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An Examination of How Longer-Term Exposure and User Experiences Affect Drivers' Mental Models of ADAS Technology

Cher Carney, MS
John Gaspar, Ph.D.
Cheryl Roe, BS
University of Iowa

William J. Horrey, Ph.D.
AAA Foundation for Traffic Safety

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Title

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Authors

Cher Carney, John Gaspar, and Cheryl Roe
University of Iowa

William J. Horrey
AAA Foundation for Traffic Safety

Author ORCID Information

Gaspar: https://orcid.org/0000-0003-1106-2488
Carney: https://orcid.org/0000-0001-6741-4433
Roe: https://orcid.org/0000-0002-9759-4743
Horrey: https://orcid.org/0000-0002-9533-4411

Foreword

New vehicle technology continues to evolve, along with the role and responsibilities of drivers. Sophisticated forms of automation can control many aspects of driving: the vehicle's speed, headway, and lane position, and these capabilities continue to grow. Past research has documented gaps in drivers' understanding of these technologies as well important safety implications of such. Less is known about how drivers' understanding of new technology—sometimes referred to as mental models—develop and evolve over time.

This technical report summarizes a study examining how the understanding of an advanced driver assistance system, adaptive cruise control (ACC), changes over the first 6 months of ownership in a sample of new owners of vehicles. The results should help researchers, the automobile industry, and government entities better understand driver performance, behavior, and interactions in vehicles with advanced technologies.

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.

C. Y. David Yang, Ph.D.

Executive Director
AAA Foundation for Traffic Safety

Dawn Marshall

SAFER-SIM Director
National Advanced Driving Simulator
The University of Iowa

About the Sponsors

AAA Foundation for Traffic Safety
607 14th Street, NW, Suite 201
Washington, D.C. 20005
202-638-5944
www.aaafoundation.org

Founded in 1947, the AAA Foundation for Traffic Safety in Washington, D.C., is a nonprofit, publicly supported charitable research and education organization dedicated to saving lives by preventing traffic crashes and reducing injuries when crashes occur. Funding for this report was provided by voluntary contributions from AAA/CAA and their affiliated motor clubs, individual members, AAA-affiliated insurance companies, and other organizations or sources.

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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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Abstract

Drivers often learn about the advanced driver assistance systems (ADAS) on their vehicles over time and through trial and error. While this experience can aid drivers' understanding about the systems, it may not necessarily lead to sufficient and accurate mental models, especially concerning less frequent "edge case" situations. This study recruited 39 new owners of vehicles equipped with ADAS technology to which the owners were naïve. The initial mental model of these owners was evaluated using a mental model assessment. To understand changes in mental models over time the assessment was repeated six times over the course of approximately 6 months. Weekly mileage, technology usage, and information regarding their exposure to edge case scenarios was also collected. At the end of the 6 months, participants completed a simulator drive using adaptive cruise control (ACC) that included several edge cases.

Over the course of the first 6 months of vehicle ownership, drivers' scores on the mental model assessment improved. These improvements were largely due to increased understanding of the technology's limitations as opposed to improvements in knowledge about system function. An evaluation of different clusters of drivers, based on knowledge as well as confidence revealed some important patterns in the evolution of these constructs. With respect to driving performance in the simulator session, the mental model scores were not predictive of responses to the edge cases. However, a comparison of the current mental model scores against weak and strong mental model benchmark scores gathered in a previous study revealed some additional insight about the role and effectiveness of exposure in mental model development. Overall, the combination of questionnaire, simulation, and naturalistic data used in the current study offers some important insight into how mental models are developed in new owners of vehicles equipped with advanced technology.

Introduction

There has been growing interest in advanced driver assistance systems (ADAS) since the early 2000s, to the point where these systems are now some of the most sought-after features drivers look for in their next vehicle. However, even as these systems can enhance safety and comfort, drivers must first accept, adopt, and use the systems in order to realize these benefits. Driver knowledge and understanding of ADAS—sometimes referred to as a driver's mental model—are important considerations in the safe and appropriate use of these systems.

A mental model has been defined as a reflection of an operator's knowledge of a system's purpose, its form and function, and its observed and future system states (e.g., Johnson-Laird, 1983; Rouse & Morris, 1986; Seppelt & Victor, 2020). It follows that an operator's mental model can have important implications in determining how they interact with a given system. An incorrect mental model can negatively impact both the potential safety benefits that are intended by the system and overall road safety. For example, Gaspar et al. (2021) found that drivers who had poor mental models concerning an adaptive cruise control system were less likely to react or slower to react to certain situations where the technology did not function compared with drivers who had strong mental models.

Mental models are based on a user's beliefs and perceptions and may be derived from various sources (e.g., a demonstration at the dealership, information on the internet, or the owner's manual). However, several studies have found that regardless of your initial mental model, real experience with the system leads to convergence to a more realistic understanding of the system functionality and limitations (Beggiato & Krems, 2013; Ojeda & Nathan, 2006; Weinberger et al. 2001; Singer & Jenness, 2020).

Actual on-road experience, or trial and error, is reportedly one of drivers' preferred methods of learning ADAS technologies (Jenness et al., 2008; Llaneras, 2006; Larsson, 2012). The amount of on-road experience necessary for the evolution of the learning process and the development of a mental model was analyzed by Beggiato et al. (2015). Researchers asked 15 drivers with no adaptive cruise control (ACC) experience to complete 10 drives on the same test route over a 2-month period. Results showed non-linear trends over time, with a steep improvement in the first session and a subsequent stabilization after the fifth drive (approximately 115 miles). They did not see any decline with ongoing experience; however, performance on the mental model questionnaire found that drivers seemed to be less aware of those system limitations that were not directly observed.

In addition to experience, or time spent using the system, mental models are impacted by exposure to situations that test their understanding of the system. Jenness et al. (2019) recently conducted several focus groups with participants who had purchased a vehicle with at least two ADAS features within the last year. Researchers used these sessions to identify sources of information that played a role in generating the mental model users had regarding the ADAS technologies. Several participants said experimentation with the system and actually encountering real-world edge cases helped them the most in understanding their ADAS features. This is supported by the results of a recent on-road study, which examined not just changes in mental models with time but changes due to encounters with specific edge cases (Novakazi et al., 2020). Naturalistic driving data from 132 participants were combined with data from in-depth interviews of twelve drivers who were showing different usage patterns. The results showed that experiencing different situations that challenged their understanding of the system helped the user to develop the appropriate mental model.

This project represents the second study in a line of research to explore the impact of drivers' mental models on performance. The previous study in this research program used a combination of screening and training to establish two groups of participants, one with weak mental models and one with strong mental models (Gaspar et al., 2020; 2021). To date, there have been very few longitudinal studies that have examined the evolution of mental models in new owners of ADAS-equipped vehicles in a naturalistic setting. Thus, the goal of this project was to assess the mental models of naïve users of specific technology and, using similar methodology as what was used in previous work, evaluate how their mental models change with greater exposure to the systems (i.e., time and experience).

Method

Drivers who had purchased their first vehicle equipped with ACC within the previous 6 weeks were recruited for the study. The quality of the participants' mental models regarding a typical ACC system was assessed at the start of the study. This mental model assessment was given again after 2 weeks, 4 weeks, 8 weeks, 16 weeks and at the end of the study (i.e., 6 months after start). They were also asked to report, on a weekly basis, the miles driven using the vehicle, miles driven using ACC, as well as any experiences they encountered in which they were confused by the actions of the ACC system. After 6 months, participants completed an experimental session in a driving simulator using an ACC system where they encountered several "edge case" scenarios. Driving performance during edge case situations was assessed and changes in the mental model were examined over time and level of usage. This study was completed with approval and oversight by the University of Iowa Institutional Review Board (IRB).

Participants

Thirty-nine experienced drivers between the ages of 25 and 65 (M=43.0, SD=12.1) were recruited via the National Advanced Driving Simulator (NADS) subject registry (Table 1).

Table 1. *Participants by Age and Gender*

	Males (N=17)	Females (N=22)
25–35 years	6	7
36–45 years	6	5
46–55 years	2	3
56–65 years	3	7

Each potential participant was screened for eligibility. They were required to have a valid drivers' license, have at least three years of driving experience, and drive at least 2,000 miles per year. Potential participants were also required to have purchased a vehicle (i.e., new or used) within the previous 6 weeks that was equipped with ACC, and ACC was not present on any vehicle they previously owned. In order to obtain the numbers necessary for data collection, recruitment took place over the course of approximately 9 months.

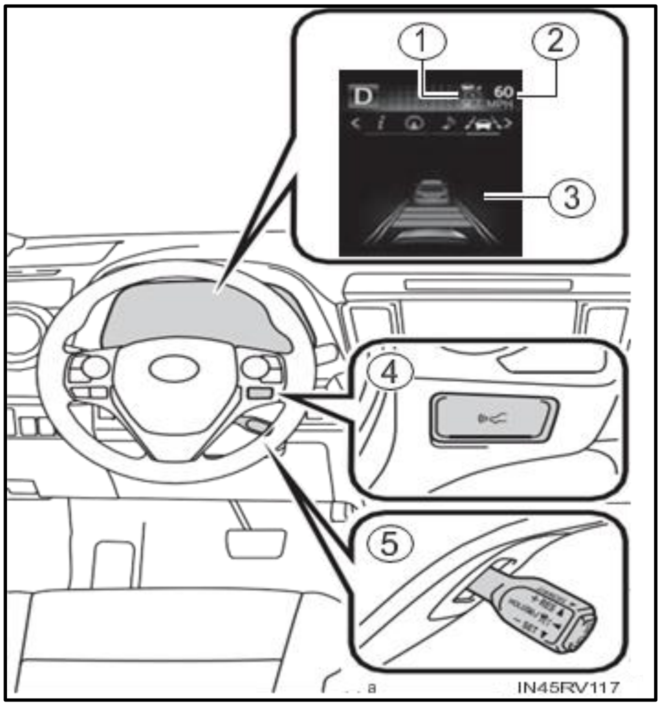
Simulator and ACC Technology

The study utilized the University of Iowa's National Advanced Driving Simulator (NADS) NADS-1 without motion (Figure 1). The simulator contained a full Toyota Camry cab and 360-degree wraparound display (Figure 2).

Figure 1 and 2. *The NADS-1 Dome Exterior and Interior with Toyota Camry Cab*

The ACC implemented in the simulator was representative of the 2019 Toyota RAV-4 and incorporated realistic features of the ACC user interface, as shown in Figures 3 and 4. To the extent possible, aspects of system functionality were designed to match the RAV-4 system (e.g., following gap distances).

Figure 3. *Location of Displays and Controls*



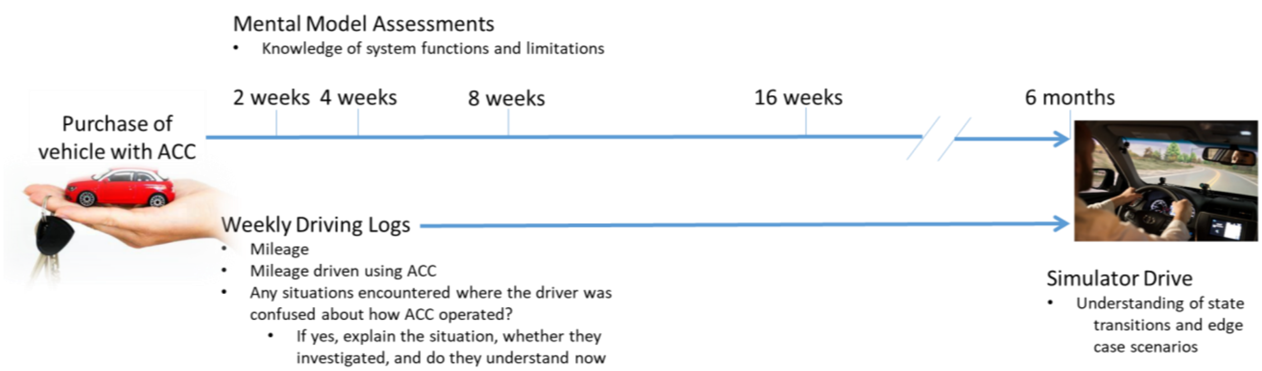
Panel indicator for (1) the system status on/off, (2) the set speed, and (3) the following gap setting are shown. (4) Shows the location of the button for setting following distance gap on the steering wheel and (5) shows the location of the ACC lever behind and to the right of the steering wheel.

Figure 4. *Close Up of ACC Interface*

Study Procedure

An overview of the study protocol is shown in Figure 5. Due to safety protocols developed in response to the COVID-19 pandemic, participants were consented over the phone and sent a link via email to complete their first mental model assessment (MMA). A second MMA was sent 2 weeks after study start, the third at 4 weeks, the fourth at 8 weeks, the fifth at 16 weeks.

Figure 5. *Study Procedure*



Note: Nine participants were unable to complete the simulator drive at the end of the 6 months due to COVID-19.

Mental Model Assessment

The Mental Models Assessment (from Gaspar et al., 2020; shown in full in Appendix A) asked questions about the participants' understanding of ACC at that point in time, according to the schedule depicted in Figure 5. The assessment was comprised of 20 true/false questions that evaluated a driver's understanding of specific functionality and limitations of the system. Examples of these questions are shown in Table 2.

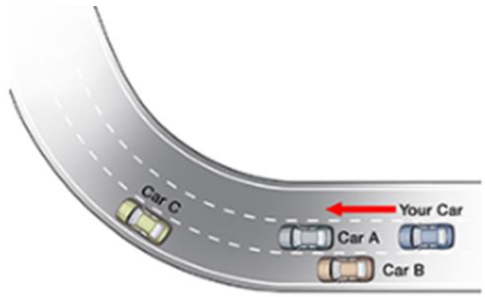
Table 2. *Examples of True/False Questions in the Mental Model Assessment*

Type of Question	Statement	Correct Answer
Functionality	Maintains the speed that you have set when there are no vehicles detected in the lane ahead	T
Functionality	Adjusts the speed to match faster vehicles ahead	F
Functionality	Will provide steering input to keep the vehicle in its lane	F
Limitation	Will correctly detect motorcycles and other smaller vehicles not driving in the center of the lane	F
Limitation	May not correctly detect stopped vehicles in your lane	T
Limitation	Reacts to stationary objects in the road (construction cone, tire, ball)	F

For each of the true/false questions, participants were asked to rate their confidence in their response on a 4-point scale (i.e., high confidence, moderate confidence, slight confidence, or no confidence).

Participants were also presented with three scenarios and asked to describe how they believed the vehicle would respond. Each of these scenarios required that they understand a potential limitation of the system. Figure 6 shows an example of one scenario.

Figure 6. *Example of Scenario Questions from Mental Model Assessment*



How might your ACC system behave in this situation? Why?

In the example above, the participant was given credit for answers that incorporated some version of the following:

- ACC may detect Car B as it goes around the curve because it is directly ahead of your vehicle
- My car might lose track of Car A as it goes around the curve. Depending on my set speed it may slow down or speed up

Overall, eight questions dealt with ACC functionality and 15 with the limitations of the system.

Weekly Mileage Readings and ACC Usage

Participants responded weekly to a questionnaire that asked them to provide their odometer reading, the number of miles (if any) driven by someone else, the number of miles driven using ACC, and whether they encountered any situations where the car behaved in a way they did not understand. If so, they were asked to provide details regarding this situation, whether or not they tried to figure out what had occurred, and what method they used to investigate (e.g., asked a friend, called the dealer, looked on the internet).

Simulator Drive

After 6 months of enrollment in the study, drivers were scheduled for a simulator drive at the NADS facility. Upon arrival, participants completed their sixth and final mental model assessment. They were then shown a PowerPoint presentation regarding the ACC system that they would be using in the simulator in case it differed from the system in the vehicle they own (i.e., the display or controls). Therefore, the presentation provided information on how to turn the ACC system on, set and adjust the speed, and turn the system off. The training presentation can be found in Appendix B.

Participants completed both a practice and an experimental drive in the simulator. These drives took place on a rural highway during daytime conditions. They were informed that the speed limits would change, however they were only to change the vehicle speed when they were instructed to do so, even if they were to see a speed limit sign with a different speed. This was done to ensure that specific events (described below) occurred as they were designed for each participant.

During the 20-minute practice drive, participants were acclimated to the simulator and interacted with the ACC system. A researcher was present in the simulator to provide instructions about how to turn ACC on, how to set a max speed, and how to adjust both the speed and the following gap. Recorded navigation instructions guided them along the route.

The experimental drive lasted about 40 minutes and required participants to interact with the ACC based on the knowledge of the system to which they had been introduced. They were instructed that during this drive they would set the ACC, make adjustments to the vehicle speed when instructed to do so, and to change the following gap if it was necessary or if they were instructed to do so. If the driver were to cancel ACC, they were instructed to set the ACC to the posted speed limit when they felt comfortable doing so. Participants were also instructed to stay in the right lane unless instructed otherwise or if they felt that the situation required a lane change.

The researcher sat in the back seat of the cab monitoring the driver's wellness, including symptoms of simulator sickness. The driving environments were designed to mimic the range of operational design domains for ACC. Specific events, described below, were integrated into the drive to measure potential errors stemming from incorrect or incomplete mental models. At the end of the study drive, participants exited the simulator and completed questionnaires relating to realism in the simulator and demographics.

Experimental Drives

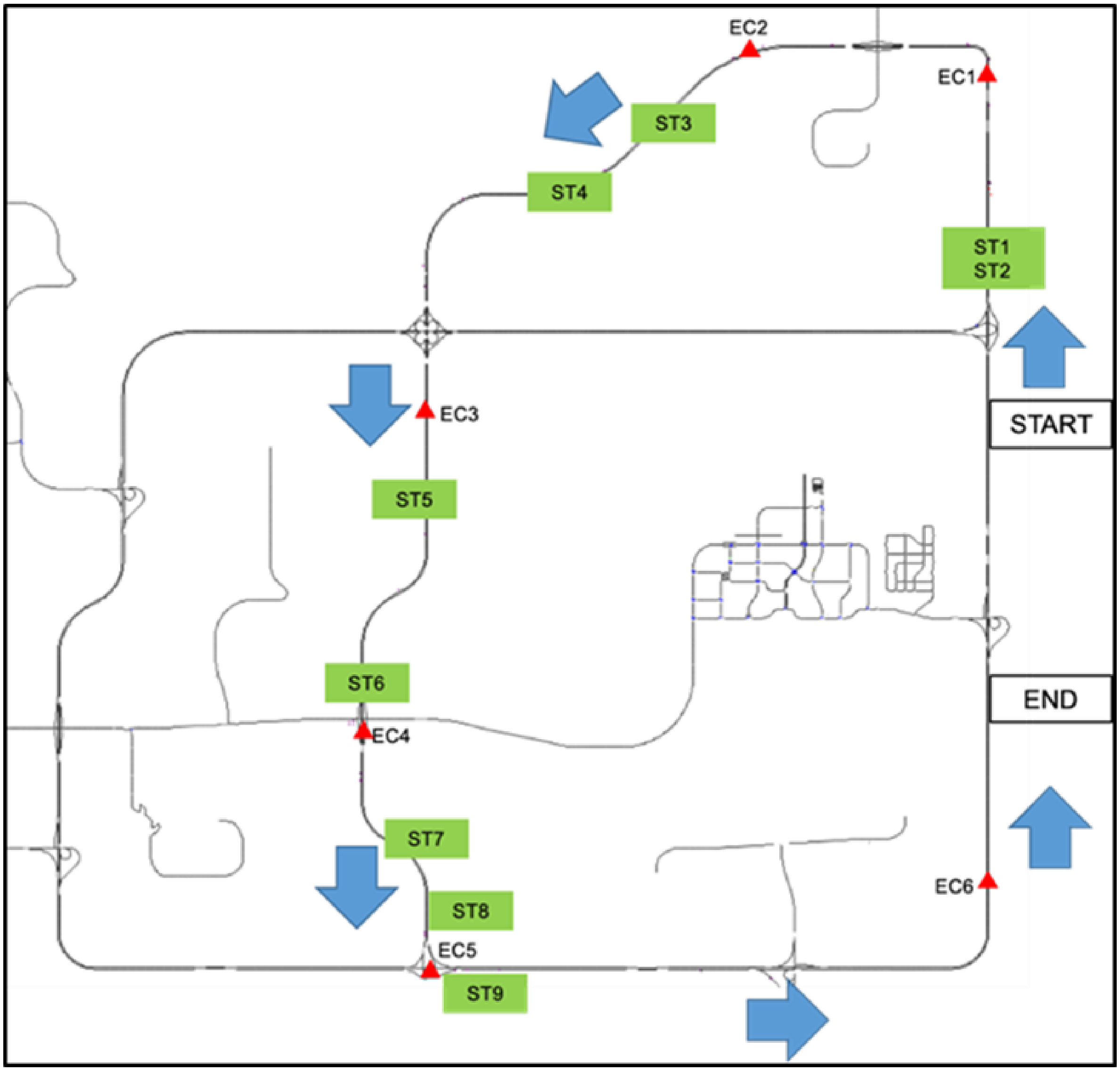
Database

Simulator drives were completed on the NADS Springfield virtual database. This experiment used a segment of the freeway portion of the database, shown in Figure 7. The roadway consisted of portions of divided highway, with either two or four lanes of traffic traveling in the same direction. Light ambient traffic was present during periods between events.

Edge Case Scenarios

The study drive included six edge case scenarios (EC1–6) as shown on the map in Figure 7. These scenarios were informed by Pradhan et al. (2020) and based on a subset of possible situations that exceeded the capability of the ACC system. Participants encountered events in the same order. All edge cases took place on the 2-lane divided highway. For most of the edge case scenarios, there were 1 to 2 vehicles in the left lane, making it more difficult for the participant to make a quick, evasive maneuver around the obstacle. Each of the scenarios is described in more detail below.

Figure 7. *Map of Experimental Drive*



ST=state transition and EC=edge case.

Figure 8. *Screenshots of Selected Edge Case Events Included in the Analysis*

Clockwise from top left, EC2 (slow-moving motorcycle), EC3 (work zone), and EC6 (offset lead vehicle)

Slow-Moving Vehicle (EC1). The participant vehicle was following the lead vehicle (LV) with the ACC speed set to 70 mph and a long following gap. The LV moved to the left lane to reveal a slow-moving vehicle (30 mph) in the right lane ahead. Although the ACC system detected the slow-moving vehicle, to avoid approaching the slow-moving vehicle at a large and uncomfortable speed differential, the participant had to slow to wait for the left lane to clear and safely pass the slow-moving vehicle.

Slow-Moving Motorcycle (EC2). The participant vehicle was following LV at 65 mph (with ACC speed set to 70 mph) when the LV moved to the left lane to reveal a slow-moving motorcycle in the right lane ahead. As ACC cannot always detect smaller vehicles, the simulation was designed to ignore the presence of the motorcycle, thus accelerating the participant vehicle to its set speed (70 mph). To avoid collision, the participant needed to slow down in order to allow the left lane to clear and safely pass the motorcycle. (Note: the drive was not stopped for collisions; the simulator vehicle simply passed through the object it collided with.) See Figure 8.

Work Zone (EC3). The participant vehicle was following LV at set speed of 55 mph. The LV moved to the left lane to reveal a work zone in the right lane ahead. The participant needed to slow down to allow the left lane to clear and safely change lanes to avoid the work zone. See Figure 8.

Fast-Moving Vehicle Merging On (EC4). The participant vehicle was travelling in the right lane with the ACC speed set at 60 mph and no LV ahead. Another vehicle was merging onto the roadway into the right lane, while travelling at a higher speed than the participant vehicle. In this case, the participant did not necessarily need to intervene with the ACC system as the merging vehicle was ahead of the participant vehicle.

Slow-Moving Semi-Truck (EC5). This scenario occurred on a curved portion of a highway on-ramp. Prior to taking the on-ramp, the participant was instructed to move to the left lane and adjust the set speed to 45 mph. A slow-moving semi-truck appeared midway through the ramp in the right lane. As ACC cannot always properly detect lead vehicles on hills or curves, the ACC detected the semi-truck as being a LV in the participant vehicle's lane, thus incorrectly reducing the participant vehicle's speed until it had passed the semi-truck. The participant did not need to intervene with the ACC system.

Offset Lead Vehicle (EC6). The participant vehicle (ACC speed set at 70 mph) followed the LV at 65 mph for about 6 minutes, at which point the LV drifted towards the right-hand shoulder. Similar to the Slow-Moving Motorcycle event (EC2), the simulation was designed to not detect the LV when it was offset in its lane as it was not positioned directly ahead of the participant vehicle. At this point, the participant vehicle's speed returned to 70 mph. The participant had to intervene in order to allow the traffic in the left lane to clear and safely pass the LV. See Figure 8.

State Transitions

Five system states that the ACC system could be in were identified and are described in Table 3. Throughout the drive participants were instructed to perform nine state transitions (ST1–9) as shown labeled in green on the map in Figure 7. These prescribed state transitions are described in Table 4. Additionally, state transitions could arise as a result of driver inputs or reactions to the edge case scenarios (e.g., to avoid a slow-moving vehicle revealed in their lane ahead). Drivers were not told what action to take in these situations and in most instances, there were several potential responses (i.e., take no action, brake to put the vehicle in standby mode, use the ACC lever to put the vehicle in standby mode, or turn the system completely off using the ACC lever). Potential state transitions related to the edge cases are described in Table 5.

Table 3. *Possible System States*

System state	Description
0	System ACC is off (neither ACC nor standard cruise control is activated)
1	ACC is on but no speed set (standby mode)
2	ACC is on with a set speed

Table 4. *Description of Prescribed State Transitions During the Experimental Drive*

	Instruction	Required Action	System State/ Transition
ST1	Turn on ACC	Press ACC button	0 to 1
ST2	Set ACC speed to 70 mph	Press ACC lever down	1 to 2
ST3	Change following gap to Short	Press gap button on steering wheel twice	2
ST4	Change ACC speed to 55 mph	Press ACC lever down to decrease speed	2
ST5	Change ACC speed to 70 mph	Press ACC lever up to increase speed	2
ST6	Change ACC speed to 60 mph	Press ACC lever down to decrease speed	2
ST7	Change following gap to Long	Press gap button on steering wheel once	2
ST8	Change ACC speed to 45 mph	Press ACC lever down to decrease speed	2
ST9	Change ACC speed to 70 mph	Press ACC lever up to increase speed	2

Table 5. *Description of Potential State Transitions During Edge Case Scenarios*

	Description	Driver Action	System State / Transition
EC1	Slow-Moving Vehicle	Brake (puts system in standby)	2 to 1
		Put system in standby using lever	2 to 1
		Turn system off using lever	2 to 0
EC2	Slow-Moving Motorcycle	Brake (puts system in standby)	2 to 1
		Put system in standby using lever	2 to 1
		Turn system off using lever	2 to 0
EC3	Work Zone	Brake (puts system in standby)	2 to 1
		Put system in standby using lever	2 to 1
		Turn system off using lever	2 to 0
EC4	Fast-Moving Vehicle Merging	No action	2
		Brake (puts system in standby)	2 to 1
		Put system in standby using lever	2 to 1
		Turn system off using lever	2 to 0
EC5	Slow-Moving Semi-Truck	No action	2
		Brake (puts system in standby)	2 to 1
		Put system in standby using lever	2 to 1
		Turn system off using lever	2 to 0
EC6	Offset LV	Brake (puts system in standby)	2 to 1
		Put system in standby using lever	2 to 1
		Turn system off using lever	2 to 0

Results

Thirty-seven participants, 16 males and 21 females, with an average age of 42 years, completed the 6 months of data collection and were included in the analysis of the mental model questionnaire by exposure to and experiences with ACC. Two participants were dropped from the study due to continued failure to provide their weekly mileage and ACC usage information.

Of those who completed data collection, twenty-seven participants, nine males and 18 females, with an average age of 45 years, were able to complete the simulator drive at the end. Nine participants were unable due to COVID-19 restrictions which coincided with the end of their 6-month window. One participant was dropped due to technical issues with the simulator. Additional analyses were performed using the data from these twenty-seven participants to map their MMA scores as well as exposure and experience onto driving performance in the simulator.

Data Reduction

For each of the MMAs completed, scores were calculated to arrive at an overall score as well as individual scores on specific items corresponding to the functionality and limitations of the ACC system. To account for a different number of items regarding functionality and limitations, percentage correct scores were used in all analyses. The open-ended questions were manually coded and scored based on key words or ideas according to a predetermined set of criteria. Confidence scores were calculated by averaging their ratings of confidence (i.e., high confidence=4, moderate confidence=3, slight confidence=2, or no confidence=1) across the different categories of questionnaire items (i.e., functionality, limitations, and overall) and converting that score to a percentage by dividing by 4.

Raw simulator data (sampled at 240 Hz) were reduced using custom MatLab scripts to generate summary measures for each participant for each event. For each driver, individual events were excluded if the setup failed (e.g., driver changed lanes just before the event) or if other aspects of the event functioned incorrectly (e.g., ambient traffic failed to maintain set gaps). Overall, 3.6% of individual events (4 of 111) were excluded from the analyses for these reasons. Analysis of driving performance included data from three of the edge case events, the offset lead vehicle (EC6), slow-moving motorcycle (EC2), and work zone (EC3) events. Initial response was calculated as the minimum of the time to deactivate ACC with the brake and time to initiate a steering response, measured by a change in steering wheel angle greater than five degrees. Data from the slow-moving vehicle (EC1) event were not included in the analysis because, unlike the three events that were included, ACC responded to the lead vehicle and therefore participants may not have responded while still avoiding a collision. Data from the fast-moving vehicle merging (EC4) and slow-moving semi-truck (EC5) events were also not included in the analysis. Ad hoc review of simulator and video data from this event indicated inconsistent responses by the ACC system to these events, which made it difficult to understand subsequent driver responses.

As noted above, this project represents the second study in a line of research to explore the impact of drivers' mental models on performance. The previous study in this research program used a combination of screening and training to establish two groups of participants, one with weak mental models and one with strong mental models (Gaspar et al. 2020). These groups were also compared against the participants in the current study to understand how mental models following exposure compare to established levels of understanding and how understanding translates to driving performance. For those analyses, the groups from the first study are labeled “strong” and “weak” and the participants from this study are labeled “exposure.” For driving data from the strong and weak groups, the same reduction procedure was applied.

All analyses were conducted in R (R Core Team, 2016) using the reduced data sets.

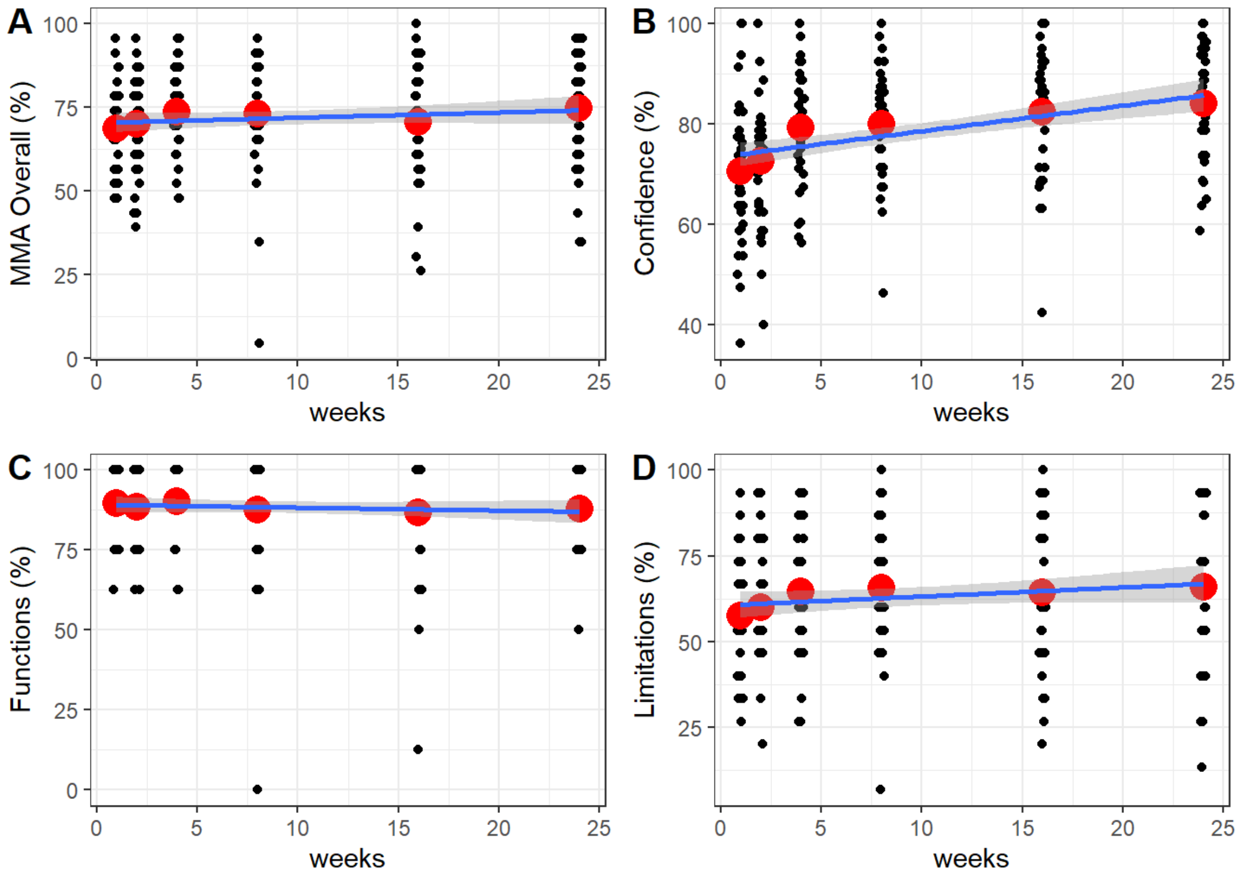
Mental Model Assessment Over Exposure

The initial analysis focused on whether performance and confidence on the MMA improved over time. The objective was to understand whether overall scores, functionality scores, and limitations scores changed over time and to what extent participants’ understanding of ACC improved over 6 months.

Figure 9 shows overall MMA scores, MMA confidence, and scores on functionality and limitation questions over the 6-month data collection window. Table 6 shows mean MMA scores and confidence by week. Paired t-tests were performed to compare the scores on these four MMA measures between weeks 1 and 24, the first and last test sessions.

There was a nominal increase in overall MMA scores between weeks 1 and 24 (approximately 6 percentage points on average), although the difference between the first and last test sessions was only marginally significant ($t(36)=1.76$, $p=0.08$). There was a significant increase in confidence (14 percentage points on average) in responses to MMA questions in the last session compared to the first ($t(36)=4.59$, $p<0.001$). There was a slight decrease in scores on MMA questions related to system functionality ($t(36)=0.66$, $p=0.51$). Figure 9 shows that this may have been due to a ceiling effect for functionality-related questions. Finally, although there was a nominal increase in MMA scores related to system limitations, the difference between sessions was only marginally significant ($t(36)=1.80$, $p=0.07$).

Figure 9. *MMA Overall (A), Confidence (B), Functionality (C), and Limitations (D) Scores*



Black points represent individual participants and red circles represent session means.

Table 6. *Mean MMA Component Scores by Week (%)*

Week	Overall	Function	Limitations	Confidence
1	68.6	89.5	57.5	70.6
2	69.9	88.5	60.0	72.6
4	73.7	90.2	64.5	79.4
8	73.2	87.5	65.6	80.2
16	70.6	86.8	64.3	82.5
24	74.9	87.8	65.9	84.1

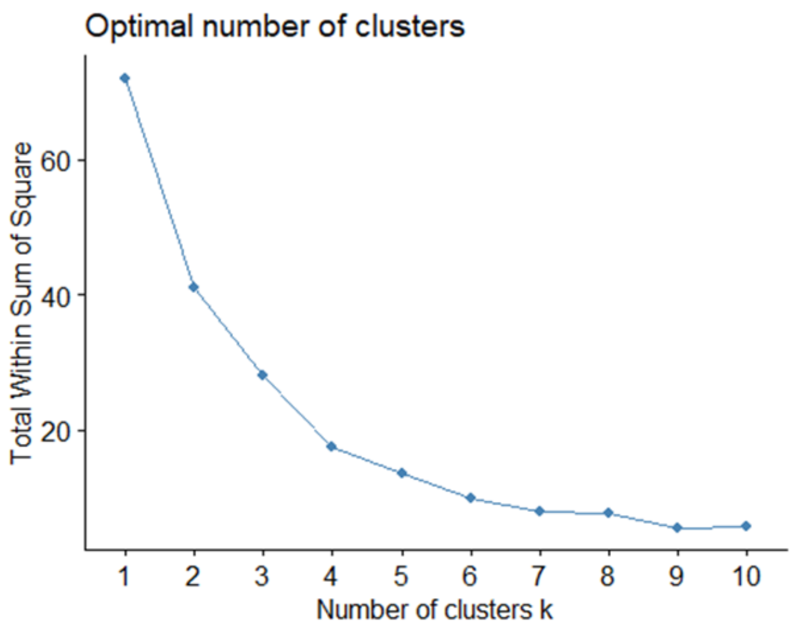
MMA Clusters

Lenneman et al. (2020) identified clusters of learners about driver support features (DSF) over a 6-month window based on semi-structured interviews and exposure to the DSF. The five resulting clusters comprised different combinations that can be roughly categorized based on level of understanding (i.e., mental model strength) and confidence in understanding. That is, clusters were defined not only by actual understanding of vehicle technology, but also by confidence in that level of understanding. Interestingly, Lenneman et al. (2020) found that one cluster of learners, dubbed “misinformed,” had poor overall understanding of the technology but high confidence in their understanding.

To identify whether there were groups of learners in this study that differed in combinations of MMA performance and confidence in MMA understanding, we performed a cluster analysis similar to that performed by Lenneman et al. (2020). Data included in the cluster analysis were overall MMA score (% correct) and MMA confidence score (%) from the final test session (i.e., week 24).

After scaling the data, we applied the elbow method in Python to determine the initial number of plausible clusters (Figure 10). This method indicated that four clusters was the optimal number.

Figure 10. *Cluster Diagnostics to Identify Optimal Number of Clusters*



A k-means cluster analysis was performed using the k-means function in R to divide participants into 4 groups (Table 7). Figure 11 shows a cluster map of the four groups based on combined MMA scores and confidence scores. They were assigned the following names:

- Strong Confident (SC). Cluster 2 in Figure 11. These participants had high final MMA scores and high confidence.
- Strong Unconfident (SU). Cluster 1 in Figure 11. These participants had high final MMA scores with lower confidence.
- Weak Unconfident (WU). Cluster 4 in Figure 11. These participants had low final MMA scores and low confidence.
- Weak Confident (WC). Cluster 3 in Figure 11. These participants had lower final MMA scores but were confident in their responses.

Figure 11. *Cluster plot showing the four clusters based on scaled (z-score) MMA score (overall %) and confidence*

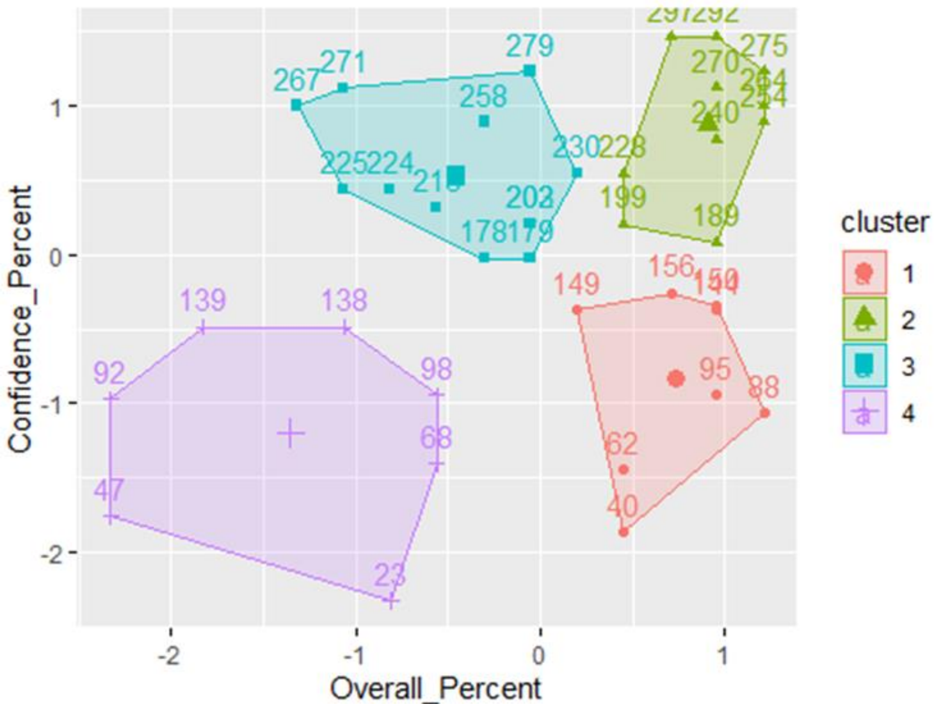


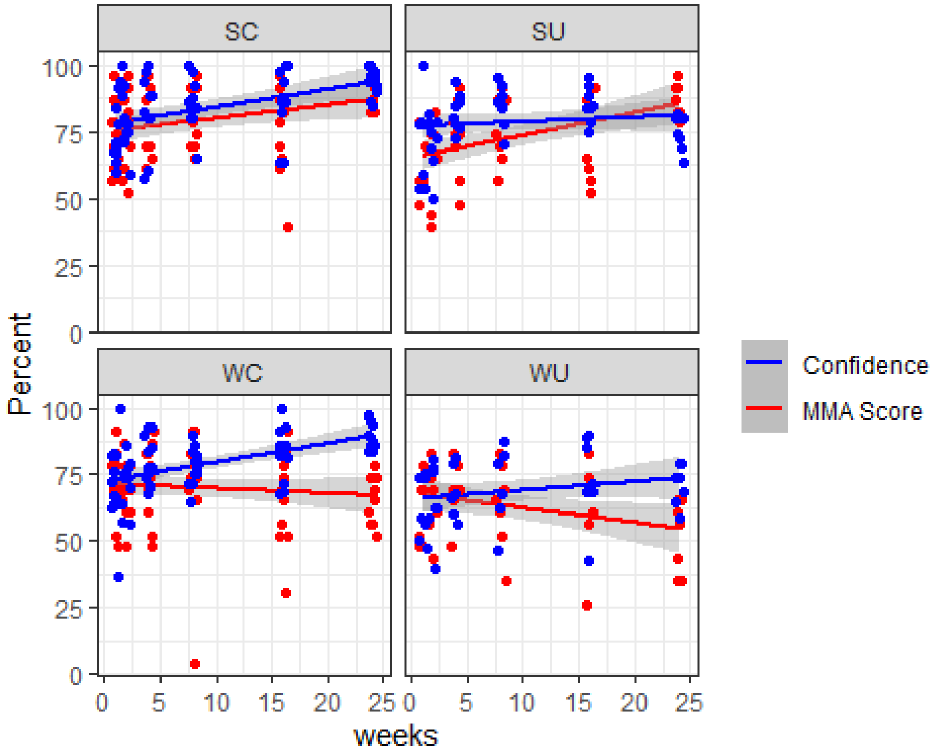
Table 7. *Number of Participants, Mean Overall MMA, and Confidence by Cluster Group*

Cluster	N	MMA	Confidence
SC	10	90.5	93.6
SU	8	87.5	75.0
WC	12	67.0	89.8
WU	7	51.6	71.1

Changes in Mental Models by Cluster Group

We were interested in whether there were differences in mental model development and confidence across the different cluster groups. Figure 12 shows MMA scores and confidence scores for the four cluster groups across the 24-week exposure. To examine whether there were differential changes in mental model strength and/or confidence, we computed ANOVAs with cluster group as a between-subjects factor and test session (first vs. last) as a within-subjects factor.

Figure 12. *MMA Scores and Confidence Scores for the Four Cluster Groups Across the 24-Week Exposure*



Differential improvement is reflected in the interaction between cluster group and test session. Table 8 shows the change in mean overall MMA score and confidence score for each of the four clusters. For overall MMA score, there was a significant interaction between cluster group and test session ($F(3,33)=2.83$, $p=0.05$). Both strong mental model cluster groups showed improvement on the MMA from the first to last session, whereas the weak cluster groups did not show improvement and actually showed lower mean scores in the final test session compared to the first. For mental model confidence, both of the confident clusters showed improved confidence scores between the first and last test session. The unconfident groups showed less of an increase in confidence scores between sessions.

Table 8. *Change in Mean MMA and Confidence by Cluster Group Between First and Last Test Session*

Cluster	N	MMA	Confidence
SC	10	15.2	19.2
SU	8	25.0	2.8
WC	12	−3.6	18.5
WU	7	−11.2	8.9

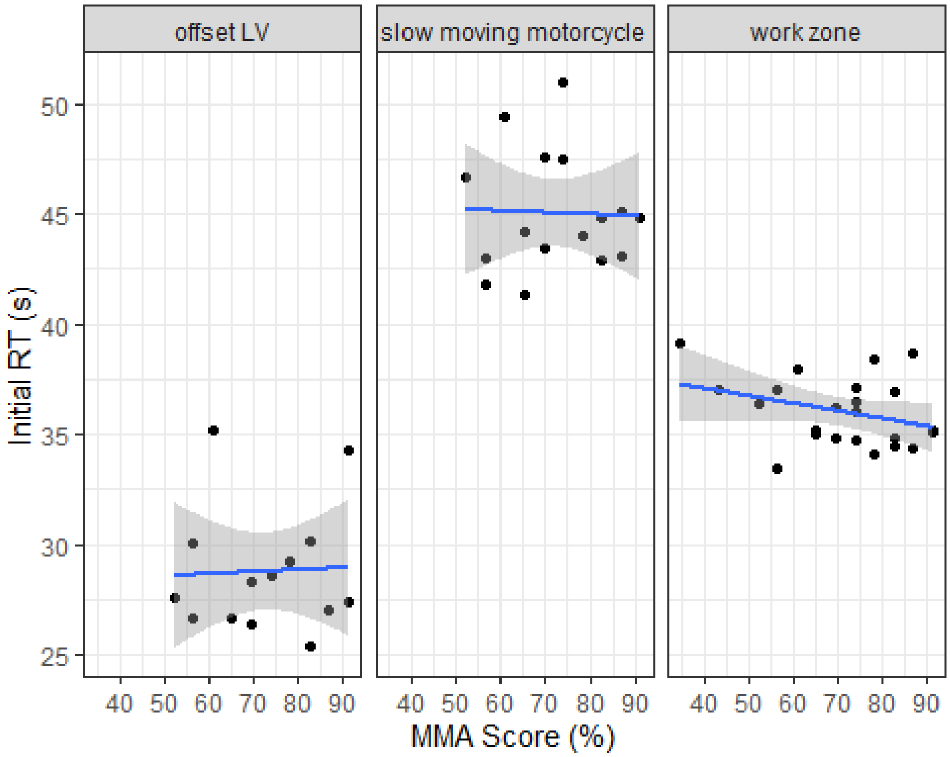
Relationship Between Mental Models and Driving Performance

The next step in the analysis was to examine the relationship between mental model quality and driving performance. Previous research showed that groups of drivers with strong and weak mental models had differences in performance in the same set of edge-case scenarios (Gaspar et al., 2021).

For driving performance, the key measure of interest was initial response time in the edge case events. Smaller initial response times indicate that drivers responded earlier, either by deactivating ACC with the brake or steering (note that all ACC deactivations occurred with the brake). Previous research showed that faster initial responses resulted in larger safety margins and seemed to reflect lower indecision in how the ACC system would respond (Gaspar et al., 2021).

To understand the relationship between mental model quality and driving performance, we computed the correlation between initial response time and MMA score from the final test session (Figure 13). The correlation between initial response time and MMA score was not significant for the offset lead vehicle event ($t=0.13$, $p=0.90$), slow-moving motorcycle event ($t=1.61$, $p=0.12$), or the work zone event ($t=0.15$, $p=0.89$). This indicates that performance on the final mental model assessment did not predict performance in the edge case driving events for this sample of 27 drivers.

Figure 13. *Initial response time by MMA score. Points represent individual participants.*



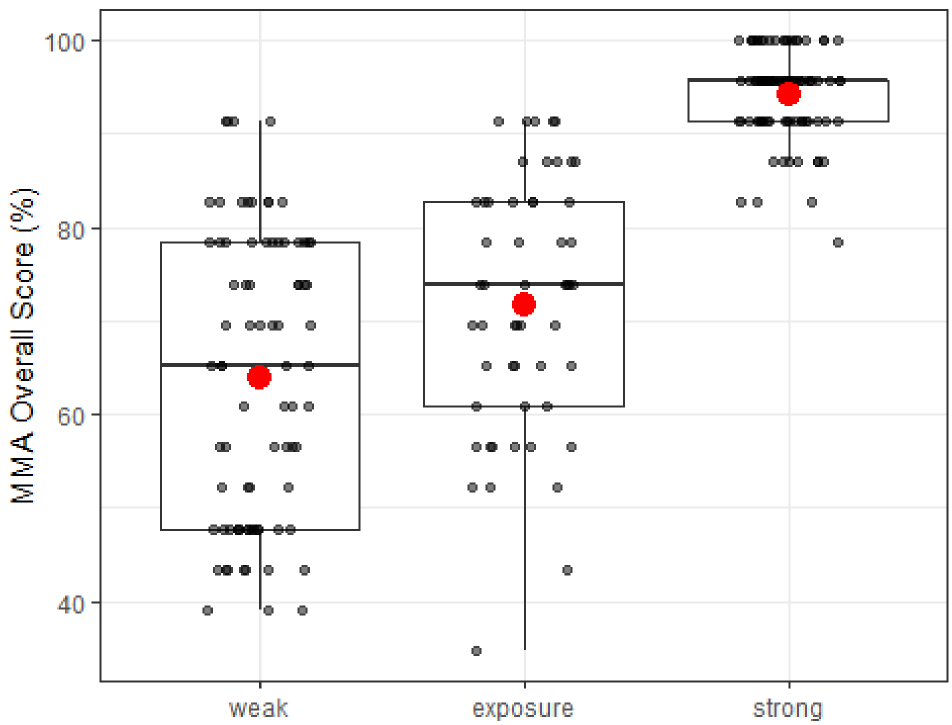
Comparison with Weak and Strong Mental Model Groups

A key interest of this study was understanding how a group of drivers with 6 months of exposure to ACC, without additional training, compared to groups of drivers with established strong and weak mental models of ACC. We hypothesized that drivers with 6 months of exposure would have stronger mental models of ACC compared to drivers who had limited training and system exposure (from Gaspar et al., 2021). We further predicted that drivers with 6 month of exposure would have weaker mental models compared to a group of drivers who received extensive training (again from Gaspar et al., 2021). We also predicted that these differences in mental model strength would translate to differences in driving performance and that these differences could be predicted by MMA score.

Driving and MMA data from this study were merged with driving data from the previous study with strong and weak mental model groups. These analyses used data from the final MMA test session (i.e., session 6). It is important to note that the instructions given to participants and the edge case scenarios they encountered were identical between these two studies.

Our first question was how the mental models of the exposure group compared to those of the strong and weak mental model groups. Figure 14 shows MMA overall scores for each of the three groups. There was a significant main effect of group on MMA score ($F(2,114)=144.0$, $p<0.001$). Paired comparisons showed the exposure group had higher MMA scores than the weak group from the previous study ($p<0.001$) and lower scores than the strong group from the previous study ($p<0.001$).

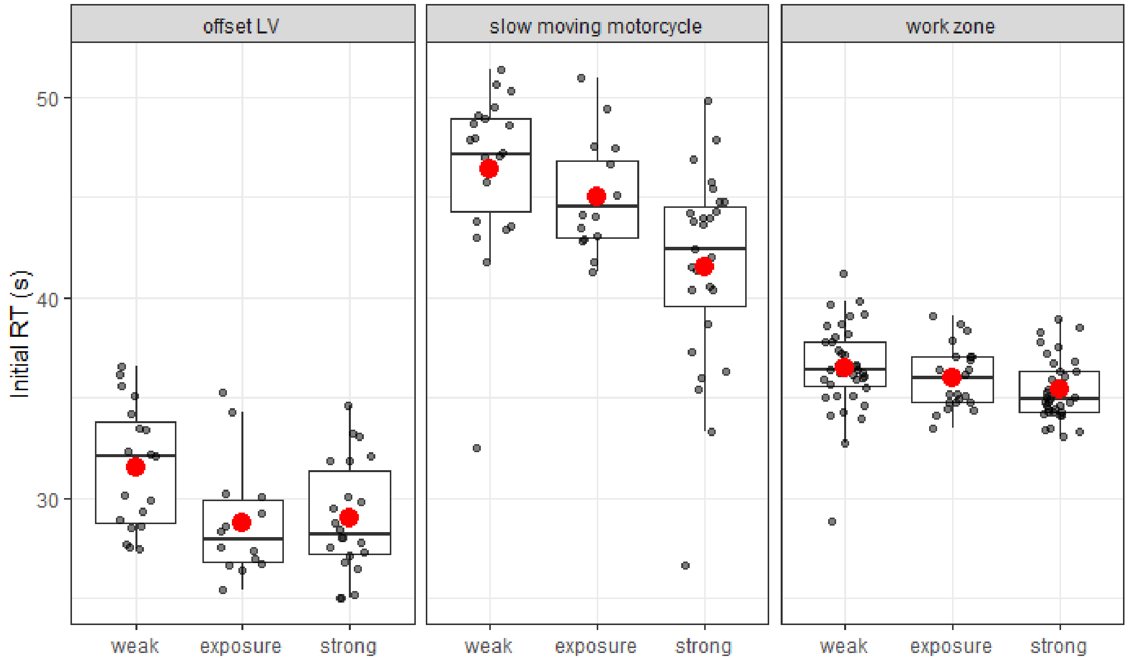
Figure 14. *Overall MMA Scores for the Exposure Group from this Study and Strong and Weak Groups from the Previous Study*



Red points represent group means and black points represent individual participants.

We next compared initial response time across the three edge case events for each of the three groups. Figure 15 shows initial response times by group and edge case event. There was a significant main effect of group on initial response time ($F(2,114)=13.68$, $p<0.001$). There was also a main effect of event ($F(2,114)=13157.65$, $p<0.001$). Finally, there was a significant interaction between group and event ($F(2,114)=3.13$, $p=0.02$). Pairwise comparisons were performed on initial response time from each event to compare group means. For the offset lead vehicle event, both the strong and exposure groups had significantly faster response times than the weak group ($p=0.02$). The difference between the strong and exposure groups was not significant ($p=0.85$). For the slow-moving motorcycle event, the strong group had significantly faster response times than both the exposure ($p=0.02$) and the weak group ($p<0.001$). For the work zone event, the strong group had significantly faster responses than the weak group ($p=0.04$). The differences between the exposure group and the strong ($p=0.42$) and weak ($p=0.41$) groups were not significant.

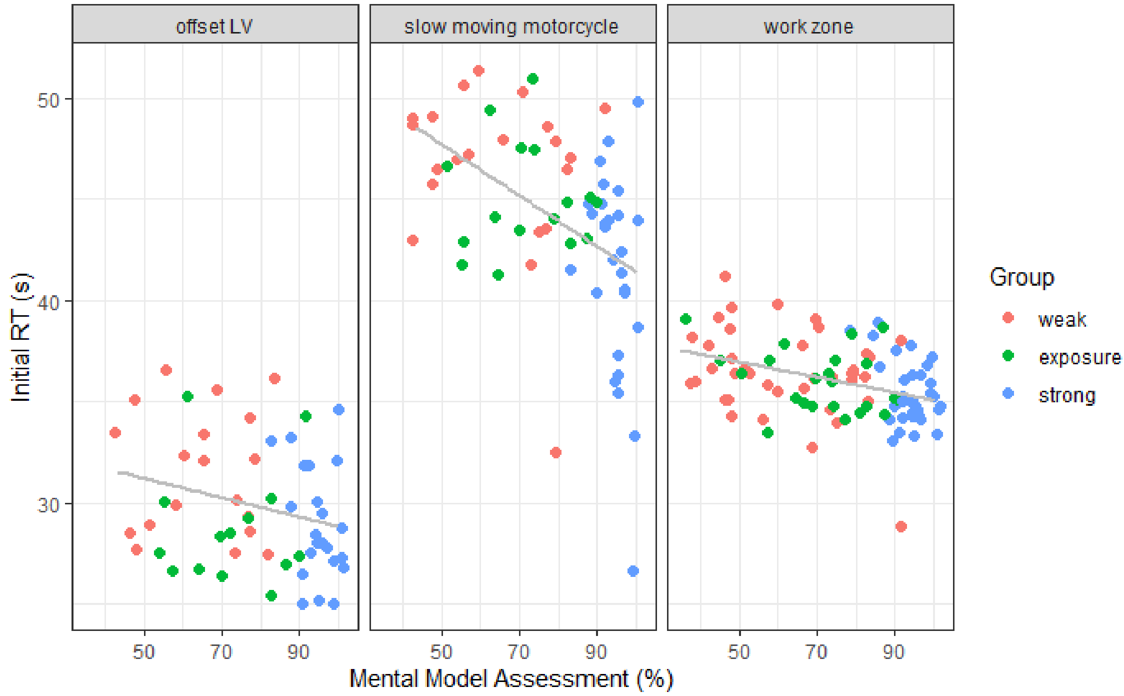
Figure 15. *Initial Response Time in Edge Case Events*



Red points represent group means and black points represent individual participants.

Finally, we examined the relationship between MMA score and driving performance in this combined dataset. We calculated the correlation between MMA score and initial response time separately for each of the three edge case events (Figure 16). There were significant negative correlations between MMA score and initial response time for the offset lead vehicle event ($p=0.05$), the slow-moving motorcycle event ($p<0.001$), and the work zone event ($p<0.001$). These results show that participants with higher scores on the MMA were faster to respond in all three edge case situations where ACC did not respond.

Figure 16. *Scatterplots of Initial Response Time by MMA Score*



Points represent individual participants, shaded by group.

Discussion

The objective of this study was to understand how mental models of ACC change over time and to map understanding of vehicle technology to driving performance. Using a mental model evaluation tool, the MMA, mental models were tracked over 6 months for a group of new owners of vehicles equipped with ACC. At the end of that 6-month period, participants completed a simulator drive in which they experienced edge case events where ACC encountered functional limitations. This group of participants, who learned through experience, was also compared with participants from an earlier study (Gaspar et al., 2021) who had strong or weak mental models instilled through experimental procedures.

Over the 6-month window, participants in this study showed slight improvements in mental models, reflected by scores on the MMA. When the MMA was decomposed into questions pertaining to functionality or limitations, it was clear that understanding of functionality was near ceiling for most of the participants throughout the exposure window and did not change over time. Understanding of system limitations, on the other hand, showed slight increases and seems to have driven the overall change in MMA scores. Confidence in responses on the MMA also increased over the 6-month window. This adds to the findings presented by Rossi et al. (2020) and Beggiato et al. (2015), which found that knowledge and understanding of the functionality of ACC occurs rather quickly while limitations are more difficult for first time users as they are mostly learned over time through experience (Larsson, 2012; Beggiato et al., 2015).

Following Lenneman et al. (2020), clusters of learners with respect to MMA scores and confidence were identified. We performed a k-means cluster analysis using data from the final mental model evaluation, consisting of overall MMA score and confidence in responses. This cluster analysis revealed four groups, with different levels of mental model quality and mental model confidence.

We examined whether cluster affiliation was associated with different learning patterns over the 6-month exposure. Two of the groups (strong confident and strong unconfident) showed significant improvement on the MMA over the 6-month evaluation period. The other two groups (weak confident and weak unconfident) did not show improvement over the 6-month window, and in fact actually showed poorer MMA performance at week 24 than at week 1. These results also revealed that some participants were well calibrated in their mental model confidence, while others were not. Specifically, the strong unconfident group performed well on the MMA but had lower confidence in their responses. Perhaps most concerningly, the weak confident cluster group had high confidence in their MMA responses—and increasing confidence over time—despite relatively low scores. Misalignment of knowledge or skills and confidence has been touted as particularly problematic in a number of domains, including driving (e.g., Kruger & Dunning, 1999; Deery, 1999; Horrey et al., 2015).

With respect to the relationship between mental models and driving performance, we examined the correlation between initial response time in the edge case events and overall performance on the MMA. There was not a significant correlation between response time and MMA scores for the twenty-seven participants in this study. The lack of a correlation between MMA scores and driving performance is most likely due to the small sample size, which was further reduced due to COVID-19 limitations. This is supported by the fact that when the same relationship was examined in the combined data set, with data from the exposure, strong, and weak mental model groups, there were strong negative correlations between MMA scores and response times for each of the three edge case events. These combined data further support the conclusion from Gaspar et al. (2021) that mental model strength is linked to driving performance. One benefit of stronger mental models appears to be that they reduce uncertainty in rare situations where the system encounters its performance boundaries (Gaspar et al., 2021; Victor et al., 2018).

Finally, the combined dataset, including both the exposure group and the strong and weak groups from the previous study, was used to compare the mental model strength and driving performance across different groups. For both MMA scores and driving performance, the exposure group from this study fell between the strong and weak mental model groups. The exposure group had stronger mental models than the weak group but weaker than the strong group. Similarly, in general the exposure group was faster to respond in edge cases than the weak group but slower than the strong group. These results suggest that 6 months of exposure yielded, on average, mental models of ACC that were better than the weak group, who received almost no training, and poorer than the strong group with extensive training. Six months of exposure was sufficient to improve performance relative to a group that received little training, but not enough to achieve the robust mental models seen in the strong group. This finding further underscores the need of training and education for proper use and interactions.

These results show that mental models improve over 6 months (for some drivers), but not to the level of understanding of a group that received a short but extensive introduction to ACC. This suggests that there is room for improvement in how drivers gain understanding about driver support features. Additional research is needed to understand how different approaches (e.g., instruction materials, in-vehicle training) might be used to augment experience in the development of mental models. The results also suggest that training methods should focus on understanding the limitations of particular driver support features, as this is often the weaker component of mental models but also more important for appropriate responses in edge case situations.

This research raises several important questions for future research. While the results show some improvement in mental models over time, particularly with respect to understanding of ACC limitations, there is little insight into what factors caused mental models to change and whether particular factors were common across drivers who showed improvement on the MMA. The data also do not speak to why some drivers improved while others did not. Additional, larger datasets are needed to understand how individual differences in learning and understanding translate to performance in the context of driver support features. Moreover, future research needs to examine how the current results relate to other forms of vehicle technology, beyond ACC.

A key unanswered question in this space is how good mental models need to be for safe, effective, and enjoyable use of a vehicle technology. What threshold do drivers need to reach in terms of understanding? The results of this study suggest that there are advantages to increasing understanding up to the point where drivers have a thorough knowledge of both the function and limitations of a particular system. However, there may be costs (e.g., time, money) that prevent such rigorous training and therefore it is important to define the minimum understanding necessary.

Another important area for further research is to examine how the quality of a driver's mental model impacts other in-vehicle behaviors, such as their willful engagement in non-driving related tasks. Though they did not focus on mental models per se, Dunn et al. (2020; 2021) found that drivers with varying degrees of exposure with new technology tended to exhibit different propensities towards distracting/secondary tasks in situations where the technology required that they remain alert and attentive.

Several limitations should be mentioned. The sample size of this study was relatively small, and the sample included in analyses of driving data was further reduced due to COVID-19 restrictions at the time some participants completed the study. One takeaway from the results is that there is considerable variability in mental models across individuals. This is reflected in the different mental model cluster groups. Larger samples are necessary to understand individual differences in mental models and learning about driver support features. A larger sample would also be necessary to understand how cluster groups differed in terms of driving performance. That is, did the cluster groups show differences in driving performance that might be explained by their levels of understanding and confidence?

Other issues with sampling may have also impacted the variability in the final dataset. Specifically, drivers were eligible to participate if they purchased a vehicle with any ACC system. However, there are considerable differences between the design, function, and limitations of different ACC features. While beyond the scope of this study, it will be important to understand whether some ACC systems are more difficult to learn than others, and how understanding of one system translates to another system (i.e., transfer of training). Driving performance was only collected at week 24, after 6 months of exposure to ACC. Because there was no initial evaluation of driving performance, it is impossible to say whether performance improved over 6 months and whether changes in driving performance were related to evolving mental models and/or mental model confidence.

In sum, this study provides an important step in understanding the relationship between mental models of driver support features and driving performance. The results can be used to help guide future research to identify minimum mental model thresholds for vehicle technology and the development and refinement of novel approaches to learning about vehicle technology.

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Appendix A—Mental Model Assessment

The following questions will ask you about your current understanding of Adaptive Cruise Control (ACC). For each question, please indicate whether the statement is "True" or "False", then rate your confidence in your response.

Please answer the following questions regarding ACC.

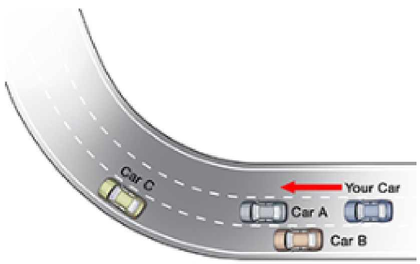
	The statement about ACC is...		Confidence in Response			
	True	False	No Confidence	Slight Confidence	Moderate Confidence	High Confidence
Maintains the speed that you have set when there are no vehicles detected in the lane ahead	○	○	○	○	○	○
Brakes and accelerates to maintain a following gap from the vehicle ahead	○	○	○	○	○	○
Adjusts the speed to match faster vehicles ahead	○	○	○	○	○	○
Will accelerate if a slower vehicle ahead moves out of the detection zone	○	○	○	○	○	○
Will provide steering input to keep the vehicle in its lane	○	○	○	○	○	○
Will correctly detect motorcycles and other smaller vehicles not driving in the center of the lane	○	○	○	○	○	○
Is meant to be used on highways and interstates	○	○	○	○	○	○
May not correctly detect stopped vehicles in your lane	○	○	○	○	○	○
Reacts to stationary objects on the road (construction cone, tire, ball)	○	○	○	○	○	○
Works well on curvy roads and hills	○	○	○	○	○	○

Please answer the following questions regarding ACC.

	The statement about ACC is...		Confidence in Response			
	True	False	No Confidence	Slight Confidence	Moderate Confidence	High Confidence
Is meant to be used in slow and heavy traffic	○	○	○	○	○	○
Adjusts the speed when there are slower moving vehicles detected ahead	○	○	○	○	○	○
Will react immediately to vehicles merging onto the road in front of you	○	○	○	○	○	○
Reacts to oncoming traffic	○	○	○	○	○	○
Adjusts the vehicle speed when approaching tight curves	○	○	○	○	○	○
Is meant to be used on rural roads	○	○	○	○	○	○
May not correctly detect vehicles ahead travelling at much slower speeds	○	○	○	○	○	○
Works even when the radar sensor is dirty	○	○	○	○	○	○
Can be activated at a standstill	○	○	○	○	○	○
Can handle operating in all weather conditions	○	○	○	○	○	○

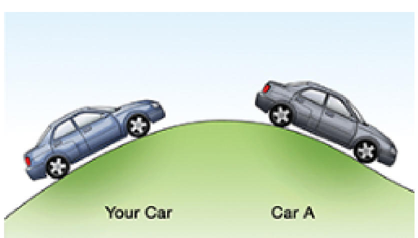
You will now be presented with three potential situations while driving with ACC activated (set speed and following gap). Please look at the illustration provided and think about how the ACC system will behave in the situation and explain why it will behave that way. Each scenario will be presented on a separate page and you will not be able to go back to a previous page. If you are unsure of your response, please feel free to type "I do not know" in the space provided.

Imagine yourself driving the blue vehicle, labeled "Your Car". Use this to answer the questions shown below.



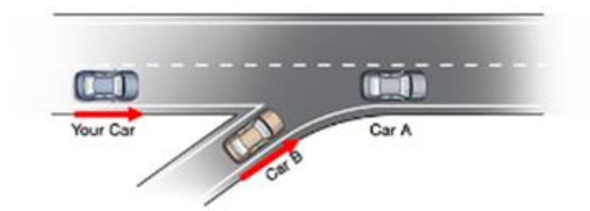
How might your ACC system behave in this situation? Why?

Look at the scenario in the image below. Imagine yourself driving the blue vehicle, labeled "Your Car". Use this to answer the questions shown below.



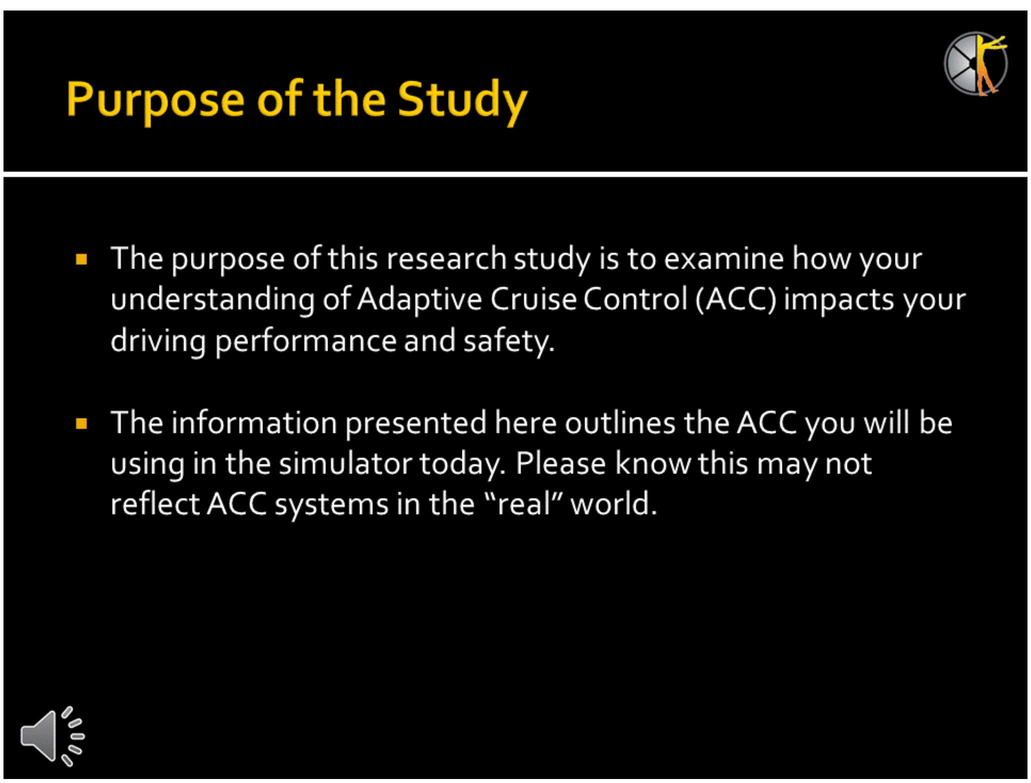
How might your ACC system behave in this situation? Why?

Look at the scenario in the image below. Imagine yourself driving the blue vehicle, labeled "Your Car". Use this to answer the questions shown below.



How might your ACC system behave in this situation? Why?

Appendix B—Training Presentation



Adaptive Cruise Control (ACC)

- Assists the driver with maintaining a set speed and a set gap from the vehicle in front of them.
- If no vehicle is detected, the system works like conventional cruise control and maintains a set speed. If you, the driver, encounter a vehicle travelling slower, the ACC will reduce your vehicle's speed and maintain the fixed gap between your vehicle and the vehicle ahead. When the slower moving vehicle is no longer in front of you, the system will accelerate your vehicle in order to resume the set speed.

Steps to Activate ACC

1. Press the 'On-Off' button on the end of the lever to turn ACC 'On'.
2. Press the ACC lever down to set the ACC speed (ACC activated).
3. To adjust speed, press lever up or down in direction needed.
4. To adjust following gap, press the button on the steering wheel.

Steps to Cancel & Resume ACC

- To cancel ACC (no longer active): 3 methods
  - Pull the ACC lever toward you
  - Press the brake
  - Press the ACC 'On-Off' button
    - To resume from the 'Off' state, you will need to push the 'on-off' button, then set speed and following gap.
- To place ACC in 'Standby' rather than 'Off':
  - Pull the ACC lever toward you or press the brake pedal
  - To resume ACC from the standby state, push the ACC lever up