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FOUNDATION FOR TRAFFIC SAFETY

SAFETY RESEARCH USING SIMULATION
UNIVERSITY TRANSPORTATION CENTER

Title

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Foreword

Research has demonstrated that many drivers have gaps in their knowledge and understanding of advanced vehicle technology—how it works and what its limitations are. These gaps can have important implications for the safe use of these systems. It is imperative to increase our understanding of how drivers' perceptions and expectations of new technology form and evolve over time such that knowledge gaps can be exposed and addressed.

This technical report summarizes a multi-session driving simulator study looking at how different types of driving experiences can influence drivers' understanding of Adaptive Cruise Control. The report should be of interest to researchers, safety advocates, and the automobile industry who are working in the domain of advanced vehicle technology.

This report is a product of an active 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 is comprised of 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, 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, pedestrian simulators.

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Executive Summary

Advanced Driver Assistance Systems (ADAS) support drivers with some driving tasks. However, drivers may lack appropriate knowledge about ADAS resulting in inadequate mental models, which can translate to drivers misusing ADAS, or mistrusting the technologies, especially after encountering edge-case events (situations beyond the capability of an ADAS where the system may malfunction or fail). Past research suggests that mental models may be improved through exposure to ADAS-related driving situations, especially those related to the system capabilities as well as its limitations. The objective of this study was to examine the impact of frequency and quality of exposure on drivers' understanding of Adaptive Cruise Control (ACC), their trust, and their workload after driving with ACC.

Sixteen novice ACC users were recruited for this longitudinal driving simulator study. Drivers were randomly assigned to one of two groups—the "Regular Exposure" group encountering *routine* edge-case events, and the "Enhanced Exposure" group encountering both *routine* and *rare* edge-case events. Each participant undertook four different simulator sessions, each separated by about a week. Each session comprised a simulator drive featuring five edge-case scenarios. The study followed a mixed-subject design, with exposure frequency as the within-subject variable, and quality of exposure (defined by two groups) as the between-subject variable. Surveys measured drivers' trust, workload, and system knowledge (i.e., mental models).

The results from the analyses revealed that drivers' mental models about ACC improve with frequency of exposure to ACC and associated edge-case driving situations. This was more the case for drivers who experienced rare ACC edge cases. The findings also indicate that for those who encountered rare edge cases, workload was higher and trust was lower than those who did not. These findings underline the importance of experience and familiarity with ADAS for safe operation. While these findings indicate that drivers benefit from increased exposure to ACC and edge cases in terms of appropriate use of ADAS, and ultimately promise crash reductions and injury prevention, a challenge remains regarding how to provide drivers with appropriate exposure in a safe manner.

Introduction

Most, if not all, modern automobiles are equipped with advanced vehicle technologies that have the capability to automate some aspects of the driving task. A report in 2019 indicated that nearly 93% of all new vehicles had at least one advanced driver assistance system (ADAS) feature, such as Automatic Emergency Braking (AEB), Adaptive Cruise Control (ACC), or Lane Keeping Assist (LKA), among others (AAA, 2019).

These technologies are often touted as driver convenience or driver assistance features and offer promises of increased driver safety. However, by virtue of their capabilities, the driver can relegate some of their traditional driving tasks to the automation systems. This results in a change in the drivers' traditional role: from that of an engaged operator responsible for controlling the vehicle, to that of an operator that shares monitoring and vehicle control tasks with one or more automated systems. That is, ADAS technologies like ACC and LKA require the driver to more closely monitor and control the systems, despite the systems' ability to manage the longitudinal and lateral vehicle control tasks.

Moreover, these vehicle technologies are inherently complex and are not immediately transparent and obvious to the everyday users. The technological sophistication of automation technologies can influence how drivers understand their vehicles (sometimes referred to as drivers' *mental models* of vehicle technology). Thus, while these systems promise safety and convenience, the complexities of these automation systems, the changing role of the driver, and the shared responsibilities between driver and vehicle automation may result in a compromising of any promised benefits. Therefore, to indeed realize the benefits, it is critical for the operator to understand the technology, its impact on their driving task, and their own new role in this modern vehicle ecosystem.

Mental Models

Drivers' mental models of systems have been described as a mental representation that contains a rich and elaborate structure about a user's understanding of the how, what, and why, of any system (Carroll & Olson, 1987). These mental models help drivers understand two very critical aspects of any system: (a) the systems' capabilities and limitations and (b) the current and the possible states/modes of the automation system. Incomplete or inaccurate mental models may lead to drivers misunderstanding the scope, purpose, operation, capabilities, and limitations of a system. This can lead to human factors–related issues including inflated expectations, uncalibrated trust, negative adaptation, or simply operational errors, which could result in safety critical consequences. Mental models are constantly being updated, with the updating of long-term knowledge based on exposure to scenarios. This is especially important in the context of ADAS and users' mental models, since ADAS technology is relatively new resulting in drivers generally starting off with no or very limited prior knowledge and hence potentially sparse and inaccurate mental models (Beggiato & Krems, 2013; Victor et al., 2018).

Past research has found that ADAS users may be generally unaware of system limitations and capabilities. McDonald et al. (2018) reported low awareness among users of ADAS features and found that only about 10% of drivers actively sought more information about equipped ADAS features. Jenness et al (2008) found that only about 28% of ADAS users (from a pool of about 370 participants) were aware of their system's functionalities and limitations. Mehlenbacher et al (2002) reported that 40% of their study population's drivers did not read the owner's manual at all, and the other 60% reported to have only read the manual partially.

With low knowledge and experience with ADAS, drivers may either lack an initial mental model (Beggiato & Krems, 2013) or have inaccurate or incomplete mental models. These flawed mental models can potentially result in driver errors that can negate any safety advantages of ADAS (Stanton & Salmon, 2009; Victor et al, 2018; Gaspar et al., 2021). Additionally, incomplete mental models may contribute to mode confusion where drivers may be unsure about the system state, system responsibility, and whether driver interventions are necessary (Endsley, 2017; Wilson et al, 2020).

The initial formation and development of mental models may be highly dependent on the source, accuracy, and accessibility of the information. For example, the informational content, the framing, and the design of owners' manuals have an impact on how drivers understand complex ADAS technologies (McDonald et al, 2018; Singer & Jenness, 2020). In addition, after an initial mental model has been established by a user, the subsequent evolution and strengthening (or weakening) of these mental models can be highly influenced by a user's unawareness of system limitations, or inflated expectations of a system. This is more pertinent when one experiences failures or malfunctions of the technology, or when experiencing situations (edge cases) where a system reaches the limits of its capabilities or is out of its operational design domain (ODD). One could then learn from these experiences and improve one's understanding, or the experiences may negatively affect trust, acceptance, and hence use of a system (Beggiato & Krems, 2013).

Moreover, research has also shown that driver trust is associated with system understanding. Incorrect expectations or miscalibrated trust levels in the system may result in misuse of the system (Dickie & Boyle, 2009). Lack of knowledge could also result in distrust and disuse of systems after encountering edge-case events (Beggiato & Krems, 2013).

Other human factors challenges in the context of ADAS include potentially adverse effects on driver workload (Hungund et al, 2021; De Winter et al., 2014). Interestingly, informing drivers about the functions, limitations, and operations of their system and therefore, improving their mental models about the system, can lead to increased workload (Khastgir et al, 2019). Thus, methods of improving knowledge without an adverse effect on workload are desirable.

Past studies have suggested that through experience and exposure, one could acquire the necessary knowledge to bridge the gaps in drivers' mental models about their systems (Beggiato & Krems, 2013; Carney et al, 2022). For example, a driver may learn that an ACC system should not be used in particular weather conditions because they have tried to do so and found that the system performed poorly. Other studies have shown that participants have some preference towards experimentation and real-world exposure to edge-case events, in terms of gaining knowledge and understanding about their systems (Jenness et al, 2019). Similarly, another study showed how exposure to on-road situations helped drivers to update and improve their mental models and improve their trust and acceptance of the system (Novakazi et al, 2020). Despite the potential benefits of real-world experience and exposure in improving a driver's understanding of a system, this approach is not without risk. This is especially so, given that system limits or failures often require a quick and decisive response and that drivers' experiences in specific situations will vary widely.

Objective

Given the importance of mental models towards safe interaction with ADAS and the various human factors challenges regarding ADAS such as miscalibrated trust and the effect on workload, it is important to understand how different types of driving experiences and exposures affect drivers' mental models about ADAS. The objective of this study was to examine how the frequency and quality of exposure (*exposure* defined as driving through events or situations that have some bearing on the functions of the ACC) affect drivers' mental models about ACC, their trust, workload, and their use of the systems as measured by their behaviors around disengaging ACC.

This research employed an experimental longitudinal driving simulation study to expose drivers to ADAS technologies as well as associated edge cases over time. Drivers with minimal experience with ACC were recruited and exposed to the technology through simulated drives over multiple visits separated by approximately a week.

Method

Participants

Sixteen drivers, aged between 21 to 54 years (mean = 29.6; SD = 4.2) were recruited for this longitudinal driving simulator study. The participants were pre-screened for the study through an online survey, which determined if they had prior experience and familiarity using ACC. Based on their responses, only novice users of ACC, i.e. those participants that indicated that they have never used ACC or indicated that they were "not at all familiar" or "slightly familiar" with ACC, were chosen to participate in the study. They were also required to hold a valid United States driver's license to be eligible for participation. The study received prior IRB approval for human subject testing.

Participants were incentivized to participate and remain in the study via the following incentive structure. Each participant was offered up to $100 for completing all four study visits. The incentives were offered on an increasing basis with each subsequent visit to encourage participants to complete all visits and minimize attrition. Specifically, participants were paid $15, $20, $30, and $35 for visits 1, 2, 3, and 4, respectively. Following their 4th visit, participants were also automatically enrolled in a raffle for an additional $100.

Equipment and Materials

Driving Simulator

The study utilized a Realtime Technologies (RTI) full-cab driving simulator (Figure 1), which is a fixed-base driving simulator running on RTI's SimCreator engine. The simulator consisted of a 2013 Ford Fusion cab and five screens situated in front of the cab giving the driver a 330-degree field of view. The simulator also provided the driver with rear views of the simulator environment with the help of two dynamic side-mirrors and a rear-view mirror. A five-speaker surround system simulated external environmental sounds and two-speakers simulated in-vehicle noise.

The SimCreator engine enabled the designing and scripting of edge-case events in the virtual world along with the ability to design visual elements on the instrument panel. Moreover, audio cues to assist the driver when traversing through the virtual world were also scripted. The SimCreator engine also utilized the SimADAS package, which enabled the simulator to include ADAS features such as Adaptive Cruise Control, Blind Spot Monitoring, Lane Keep Assist, etc. The ACC system that was utilized for this study had functionalities and limitations mirroring those of ACC systems found in the real world and could maintain the vehicle's speed and distance from the lead vehicle based on the driver-defined settings. The simulator collected vehicle measures and real-time recordings of the participants' eye, foot, and hand movements. A Smart Eye Pro eye-tracker system was also utilized, however, data from this component are not considered in the current report.

Figure 1: University of Massachusetts Human Performance Laboratory Driving Simulator

Scales and Surveys

Participants' *trust* in the ACC system was measured after each drive using the trust survey by Jian et al (2000) and an overall trust score was derived from the mean of twelve items on this survey. *Workload* was similarly assessed after each drive using the NASA Task Load Index (Hart & Staveland, 1988; see Appendix A).

To measure changes in the participants' mental models about ACC, the research team developed a mental model survey. The survey consisted of 54 items and each item included a true or false statement regarding ACC functions, limitations, and operational capabilities. The participant rated their agreement with each statement on a ten-point scale (ranging from 1 to 10, with higher ratings suggesting higher agreement). An example for an item that is a true statement would be, "ACC will accelerate if a slower vehicle ahead moves out of the detection zone." Similarly, an example for an item that is a false statement would be, "ACC can steer your vehicle automatically." The agreement/disagreement rating was then followed by a 3-point confidence rating, i.e., low confidence, medium confidence, and high confidence, for each response. The complete survey can be found in Appendix A.

For each item, a composite score was derived based on the participant's responses on both the agreement and confidence scales. To derive the scores, the ten-point agreement scale was translated on a scale ranging between −5 and 5 indicating the lowest and highest agreement range respectively. Next, the confidence scale was translated to a multiplier scale. If a response on the agreement scale was leaning towards the right direction, i.e., greater than 0, the response was deemed correct, and the subsequent confidence multiplier would be either 1, 2, or 3 (for low, medium, and high confidence ratings, respectively). However, if a response on the agreement scale was leaning towards the wrong direction, i.e., less than 0, the response was deemed incorrect, and the subsequent confidence multiplier would be either 1, 2, or 6 (for low, medium, and high confidence ratings respectively). This approach was taken to introduce an additional penalty in the score for a high-confidence rating for an incorrect response. Therefore, each item on the mental model survey would have a composite score ranging from −30 to 15 based on the scoring described above. An overall *Mental Model Score* was derived from the mean of all composite scores on the survey.

Experimental Design

The experimental design was a mixed design, with *quality of exposure* as the between-subject variable, and *exposure frequency* as the within-subject variable. Quality of exposure was defined by two conditions (and participant groups)—the Regular Exposure group encountering *routine* edge-case events and *non-events*, and the Enhanced Exposure group encountering *routine* and *rare* edge-case events. In this study, edge-case events were defined as driving situations where ACC can no longer operate appropriately due to the system having reached the limits of its operational design domain. Routine edge-case events refer to edge-case events that are more commonly encountered when driving, while rare edge-case events refer to those that occur with a lower frequency during driving. The non-events encountered by the Regular Exposure group were situations that had no consequence to the normal functioning of ACC. Given the lack of real-world crash datasets from which one could derive crash types and frequency of occurrence, the categorization of the edge-case events was based on the team's expert opinions, taking into account the nature of the events and thus their potential rarity (or commonness) in everyday driving.

Exposure frequency was defined by the number or visits (sessions) made by the participants for the study. Participants in both groups were required to drive through a total of four counterbalanced drives during four separate visits (one drive per visit). A gap of at least five days was maintained between each of the visits. Each drive featured five scenarios based on the participants' group assignments. For the Regular Exposure group, participants encountered four different drives each containing five scenarios—three featuring routine edge-case events (shown in blue in Figure 2 and Table 1) and two non-events (shown in grey in Figure 2 and Table 1). The drives for the Enhanced Exposure group contained five scenarios as well—three featuring routine edge-case events (shown in blue in Figure 2 and Table 2) and two rare edge-case events (shown in yellow in Figure 2 and Table 2). These conditions have been visualized in Figure 2, where each visit involves one drive with five scenarios each. As a result of this design, the Enhanced Exposure group encountered two more edge-case events per drive compared to the Regular Exposure group due to the inclusion of the two additional rare edge-case events. The color-coded scenarios represent the type of events encountered (routine edge-case, rare edge-case, or non-events). The order of scenarios within each drive was fixed ensuring that every participant encountered the scenarios at the same instance within the drive. The order of the drives received by each participant was counterbalanced across and within each group. For descriptions of scenarios within each drive, please refer to Table 1 and Table 2.

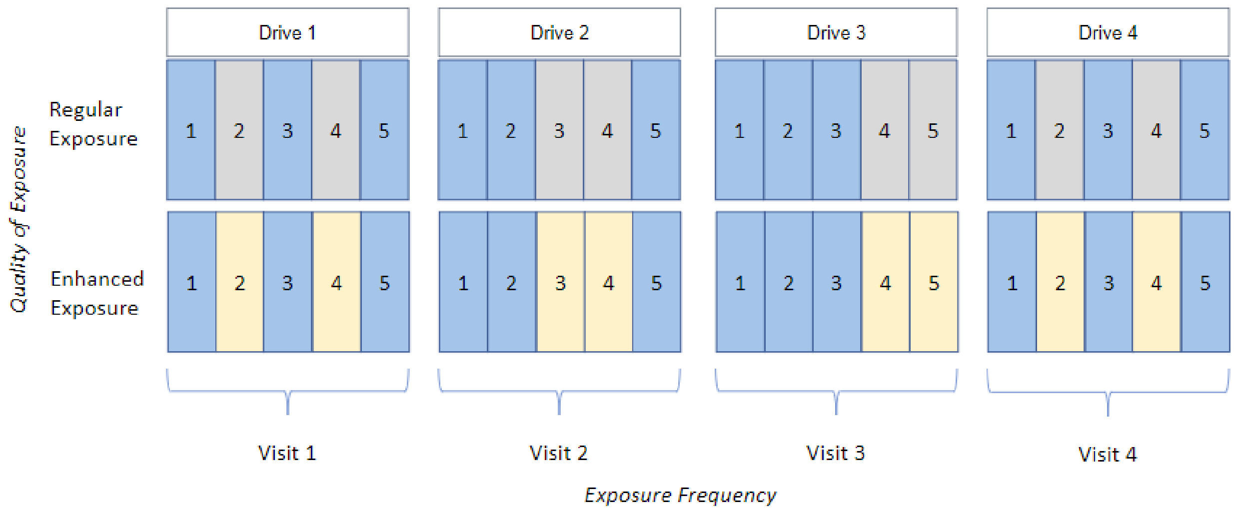

Figure 2. Typical representation of scenario order in each drive for each group for each visit

Table 1. Description of Drives and Scenarios for the Regular Exposure group (blue = routine edge-cases; gray = non-events).

Drive No.	Scenario No.	Description
1	1	Traffic cones—the driver encounters traffic cones that are placed near the shoulder, slightly encroaching into the right lane
	2	Bridge—the driver encounters a bridge
	3	Slow-moving traffic—the driver reaches a line of slow-moving vehicles on the highway
	4	Car on the right shoulder—the driver encounters a car parked on the right shoulder
	5	Merging lane—the driver encounters a merging of lanes
2	1	Lack of lane markings—the driver reaches a roadway section where the lane markings are deteriorated causing surrounding vehicles to drive erratically
	2	Exit—the driver is instructed to take the exit approaching on their right
	3	Police car—the driver encounters a police car parked on the right shoulder
	4	Pedestrians on sidewalk—the driver encounters pedestrians walking on the sidewalk on their right
	5	Group of bicyclists—the driver encounters a group of bicyclists in the right lane
3	1	Roundabout—the driver encounters a roundabout in nighttime conditions
	2	Poor visibility due to fog—the driver encounters bad visibility conditions due to fog
	3	Lead vehicle with no taillights—the driver encounters a lead vehicle whose taillights are not visible, i.e. not switched on
	4	Digital billboards—the driver reaches a roadway section with several brightly lit digital billboards
	5	Construction zone on opposite side—the driver encounters a construction zone on the opposite side of the roadway
4	1	Pedestrian crossing—the driver approaches an intersection with the traffic lights (lit green) and a pedestrian approaches the edge of the crosswalk in the driver's travel path
	2	Billboards—the driver reaches a roadway section with several billboards placed close to each other
	3	Heavy traffic near exit—the driver encounters slow-moving traffic near an exit
	4	Shopping area—the driver encounters a shopping area on their right side with stores and several parked vehicles
	5	Motorcyclist in travel lane—the driver encounters a motorcyclist that cuts into their travel lane

Table 2. Description of Drives and Scenarios for the Enhanced Exposure group (blue rows = routine edge-cases; yellow = rare events).

Drive No.	Scenario No.	Description
1	1	Traffic cones—the driver encounters traffic cones that are placed near the shoulder, slightly encroaching into the right lane
	2	Straddling lead vehicle—the driver encounters a lead vehicle that is straddling the lane lines
	3	Slow-moving traffic—the driver reaches a line of slow-moving vehicles on the highway
	4	Swerving lead vehicle—the driver encounters a lead vehicle that is swerving in and out of their travel lane
	5	Merging lane—the driver encounters a merging of lanes
2	1	Lack of lane markings—the driver reaches a roadway section where the lane markings are deteriorated causing surrounding vehicles to drive erratically
	2	Exit—the driver is instructed to take the exit approaching on their right
	3	Non-standard-shaped lead vehicle—the driver encounters a non-standard-shaped lead vehicle, i.e., a cement truck
	4	Sharp curve—the driver reaches a sharp curved section of an undivided highway
	5	Group of bicyclists—the driver encounters a group of bicyclists in the right lane
3	1	Roundabout—the driver encounters a roundabout in nighttime conditions
	2	Poor visibility due to fog—the driver encounters bad visibility conditions due to fog
	3	Lead vehicle with no taillights—the driver encounters a lead vehicle whose taillights are not visible, i.e. not switched on
	4	Bad weather—the driver encounters a lead vehicle in bad visibility conditions due to fog
	5	Oncoming vehicle—the driver encounters a construction zone on the opposite side of the roadway and a vehicle moves into their travel lane from the opposite direction to pass the construction zone
4	1	Pedestrian crossing—the driver approaches an intersection with the traffic lights (lit green) and a pedestrian approaches the edge of the crosswalk in the driver's travel path
	2	Stopped truck and lead vehicle—the driver encounters a lead vehicle in their (right) lane that suddenly changes to the left lane to pass a stopped truck with hazard lights
	3	Heavy traffic near exit—the driver encounters slow-moving traffic near an exit
	4	Sharp curve—the driver encounters a sharp curve on a divided highway
	5	Motorcyclist in travel lane—the driver encounters a motorcyclist that cuts into their travel lane

Procedure

During the participants' first visit, they provided their informed consent and were given a document that provided an overview of ACC, summarizing the functions and operations of ACC in a succinct manner. Next, they filled out a demographics questionnaire that collected basic information about age, gender, licensure, as well as driving frequency, followed by a pre-drive Simulator Sickness Questionnaire (SSQ). Calibration of the eye-tracker was conducted followed by a short practice drive where drivers could familiarize themselves with the controls of the simulator, the virtual environment, as well the controls for the ACC system. The practice drive lasted for up to five minutes. Following the practice drive, the participants drove through the main drive, which was the counterbalanced drive according to their group assignment (see Tables 1 and 2). Following the drive, the post-drive SSQ, the mental model survey, the NASA TLX, and the trust survey were administered. The participants were compensated for each visit. The experimental procedure remained similar for each subsequent visit, except for the demographics survey, which was administered only during the first visit.

Data Analysis

The overall trust score was derived from the mean of twelve items on the survey (Jian et al., 2000). Workload was analyzed according to each of the six sub-scales of the NASA-TLX. An overall *Mental Model Score* was derived from the mean of all composite scores on the survey, based on the combination of accuracy and confidence (see above).

Participants' use of the ACC system was measured by the proportion of events for which they disengaged ACC, and by the quality of their handling of the vehicle after disengaging ACC. For the former, the proportion of disengagements for types of events (routine, rare, and non-event) was recorded. With respect to quality of vehicle handling, the drivers' speed variability (i.e., standard deviation of velocity, SD-V), lane keeping variability (i.e., standard deviation of lane offset, SD-LO), and their maximum resultant acceleration (MaxRA) were derived for each disengagement event from the point of disengagement until the end of the predefined event window (Du et al, 2020).

Linear regression models were used to statistically analyze the associations between the independent variables and dependent variables. Separate models examined participants' trust, workload, *Mental Model Score,* SD-V, SD-LO, and MaxRA, and interaction effects were considered between the independent variables in the models. The significance level was set to 0.05.

Results

Mental Model Scores

There was a main effect of exposure frequency ($\beta = 1.55$, $p = 0.02$, $\eta^2 = 0.19$), and a main effect of quality of exposure ($\beta = 2.25$, $p < 0.001$, $\eta^2 = 0.29$) on mental model scores (Figure 3). Drivers' scores increased significantly over exposure, and the Enhanced Exposure group had significantly higher scores (mean = 8.1, SD = 2.1) as compared to the Regular Exposure group (mean = 5.8, SD = 1.8). No significant interaction effects were found.

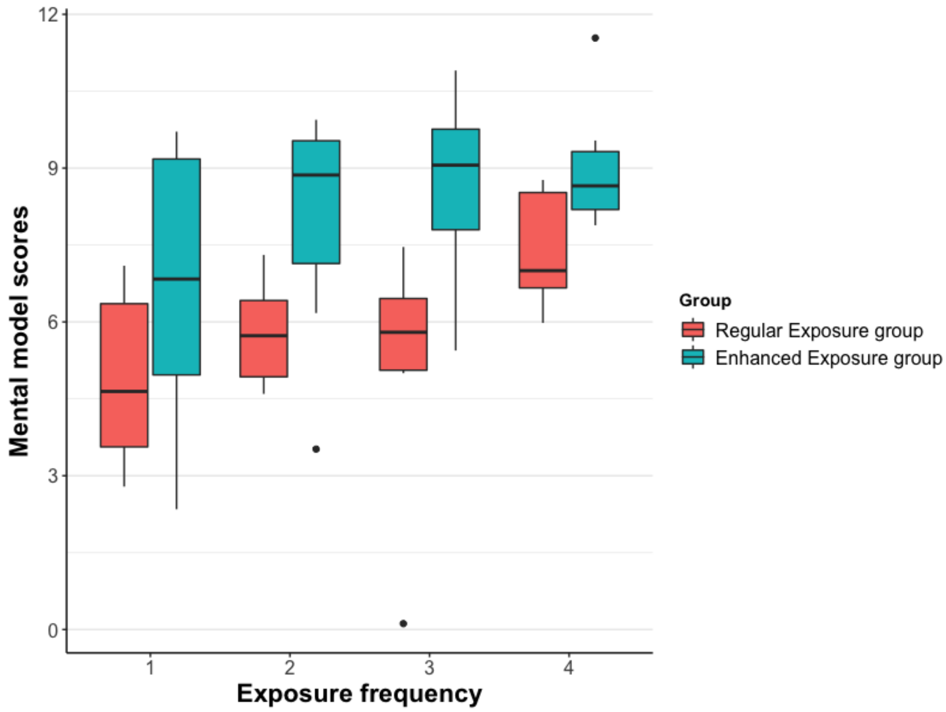

Figure 3. Mental Model Scores across multiple exposures for the Regular Exposure and Enhanced Exposure groups

Trust

There was no main effect of exposure frequency on trust; however, there was a main effect of quality of exposure ($\beta = -1.09$, $p < 0.001$, $\eta^2 = 0.17$) on trust, with the Enhanced Exposure group having significantly lower trust. Specifically, as compared to the Regular Exposure group (mean = 4.7, SD = 1.2), participants of the Enhanced Exposure group (mean = 3.6, SD = 1.3) rated themselves as having lower trust in the system (Figure 4). There was no significant interaction between quality of exposure and exposure frequency on participants' trust.

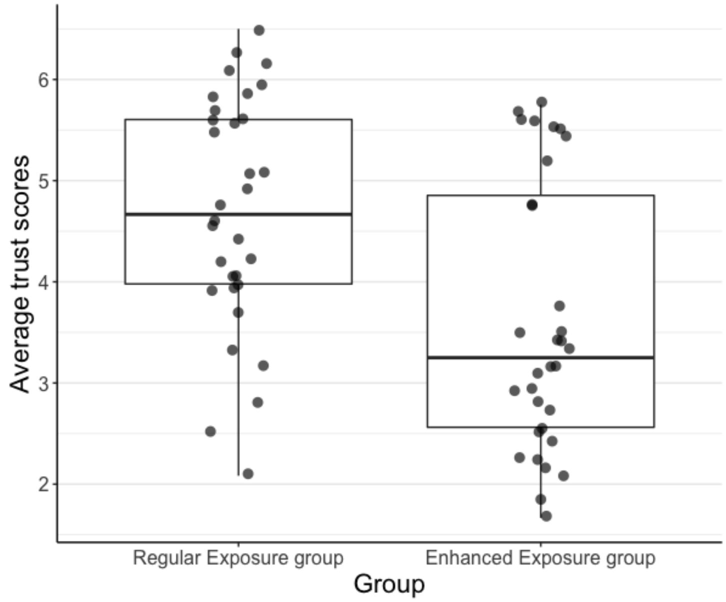

Figure 4. Trust Scores across the two groups

Workload

There was no main effect of exposure frequency on any of the task load indices (subscales of the NASA-TLX), with two exceptions. There was a main effect of quality of exposure on Mental Demand ($\beta = 1.59$, $p < 0.001$, $\eta^2 = 0.21$), with the Enhanced Exposure group (mean = 3.5, SD = 1.7) having significantly higher ratings than the Regular Exposure group (mean = 1.9, SD = 1.5) (see Figure 5). Similarly, there was a main effect of quality of exposure on Effort ($\beta = 12.78$, $p = 0.02$, $\eta^2 = 0.09$), with the Enhanced Exposure group (mean = 34.0, SD = 23.0) also having significantly higher ratings than the Regular Exposure group (mean = 21.2, SD = 17.7) (see Figure 6). No significant interaction effects were found for both Mental Demand and Effort.

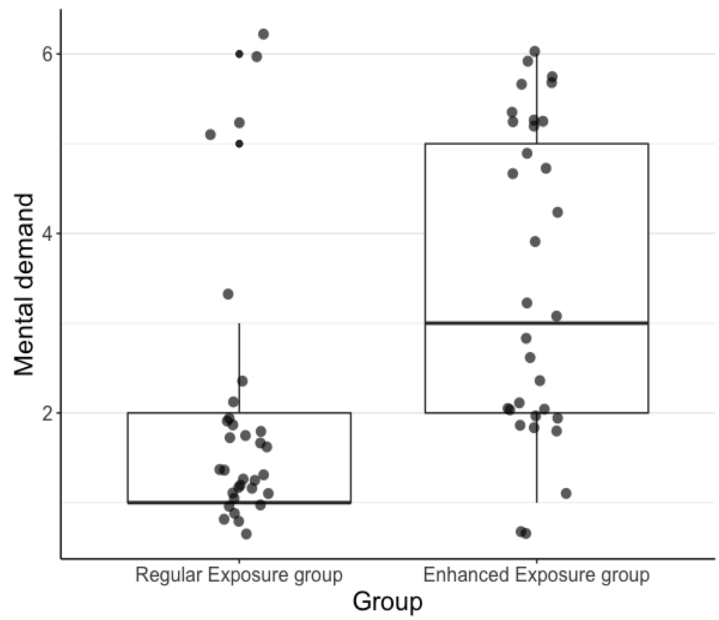

Figure 5. Mental Demand ratings across the two groups

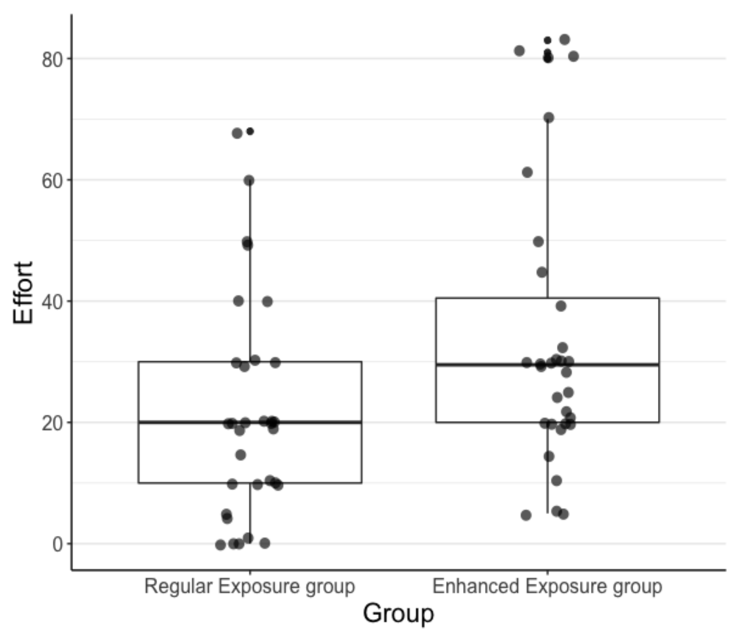

Figure 6. Effort ratings across the two groups

ACC Disengagements

ACC disengagements were recorded for each type of event in the drives: routine events, rare events, or non-events. The Regular Exposure group and the Enhanced Exposure group were collectively exposed to a total of 320 events. Both groups were exposed to 96 routine events, the Regular Exposure group had an additional 64 non-events, and the Enhances Exposure group had an additional 64 rare events. The table below shows the proportion of disengagements that each group had for the various event types.

Table 3. Proportion of Disengagement for Both Groups by Event Type

Group	Routine Events	Rare Events	Non-Events
Regular Exposure	25.8%	NA	3.2%
Enhanced Exposure	15.6%	20.3%	NA

Disengagement Behaviors

The disengagement data were reduced to only include those with actual post-disengagement values. (i.e., those drivers who disengaged). Regression analyses were run to examine the associations between SD-V, SD-LO, and MaxRA and exposure frequency (session number) and quality (group). No statistically significant associations were found. Figures 7–9 describe these disengagement behavior measures across groups and across time.

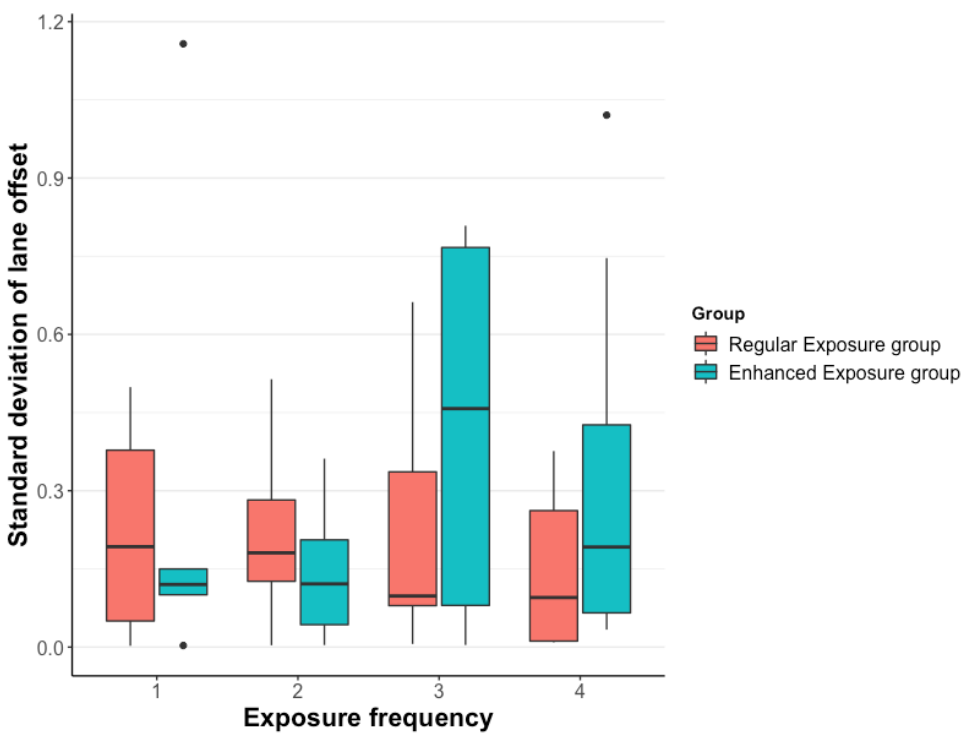

Figure 7. Standard deviation of lane offset by exposure quality (left panel) and frequency (right panel).

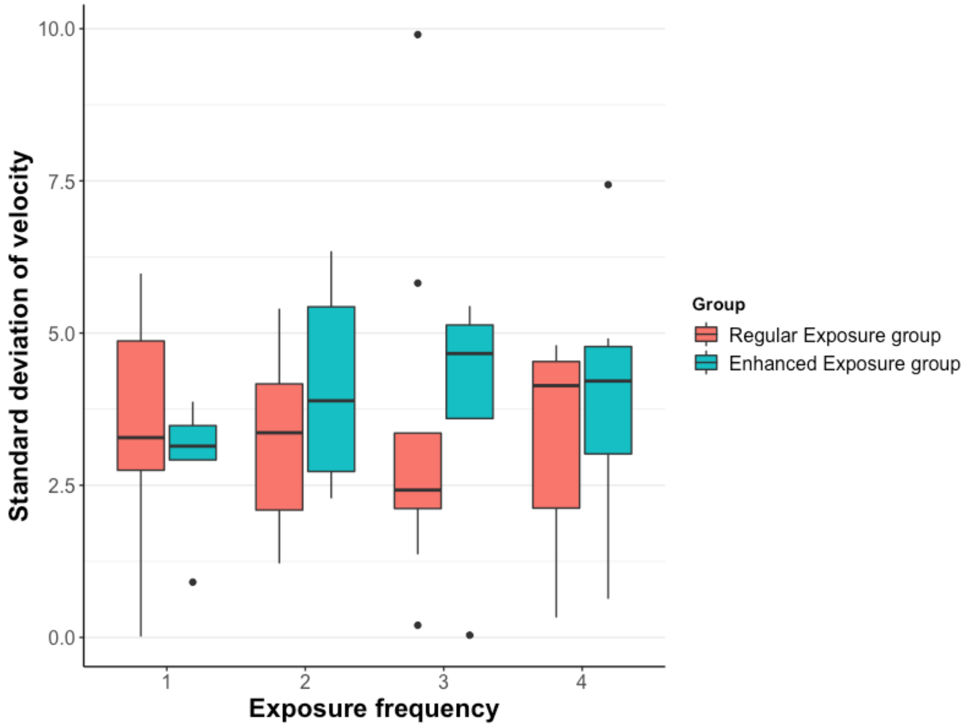

Figure 8. Standard deviation of velocity by exposure quality (left panel) and frequency (right panel).

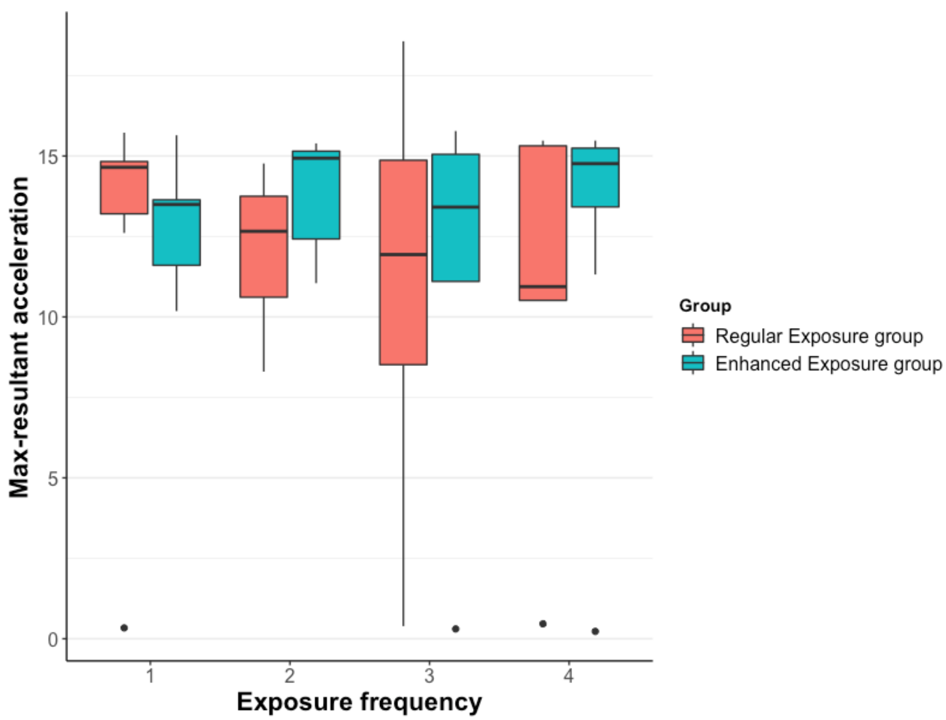

Figure 9. Maximum resultant acceleration by exposure quality (left panel) and frequency (right panel).

Discussion

Previous research has indicated that mental models (i.e., driver's knowledge and understanding) of system functions and limitations may be improved through repeated exposure and exposure to edge-case events (Beggiato & Krems, 2013; Novakazi et al, 2020; Carney et al, 2022). As such, this study investigated the effects of different types of exposure on drivers' mental models about ACC in a longitudinal driving simulator study. Specifically, the study examined how quality of exposure, characterized by different types of events and edge cases, and exposure frequency affected drivers' mental models of ACC, their trust, their workload, and their disengagement behaviors. The study recruited sixteen novice ACC users and randomly assigned them to either of two groups—one that encountered routine edge-case events only; the other that encountered both routine and rare edge-case events. All drivers made four visits and, in each visit, drove through a unique counterbalanced drive on the simulator featuring several ACC edge-case events.

The results from the analyses indicated that both exposure frequency and quality of exposure had effects on drivers' mental models. Participants' mental models about ACC improved with repeated driving exposure to ACC, with scores increasing with each subsequent visit. Results also showed that those drivers that encountered both rare and routine edge-case events (Enhanced Exposure group) had higher mental model scores than those who only encountered routine events (Regular Exposure group). These differences in the mental model scores could be due to the inclusion of rare edge-case events for the Enhanced Exposure group, which were intended to provide drivers with rich information about system limitations. It is also possible that the group differences were due to the increased frequency of edge-case events encountered by the Enhanced Exposure group per drive (five events) compared to the Regular Exposure group (three events), although the inclusion of mundane non-events was intended to counter this to some degree.

Results also indicated that there was no interaction effect between quality and frequency of exposure, suggesting that the rate of mental model improvement between the two participants groups over multiple exposures to ACC was comparable. These findings are significant since they underline the importance of experience and familiarity with ADAS in terms of knowledge improvement. Exposure to both rare and routine edge cases (as experienced by the Enhanced Exposure group) may also fast-track mental model development in novice ADAS users as opposed to simple exposure to routine edge cases and events where the ACC system functions as intended (as experienced by the Regular Exposure group). For example, as shown in Figure 3, it took the Regular Exposure group until the fourth session to match the level of system understanding exhibited by the Enhanced Exposure Group in the first session.

Since accurate mental models about a system are likely to promote safe operations, a practical implication that can be drawn from this study is that when introducing ADAS-equipped vehicles to new users, an effective strategy could include targeted exposure to different situations either through direct experience or through training, so that they can develop appropriate initial mental models about their systems. Prior driver training studies (Pradhan et al, 2005; Pradhan et al, 2011) have used an error-feedback approach (Ivancic & Hesketh, 2000) to provide a controlled but enhanced exposure to risk and such approaches could form an important pillar in terms of future training or consumer education research about ADAS and other advanced vehicle technologies.

Results from the analyses for trust and workload indicate that exposing novice ADAS users to rare edge cases may have an impact on trust. The Enhanced Exposure group exhibited lower trust in the system than the Regular Exposure group. This could suggest that trust decreased on encountering rare edge cases—a finding that is in line with past literature where encountering edge-case events without prior knowledge about them had an adverse impact on trust (Beggiato & Krems, 2013). However, as noted by Novakazi et al (2020), trust is a construct that develops over time with repeated exposure and interaction with the system. This evolution of trust may manifest different after more experience with the system, but this was unfortunately outside the scope of the current study (limited to four visits and relatively short driving sessions). The Enhanced Exposure group also experienced a higher mental demand and perceived effort than their Regular Exposure group counterparts. This is somewhat in line work by Khastgir et al. (2019), which showed an increase in workload following an increase in knowledge. The higher mental model scores of the Enhanced Exposure group and their higher ratings on certain task load indices may suggest such a relationship between knowledge and workload.

The analyses of the disengagement behavior from this study find some interesting outcomes. First, the enhanced exposure group had approximately half the proportion of disengagements for routine edge-case events compared to the other group. However, their overall engagement rate was comparable when the rare edge-case events are also considered. There is insufficient evidence to conclude if the fewer disengagement in routine edge-case events is because of an attribution of lower risk or importance to these routine events given the same group's exposure to rare events, or if it is due to other factors. For the Regular Exposure group, the low proportion of disengagements relative to routine edge-case events helps to corroborate the selection and classification of scenarios as does the higher proportion of disengagements to rare edge-case events for the Enhanced Exposure group. Additionally, the analyses found no differences in driving related behaviors (i.e., disengagement quality as measured by kinematic vehicle handling) across groups or across exposure frequency. It is possible that these vehicle-handling kinematics were not sensitive enough in the current context to differentiate levels of knowledge or expertise with the system.

Study Limitations

The study had a few limitations to note. First, the study was a longitudinal study conducted on a driving simulator; an on-road study over a longer time course would be useful in generalizing the results. However, it is worth pointing out that conducting such an experiment involving novice ADAS users could present potential safety-related risks in a real-world setting, and hence, a driving simulator study may be more appropriate in this regard. Additionally, the simulator setting allowed for greater control over the occurrences of critical events—outcomes whose prevalence in real-world interactions are much more uncertain. Second, the sample size was small due to difficulties in enrolling and scheduling participants arising from the pandemic, especially considering the longitudinal design. A larger sample size may help in better generalizing these results and to examine which components of the drivers' understanding (i.e. which components of the mental model survey) showed the most improvement after subsequent exposures to ACC. It should be noted however that the observed outcomes for the two independent variables for the three linear regression models were associated with medium to large effect sizes, and therefore may compensate for potential negative effects due to the small sample size. Third, the number of visits was limited to four, and it is unknown if any more visits could have affected the driver's mental models, trust, or workload differently. Fourth, it is unknown what effect participants' background characteristics such as age and propensity toward technology may have had on their trust in ACC. The current study was not designed to collect information about the participants' previous technology usage. Fifth, it is unknown if the differences in the mental model scores between the Enhanced Exposure group and the Regular Exposure group were driven due to the inclusion of rare edge-case events in the former group's drives, or due to the former encountering edge-case events at a higher frequency per drive than the latter. Future work could address this by having both the Enhanced Exposure and Regular Exposure groups encounter the same number of rare or routine events per drive, respectively. Lastly, all dependent measures considered for this study were self-reported survey measures, which may suffer from issues regarding reliability and user bias (Schacter, 1999).

Conclusion and Implications

Results from this study have positive implications in terms of ADAS usage and exposure and the improvements to one's mental model as a result. Stronger mental models may promote accurate and safer interactions with ADAS and prevent gaps in one's expectations and understanding of the system functions and limitations. This may ultimately lead to crash reductions and injury prevention, and improve general on-road safety. Importantly, exposure to both rare and routine edge cases may also afford a more effective path to mental model development in novice users as opposed to simple routine exposure. Approaches that include targeted exposure to different situations either through direct experience or through training or education should be considered.

While the findings indicate that drivers benefit from increased exposure to ACC and edge cases, the study also revealed differences in trust and workload between the groups. Exposure to rare edge-case events seems to be associated with a lower trust as compared to a group without that exposure. It is unclear if this lower trust reflects an appropriate calibration of trust, or if it may reflect a negative impact. Future work should consider this question. Additionally, it is unclear how trust would be affected in a hybrid "quality of exposure" condition (i.e., introducing rare edge-case events after multiple exposures to regular edge-case events or vice versa). However, this underlines the need for further investigation to understand and, if necessary, mitigate any adverse effects on trust and workload. One solution may be presenting the more rare and challenging edge-case events to drivers much later in their exposure cycle rather than consistently presenting such events from the start, where novice users most likely lack an appropriate initial mental model about the system functions and limitations. Another important challenge that may need to be addressed is regarding how to provide drivers with appropriate exposure in a safe manner. The study provided exposures on a driving simulator in a laboratory setting, which present almost no safety-related risks. However, exposure in the real world may not be as safe, and future work could explore methods or platforms to provide novice ADAS users with safe exposures in the real world to improve their mental models.

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Appendix A

Trust Survey (Jian et al., 2000)

1) **The system is deceptive**

1 2 3 4 5 6 7

2) **The system behaves in an underhanded manner**

1 2 3 4 5 6 7

3) **I am suspicious of the system's intent, action, or outputs**

1 2 3 4 5 6 7

4) **I am wary of the system**

1 2 3 4 5 6 7

5) **The system's actions will have a harmful or injurious outcome**

1 2 3 4 5 6 7

6) **I am confident in the system**

1 2 3 4 5 6 7

7) **The system provides security**

1 2 3 4 5 6 7

8) **The system has integrity**

1 2 3 4 5 6 7

9) **The system is dependable**

1 2 3 4 5 6 7

10) **The system is reliable**

1 2 3 4 5 6 7

11) **I can trust the system**

1 2 3 4 5 6 7

12) **I am familiar with the system**

1 2 3 4 5 6 7

NASA Task Load Index (Hart & Staveland, 1988)

NASA Task Load Index

Hart and Staveland's NASA Task Load Index (TLX) method assesses work load on five 7-point scales. Increments of high, medium and low estimates for each point result in 21 gradations on the scales.

Participant ID:	Date:

Mental Demand — How mentally demanding was the task?

Very Low — Very High

Physical Demand — How physically demanding was the task?

Very Low — Very High

Temporal Demand — How hurried or rushed was the pace of the task?

Very Low — Very High

Performance — How successful were you in accomplishing what you were asked to do?

Perfect — Failure

Effort — How hard did you have to work to accomplish your level of performance?

Very Low — Very High

Frustration — How insecure, discouraged, irritated, stressed, and annoyed wereyou?

Very Low — Very High

Mental Model Survey Items

For each statement below, please answer these two questions. (i) On a scale of 1-10, with 1 being strongly disagree, and 10 being strongly agree, please indicate how much you agree with the statement, and (ii) How confident are you about your response? (1–low confidence, 2–medium confidence, 3–high confidence).

1. ACC can regulate the vehicle’s distance from any type of lead vehicle
2. ACC helps a vehicle stay at a selected distance from the vehicle in front by signaling the lead vehicle to slow down if the distance between them is too large
3. When ACC is regulating a vehicle’s distance, there is no limit to how near or how it can follow another vehicle
4. The driver can select at what distance ACC will help their vehicle to follow another vehicle
5. ACC is able to Keep a safe distance from a truck with a pole extending 15 feet out from the back of the truck
6. ACC can operate the vehicle at the selected speed even if there is no vehicle in front
7. ACC will accelerate if a slower vehicle ahead moves out of the detection zone
8. ACC will react appropriately when Slower-moving vehicle in lane next to you changes lanes in front of you, leaving a very small gap
9. ACC Will react appropriately when the Car in front of you in your lane suddenly brakes hard
10. The driver can control how fast ACC 'drives' the car
11. When first activated, the ACC controls the vehicle at the speed the vehicle is currently travelling at
12. ACC works at any speed
13. The vehicle needs to be driving at 25 mph to turn on ACC
14. ACC is able to Reduce speed when the speed limit drops from 65 mph to 55 mph
15. ACC is able to merge one lane to the left when the right lane ends
16. ACC is able to Change lanes to pass a slower vehicle in your lane
17. ACC can steer the vehicle automatically
18. ACC can steer the vehicle, but only to keep the vehicle within the travel lane
19. ACC can be “turned on” or “turned off” using buttons on the steering wheel
20. The driver can turn off ACC using brake pedals
21. The driver cannot turn off ACC by turning the steering wheel
22. The driver can temporarily deactivate the ACC using the gas pedal
23. The driver can temporarily deactivate the ACC using a button or lever on the steering wheel
24. The driver can change the speed that the ACC is set to by simply pressing the gas pedal
25. The driver can adjust ACC's desired distance by using the brake pedal
26. The steering wheel buttons are the only way to control the desired distance setting.
27. The status of the ACC is shown on the instrument panel
28. ACC remains activated if a lead vehicle changes lanes
29. ACC slows down the vehicle when it detects driver inactivity
30. Some ACC systems may alert a driver if their hands are not on the wheel
31. ACC requires that the driver has their eyes on the road at all times
32. While driving with ACC activated, the driver can safely use their smartphone for texting
33. ACC is able to Bring the vehicle to a stop if the driver loses consciousness due to a

medical emergency
34. ACC can be ‘turned OFF’ by the driver at any time
35. ACC is designed to allow a driver to drive with their hands off the wheel
36. ACC is capable of operating without any involvement from a human driver
37. ACC is a 'self-driving' feature
38. ACC can help a vehicle react to non-standard shaped vehicles (eg. Tractors, Trailers, etc.)
39. ACC cannot help a vehicle to react to stationary objects on the road
40. ACC can help a vehicle react to all moving traffic in its lane
41. ACC can help a vehicle react to oncoming traffic
42. ACC does not help a vehicle react to pedestrians and animals
43. ACC reacts to potholes in the same lane
44. ACC cannot stop the vehicle at stop signs or stop lights
45. ACC is able to drive where lane lines are badly faded
46. ACC may not work in poor lighting conditions
47. ACC works on all roadway conditions
48. ACC works when Driving down a steep hill
49. ACC can work on all road types (eg. residential areas, highways, etc.)
50. ACC works when exiting onto a ramp from one freeway to another freeway
51. ACC works when Driving in stop-and-go traffic due to a traffic jam
52. ACC features may differ between manufacturers
53. ACC cannot alert a driver if erratic driving is detected from the vehicle ahead
54. ACC can help drivers navigate automatically