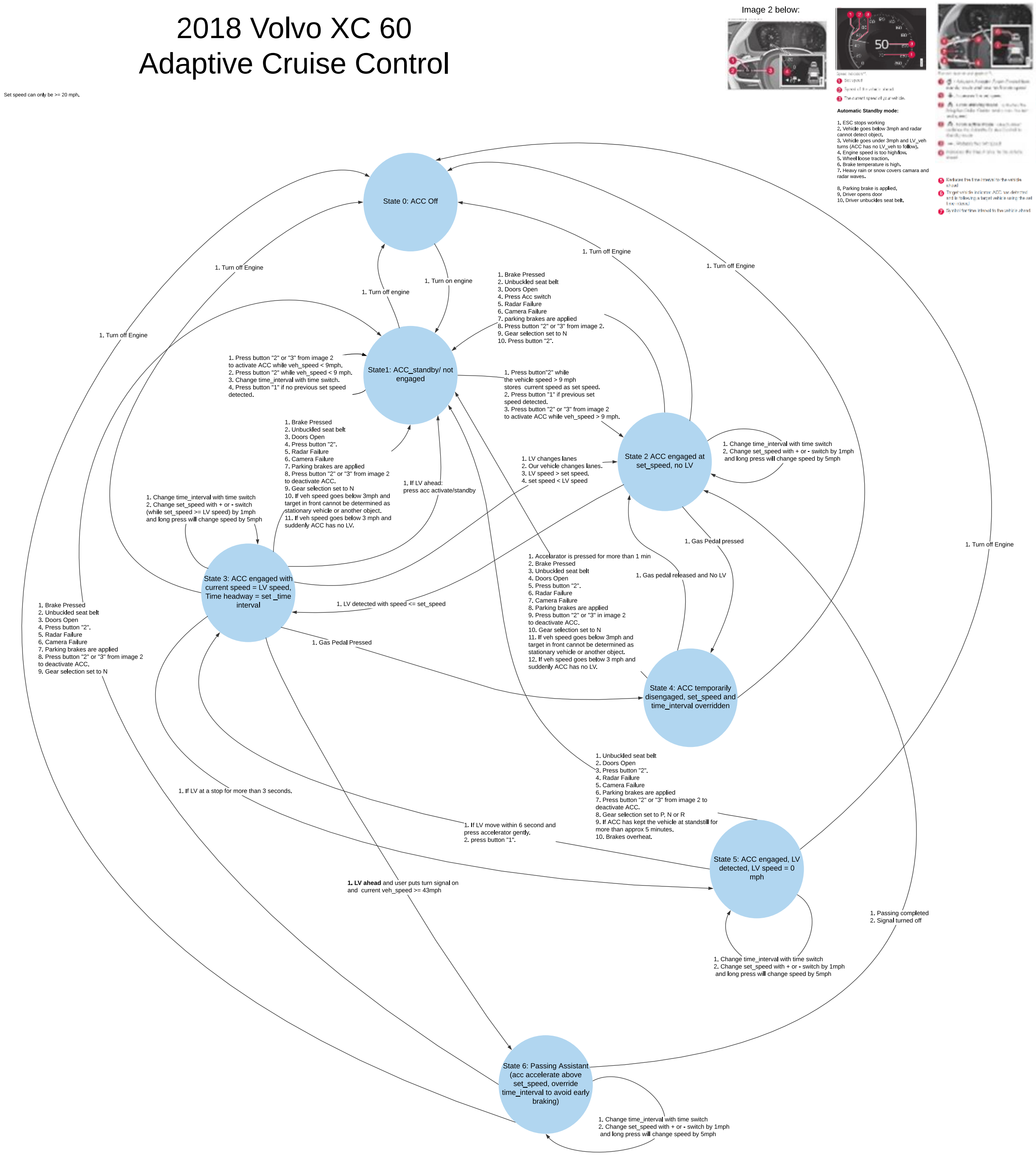
Appendix A

Ford F-150



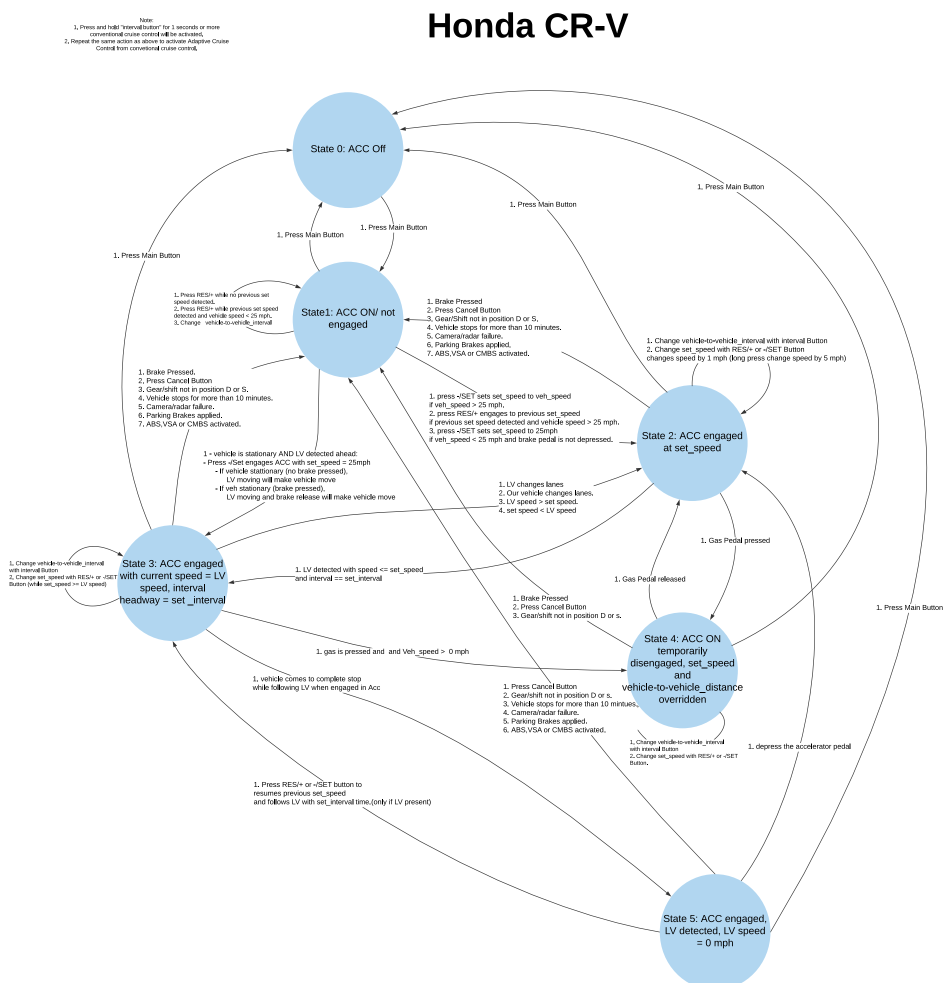
Toyota RAV4


RADAR READY
Toyota RAV4
Note: If the On/Off button pressed for 1.5 seconds or more
then the system will turn On in constant speed control mode
if the cruise control lever is off initially.
State 0: DRCC Off
1. Press "Off" switch.
1. Press "On" switch.
1. Press "Off" switch.
1. Press "Off" switch.
1. Press "Off" switch.
State 1: DRCC ON/ No set_speed, not engaged
1. Push the lever up
while veh speed < 25 mph.
2. Push the lever down while veh speed
< 30 mph.
3. Change vehicle-to-vehicle_distance
1. Brake Pressed
2. Pull the lever towards you.
3. Radar Failure
4. Camera Failure
5. Veh_speed < 25mph and no LV
6. VSC is activated
7. TRAC is activated for period of time
8. VSC or TRAC is turned off
9. Pre-collision braking is activated
10. The shift lever is not in D positoin nor
in range 4 nor higher of S.
1. Change vehicle-to-vehicle_distance
with distance switch
2. Change set_speed with + res or - set
lever changes speed by 1 mph
(long press change speed by 5 mph)
The shift lever is in D position or range 4 or higher of S
And
1. Push the lever down with vehicle speed >= 30 mph
2. Push the lever up to
engage previous set_speed
while current veh_speed > 25mph
State 2: DRCC engaged at set_speed, No LV
1. Brake Pressed
2. Pull the lever towards you.
3. Radar Failure
4. Camera Failure
5. Veh_speed < 25mph and no LV
6. VSC is activated
7. TRAC is activated for period of time
8. VSC or TRAC is turned off
9. Pre-collision braking is activated
10. The shift lever is not in D position nor
in range 4 nor higher of S.
1. Change vehicle-to-vehicle_distance
with distance switch
2. Change set_speed with + res or -
set lever (while set_speed >= LV speed)
1. LV detected with speed <= set_speed
1. Gas Pedal pressed
State 3: DRCC engaged with current speed = LV speed, distance headway = set _distance
1. LV changes lanes
2. Our vehicle changes lanes.
3. LV speed > set speed.
4. set speed < LV speed
1. Pull the lever towards you.
2. Radar Failure
3. Camera Failure
4. Veh_speed < 25mph and no LV
5. VSC is activated
6. TRAC is activated for period of time
7. VSC or TRAC is turned off
8. Pre-collision braking is activated
9. The shift is not in D position nor
in range 4 nor higher of S.
1. Gas Pedal released
1. gas pedal pressed
State 4: DRCC ON temporarily disengaged, set_speed and vehicle-to-vehicle_distance overridden
1. Change vehicle-to-vehicle_distance
with distance switch
2. Change set_speed with + res or - set
lever changes speed by 1 mph
(long press change speed by 5 mph)



2018 Volvo XC 60
Adaptive Cruise Control
Set speed can only be >= 20 mph.
Image 2 below:
Automatic Standby mode:
1. ESC stops working
2. Vehicle goes below 3mph and radar cannot detect object.
3. Vehicle goes under 3mph and LV_veh turns (ACC has no LV_veh to follow).
4. Engine speed is too high/low.
5. Wheel loose traction.
6. Brake temperature is high.
7. Heavy rain or snow covers camara and radar waves.
8. Parking brake is applied.
9. Driver opens door
10. Driver unbuckles seat belt.
State 0: ACC Off
1. Turn off Engine
1. Turn off Engine
1. Turn off engine
1. Turn on engine
1. Turn off Engine
1. Turn off Engine
1. Turn off Engine
State1: ACC_standby/ not engaged
1. Brake Pressed
2. Unbuckled seat belt
3. Doors Open
4. Press Acc switch
5. Radar Failure
6. Camera Failure
7. parking brakes are applied
8. Press button "2" or "3" from image 2.
9. Gear selection set to N
10. Press button "2".
1. Press button "2" or "3" from image 2 to activate ACC while veh_speed < 9mph.
2. Press button "2" while veh_speed < 9 mph.
3. Change time_interval with time switch.
4. Press button "1" if no previous set speed detected.
1. Press button"2" while the vehicle speed > 9 mph stores current speed as set speed.
2. Press button "1" if previous set speed detected.
3. Press button "2" or "3" from image 2 to activate ACC while veh_speed > 9 mph.
State 2 ACC engaged at set_speed, no LV
1. Change time_interval with time switch
2. Change set_speed with + or - switch by 1mph and long press will change speed by 5mph
1. Brake Pressed
2. Unbuckled seat belt
3. Doors Open
4. Press button "2".
5. Radar Failure
6. Camera Failure
7. Parking brakes are applied
8. Press button "2" or "3" from image 2 to deactivate ACC.
9. Gear selection set to N
10. If veh speed goes below 3mph and target in front cannot be determined as stationary vehicle or another object.
11. If veh speed goes below 3 mph and suddenly ACC has no LV.
1. If LV ahead: press acc activate/standby
1. LV changes lanes
2. Our vehicle changes lanes.
3. LV speed > set speed.
4. set speed < LV speed
1. Change time_interval with time switch
2. Change set_speed with + or - switch (while set_speed >= LV speed) by 1mph and long press will change speed by 5mph
State 3: ACC engaged with current speed = LV speed, Time headway = set _time interval
1. Gas Pedal pressed
1. Gas pedal released and No LV
1. Accelarator is pressed for more than 1 min
2. Brake Pressed
3. Unbuckled seat belt
4. Doors Open
5. Press button "2".
6. Radar Failure
7. Camera Failure
8. Parking brakes are applied
9. Press button "2" or "3" in image 2 to deactivate ACC.
10. Gear selection set to N
11. If veh speed goes below 3mph and target in front cannot be determined as stationary vehicle or another object.
12. If veh speed goes below 3 mph and suddenly ACC has no LV.
1. LV detected with speed <= set_speed
1. Brake Pressed
2. Unbuckled seat belt
3. Doors Open
4. Press button "2".
5. Radar Failure
6. Camera Failure
7. Parking brakes are applied
8. Press button "2" or "3" from image 2 to deactivate ACC.
9. Gear selection set to N
1. Gas Pedal Pressed
State 4: ACC temporarily disengaged, set_speed and time_interval overridden
1. Unbuckled seat belt
2. Doors Open
3. Press button "2".
4. Radar Failure
5. Camera Failure
6. Parking brakes are applied
7. Press button "2" or "3" from image 2 to deactivate ACC.
8. Gear selection set to P, N or R
9. If ACC has kept the vehicle at standstill for more than approx 5 minutes.
10. Brakes overheat.
1. If LV at a stop for more than 3 seconds.
1. If LV move within 6 second and press accelerator gently.
2. press button "1".
State 5: ACC engaged, LV detected, LV speed = 0 mph
1. LV ahead and user puts turn signal on and current veh_speed >= 43mph
1. Passing completed
2. Signal turned off
1. Change time_interval with time switch
2. Change set_speed with + or - switch by 1mph and long press will change speed by 5mph
State 6: Passing Assistant (acc accelerate above set_speed, override time_interval to avoid early braking)
1. Change time_interval with time switch
2. Change set_speed with + or - switch by 1mph and long press will change speed by 5mph

Honda CR-V


Note:
1. Press and hold "interval button" for 1 seconds or more conventional cruise control will be activated.
2. Repeat the same action as above to activate Adaptive Cruise Control from convetional cruise control.
Honda CR-V
State 0: ACC Off
1. Press Main Button
1. Press Main Button
1. Press Main Button
1. Press Main Button
1. Press Main Button
State1: ACC ON/ not engaged
1. Press RES/+ while no previous set speed detected.
2. Press RES/+ while previous set speed detected and vehicle speed < 25 mph.
3. Change vehicle-to-vehicle_interval
1. Brake Pressed
2. Press Cancel Button
3. Gear/Shift not in position D or S.
4. Vehicle stops for more than 10 minutes.
5. Camera/radar failure.
6. Parking Brakes applied.
7. ABS,VSA or CMBS activated.
1. Brake Pressed.
2. Press Cancel Button
3. Gear/shift not in position D or S.
4. Vehicle stops for more than 10 minutes.
5. Camera/radar failure.
6. Parking Brakes applied.
7. ABS,VSA or CMBS activated.
1. press -/SET sets set_speed to veh_speed
if veh_speed > 25 mph.
2. press RES/+ engages to previous set_speed
if previous set speed detected and vehicle speed > 25 mph.
3. press -/SET sets set_speed to 25mph
if veh_speed < 25 mph and brake pedal is not depressed.
1. Change vehicle-to-vehicle_interval with interval Button
2. Change set_speed with RES/+ or -/SET Button
changes speed by 1 mph (long press change speed by 5 mph)
State 2: ACC engaged at set_speed
1 - vehicle is stationary AND LV detected ahead:
- Press -/Set engages ACC with set_speed = 25mph
- If vehicle stattionary (no brake pressed),
LV moving will make vehicle move
- If veh stationary (brake pressed),
LV moving and brake release will make vehicle move
1. LV changes lanes
2. Our vehicle changes lanes.
3. LV speed > set speed.
4. set speed < LV speed
1. Change vehicle-to-vehicle_interval
with interval Button
2. Change set_speed with RES/+ or -/SET
Button (while set_speed >= LV speed)
State 3: ACC engaged with current speed = LV speed, interval headway = set _interval
1. LV detected with speed <= set_speed
and interval == set_interval
1. Gas Pedal pressed
1. Gas Pedal released
1. Brake Pressed
2. Press Cancel Button
3. Gear/shift not in position D or s.
1. Press Main Button
State 4: ACC ON temporarily disengaged, set_speed and vehicle-to-vehicle_distance overridden
1. gas is pressed and and Veh_speed > 0 mph
1. vehicle comes to complete stop
while following LV when engaged in Acc
1. Press Cancel Button
2. Gear/shift not in position D or s.
3. Vehicle stops for more than 10 mintues.
4. Camera/radar failure.
5. Parking Brakes applied.
6. ABS,VSA or CMBS activated.
1. Change vehicle-to-vehicle_interval
with interval Button
2. Change set_speed with RES/+ or -/SET
Button.
1. depress the accelerator pedal
1. Press RES/+ or -/SET button to
resumes previous set_speed
and follows LV with set_interval time.(only if LV present)
State 5: ACC engaged, LV detected, LV speed = 0 mph

Subaru Outback