Countermeasures to Detect and Combat Inattention While Driving Partially Automated Systems

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16. Abstract
Vehicle manufacturers are introducing increasingly sophisticated vehicle automation systems to improve driving efficiency, comfort, and safety. Despite these improvements, partially and fully automated vehicles introduce new safety risks to the driving environment. Driver inattention can contribute to increased risk, especially when control transfers from automation to the human driver. To combat inattention and ensure safe and timely transitions of control, this study investigated the effectiveness of a vehicle cuing system that engages different sensory modalities (e.g., visual, auditory, and tactile) and both simple and complex cue messages to announce the need for manual takeover. Twenty-four participants completed a driving simulator study involving scripted driving sections with and without partial automation. Participants navigated six scripted automation failure events, some preceded by takeover cues. Measures of driving performance, safety, secondary task performance, and physiological indices of workload did not differ significantly based on display type or complexity. However, a clear trend showed that, compared to events not associated with takeover cues, driver reaction time to automation failure is substantially faster when preceded by cues of any type or complexity. This study provides evidence of the benefit of supporting driver situational awareness, safety, and performance by issuing cues and guiding drivers in taking control when the vehicle system predicts a likely automation failure.

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Abstract

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Table of Contents

List of Figures

List of Tables

Introduction

Advancements in driver assistance technologies for partially automated vehicles have improved efficiency, safety, and driver comfort in ground transportation. These technologies reduce the physical demands on the human driver by executing physical activities that would otherwise be performed by the human. The cognitive demands on the driver, however, do not necessarily decrease when automation is introduced. This can be explained by the fact that the human's responsibilities in a partially automated system now include additional tasks such as supervising the automation to ensure it functions appropriately, detecting potential automation failures, and taking over manual control when automation faults are detected (Bainbridge, 1983). To mitigate the performance and safety implications of these additional cognitive demands, vehicle designers can emphasize providing human-centered support in the design of automation systems. Human-centered design goals include ensuring that drivers sufficiently understand the capabilities and limitations of vehicle automation, can maintain awareness of the state of automation systems, and are attentive to the performance of the vehicle automation, transitioning control to manual driving when warranted.

Driver inattention is one of the main causes of roadway accidents (National Highway Traffic Safety Administration [NHTSA], 2020). Therefore, one human-centered design goal for vehicle automation is to guide drivers' attention to relevant data (Cummings & Ryan, 2014). An example of such automation is a blind spot warning system that uses visual, auditory, vibrotactile, or multisensory cues to capture the driver's attention and quickly convey the warning message. Surprisingly, despite improving driver awareness of some aspects of the vehicle and surrounding environment, the introduction of vehicle automation technologies has paralleled a general decrement in driver situational awareness (Walch et al., 2017), and this decrement in situational awareness can then contribute to extreme consequences. At the time of the current research, these problems had contributed to eight documented cases of fatal accidents involving partially automated vehicles operating at either SAE Level 2 or Level 3 of automation (Associated Press, 2020; Boudette, 2016; The Guardian Staff, 2018; Vlasic & Boudette, 2016; Yadron & Tynan, 2016). While we strive to better understand the root causes of these accidents, it is also important to examine how cuing mechanisms, such as those employed with blind spot warning systems, may better support generalized driver situational awareness and reduce the likelihood of inattention-related mishaps.

Several research studies have investigated the design of cues for vehicle automation systems. One prominent set of design questions involves the best way to cue a driver to reduce inattentiveness and facilitate a smooth transition to manual control of the vehicle when that transition is best for the overall safety and performance of the system (Bazilinskyy et al., 2015; Clark & Feng, 2017; Roche & Brandenburg, 2018). Studies addressing this question have advanced the knowledge of which sensory channels to engage, when to engage them regarding automation states and anticipation of upcoming need to transition, and from where to display takeover cues within the vehicle cockpit to support a smooth transition of control.

Few of these studies have comprehensively compared visual, auditory, and tactile cuing mechanisms, or multisensory combinations, in a common experimental environment. Another question that few have investigated involves the tradeoff between the amount of information the cue conveys and the time and resources required to process that information while taking over control of a vehicle. The current study attempts to address these knowledge gaps by investigating driver behavior in response to takeover cues that precede realistic contexts modeled after true events in which automation failures have been observed (e.g., the eight documented fatal accidents). The attention-directing cues varied with regard to the sensory channels they engaged and the complexity/information content conveyed by the cue. The results of the study can provide design guidance on the most effective forms of driver cuing to counter the natural human inattentiveness to aspects of the driving task when cooperating with automation.

Background

In partially automated vehicles, levels of automation are characterized according to the degree of human involvement in the driving task. SAE International developed the taxonomy for vehicle automation (SAE, 2018), which has been adopted by car manufacturers and NHTSA (2016). SAE (2018) describes automation levels on a scale from 0 to 5 based on the responsibilities primarily handled by the automation and the level of involvement for the human in those responsibilities.

In partially automated vehicles, the failure modes of human-automation interaction differ somewhat based on the level of vehicle automation. At Level 0 (fully manual operation; SAE, 2018), driver inattentiveness can stem from mind-wandering (Baldwin et al., 2017; Galéra et al., 2012; Yanko & Spalek, 2014), low workload (Horrey & Lesch, 2009; Jin et al., 2012), or in-vehicle distractions (Klauer et al., 2006; Regan et al., 2011) such as secondary tasks (Horberry et al., 2006; Lansdown et al., 2004). SAE Levels 1 and 2 include automation that the driver can enable to assist in manual tasks, such as lateral and longitudinal vehicle control (SAE, 2018), and the driver needs to actively monitor the vehicle and roadway to take over control of the vehicle when the automated system reaches/exceeds its capabilities. Several fatal crashes have occurred when drivers have failed to recognize the need to transition control while operating vehicles at Level 2 automation (Dikmen & Burns, 2017; Kohli & Chadha, 2019). In these cases, system warnings were often present but went unnoticed or were otherwise disregarded, which suggests that countering driver distraction issues may require new types of cuing systems (Merat et al., 2014).

At Level 3, the automation actively monitors the driving environment and the system makes control decisions (SAE, 2018); thus, the decision to transition control to human drivers may come from the automation itself when it senses a context that it is not well prepared to handle. The quality of the transition of control from automation to human depends on the orientation of driver attention, and automation-issued takeover cues can help prepare the driver to assume control. SAE Level 4 involves automation performing most aspects of the driving task, responding to factors in the environment that Level 3 automation would defer to the human driver to handle (SAE, 2018). At this level, the driver is advised to take over control at certain times, but if the driver does not take over manual control, the automation remains in control and attempts to minimize any potential failure consequences, which suggests a safety advantage for Level 4 over Level 3 (Christensen et al., 2015). SAE Level 5 represents full automation of the driving task, with no human involvement required (SAE, 2018), and is mostly outside the scope of research involving human-automation interaction.

While higher levels of automation include more automated safety features and are largely beneficial to safety, previous studies have shown that these levels also naturally decrease human involvement in the driving task. This leads to problems with driver inattention (Llaneras et al., 2013) and decreased situational awareness (Parasuraman et al., 2008), which contribute to consequences in cases of automation failures and clumsy control transitions. All types and levels of automation are subject to failure, so we must continue to consider and design to support the important role of the human in a shared control system. Automation system developers should strive to support a driver's awareness of the state of automation and use adequate messaging to prepare the driver to act appropriately during and after the transition of control.

In most cases, vehicle automation improves system performance. However, studies have illustrated how some aspects of driver performance suffer when vehicle automation is active (Desmond & Matthews, 1997; Funke et al., 2005), and these aspects may be targeted for design improvements. There is a tendency for drivers to adopt a higher threshold for risk acceptance in partially automated vehicles and to engage more readily in tasks that are not related to driving, leading to a decrease in overall situational awareness (Walch et al., 2017). Due to the combined influence of distracting secondary tasks and reduced situational awareness, drivers may not be adequately prepared to effectively take over manual control from the vehicle when an automation-triggered takeover request cue is issued. To address these problems, the current study investigated cue presentation modality (visual, auditory, and vibrotactile) and format (simple alerting or alerting and guiding attention to the relevant control systems) to determine the relative effectiveness of these cuing attributes in a driving simulation study. To this end, we aimed to identify design factors that best support manual takeover and overall vehicle system performance and safety.

Method

Driving Scenario and Vehicle Automation

The driving scenario was designed in STISIM Drive (Systems Technology Inc., 2023), a desktop driving simulator. The scenario included stretches of suburban and highway driving and, depending on driving speed, took approximately 30 minutes to complete. Participants drove manually through a suburban scenario for a predetermined distance (approximately 10 minutes) to obtain a driving baseline. After the baseline was established, the software engaged the automation, accompanied by a voice command: "automation engaged." At this point, participants were instructed to relinquish control of the vehicle and to begin performing the mental rotation secondary task (see the Secondary Tasks section description) while monitoring the automation performance to ensure roadway safety as a top priority. Additionally, participants were instructed to count the number of chickens along the side of the road that appeared throughout the scenario, regardless of driving condition, which encouraged participants to maintain situational awareness of the driving environment outside of the vehicle.

The engagement of the automation effectively represented the end of the "driving baseline" period and the beginning of the experimental phase of the drive. Road conditions changed through the driving scenario, incorporating bad weather, decrease in visibility, and the presence of roadway obstacles to vary the difficulty of monitoring the automation. These conditions were based on actual event conditions that were causal factors in previous automated vehicle control incidents and accident case studies.

Six unique automation failure (partial or total) events were presented through the driving scenario and required takeover by the human driver. Partial failures involved either the steering (lateral control) or pedals (longitudinal control) failing, and complete failures involved a failure of both systems. Both types of failure required manual driving takeover. The automation failure was indicated by the concurrent onset of the display cue (visual, auditory, or tactile). A total of six different automation failure events were included in the driving scenario (Table 1).

Table 1. Summary of Automation Events

Event Number	Steering or Pedals Automation Failure	Display On or Off	Obstacle
1	Steering	On	Parked car on foggy road
2	Pedals	On	No obstruction
3	Both	Off	Boxes on the road
4	Both	On	No obstruction
5	Steering	On	No obstruction
6	Pedals	Off	Curve

The first automation failure event consisted of a parked car in the middle of the road in foggy weather, modeled after failure modes in which the vehicle's visual sensors malfunctioned due to adverse weather conditions. The display cue was turned on for this event. The second event had no obstruction, but the vehicle would stop accelerating, prompting the users to take control of the pedals. The display was also on to signal the beginning of this event. The third event presented a complete automation failure (steering and acceleration), prompting complete takeover by the human driver, and some boxes were strewn on the road (Figure 1). This was the first time in the drive where the display cue was off. Similarly, the fourth event presented a full automation failure, but with no obstacles and with the display on. The fifth event was a steering failure with no obstruction and was indicated by the display. Lastly, the sixth event presented a pedal malfunction and no display to indicate the automation failure on a curved road. The automation failures were presented in the same order for all participants.

The automation failure events were associated with roadway dynamics (such as curves) that, without manual takeover, would lead to the vehicle deviating from its current lane or the roadway altogether. Performance metrics (driving performance [crashes], takeover reaction time, secondary task performance) were collected throughout the scenario.

Figure 1. Image. Example of road obstacles.

Each cue (visual, auditory, or tactile) was triggered by the experimenters at pre-set distances that allowed for approximately 2 to 3 seconds of travel time before the automation failure occurred.

Takeover Cue Displays

Three types of experimental displays (visual, auditory, tactile) were integrated into the driving simulator environment. Each display was designed to convey information about a predicted automation failure and a need for the human driver to take over manual control of steering and/or foot pedals. The types of displays differed according to the engaged sensory modality. The *visual* displays relayed takeover cues via an LED strip that illuminated the dashboard space underneath the primary monitor display, including the steering wheel and control pedals, with a bright red light. The *auditory* displays consisted of a beeping alarm sound played from speakers embedded in the dashboard space, and the *tactile* displays involved patterns of vibration presented to participants' arms and legs via solenoid-based C-2 tactors (Engineering Acoustics Inc.) that were affixed with Velcro straps (Figure 2).

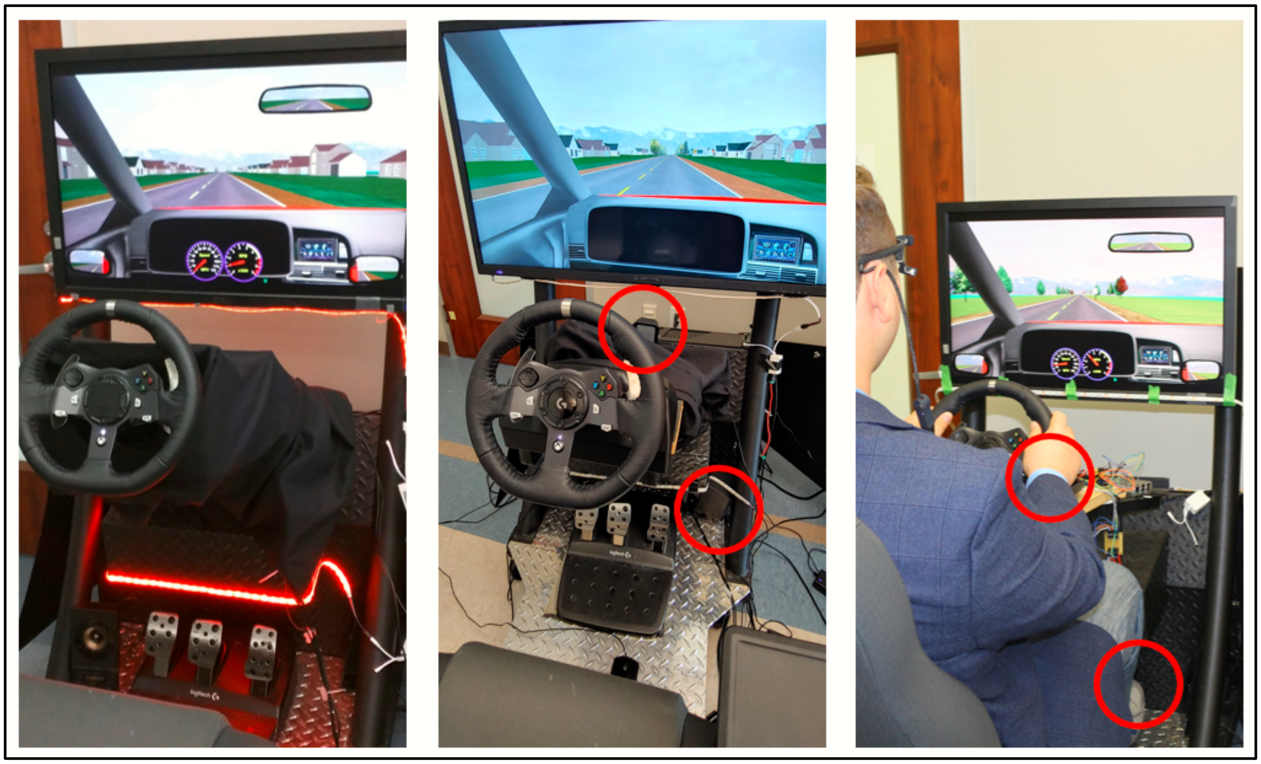

Figure 2. Photos. Takeover cue display types. From left to right: light display, auditory display, and tactile display. The red circles represent the source location of the cues.

For each type of display, the takeover cue message was encoded at two levels of complexity. *Simple* cues announced that an automation failure was expected to occur in the near future (2–3 seconds before automation failure), and the human driver would determine, via other simulator cues (e.g., vehicle decelerates or veers off road) or trial and error (trying to take over the automation), whether the steering and/or pedal system required manual takeover of control. *Complex* cues announced an upcoming failure and additionally conveyed information about which automation system (steering or pedals) was expected to require takeover. For example, the complex visual display illuminated the steering wheel to indicate the need to take over lateral control of the vehicle or illuminated the pedal space in the footwell to indicate the need to take over longitudinal/speed control. The complex auditory cue similarly originated from speakers at the steering wheel and in the footwell, and complex tactile cues vibrated at the driver's wrists for steering takeover cues and on their ankles for pedal takeover cues.

To maximize driving scenario realism and avoid overexposing scenario events (thus avoiding that scripted scenario events become predictable), participants experienced only six (unique) automation failure events. To emphasize the potential differences between *simple* and *complex* cues, the events were balanced in terms of which automation subsystem(s) failed (steering, pedals, or both). After pilot testing the scenario and automation failure events, decisions were made to make display type (*visual*, *auditory*, or *tactile*) and complexity (*simple* or *complex*) between-subjects variables to ensure at least two replications of a given display type and complexity for each type of automation failure. Thus, each participant received only one type of takeover cue throughout the experimental scenario. Every participant also experienced two of the events without the benefit of a takeover cue (i.e., the automation failed at a predetermined time/place but was not preceded by a displayed takeover cue). These events thus served as control conditions for comparison with event conditions that did present cues.

Secondary Tasks

With "safe and effective driving" as the primary task priority, participants were instructed to engage in a secondary task whenever possible, which involved playing "Mental Rotation" (Mandrysz, 2019), a self-paced game hosted on an iPad that was mounted next to the steering wheel. This game provides a complex three-dimensional object that the participant rotates using their finger to explore all sides and faces. This rotatable object is located at the top of the screen, while three static objects (possible matches to the rotatable object) are displayed on the bottom of the screen. Participants were instructed to select the figure that matches the rotatable object as quickly as possible. This game was selected as the secondary task to engage spatial processing resources, which are also required for driving and other in-vehicle activities, such as navigating by using a GPS. The performance metric collected for this task was the *percent correct*, the number of correctly selected figures divided by the total number of completed trials.

An additional secondary (tertiary) task required participants to count the number of chickens they observed throughout the scenario. Five chickens were placed by the side of the road at different points in the scenario to measure each participant's attentiveness to the road conditions. Performance for the tertiary task consisted of the total *number of chickens* the participant reported at the end of the scenario.

Procedure

After consenting to participate, participants completed a demographic questionnaire concerning their driving experience and their familiarity with driving simulators and automated vehicles. Next, they were affixed with physiological sensors, which included the Empatica E4 (skin conductance, cardiovascular measures; Empatica, 2019), Polar OH1 (cardiovascular measures; Polar, 2019b), Polar H10 (cardiovascular measures; Polar, 2019a), and Pupil by Pupil Labs (pupil diameter; Pupil Labs, 2019). Physiological baseline data were then collected while participants performed paced breathing exercises and listened to nature sounds for 10 minutes. The physiological baseline data was used as a covariate in the analysis to compare to the physiological data collected during each automation failure.

Next, participants were trained in how to drive in the simulated environment, including how to use the steering and pedal controls. At this point, the secondary tasks (counting the number of chickens and the mental rotation game) were also explained. The takeover display assigned to each of the participants was also explained. The experimenters emphasized that participants should always treat driving safely and effectively as the primary task, completing either of the secondary tasks only when there were additional attentional resources available.

Participants then encountered a training driving scenario that included segments of manual control and segments in which the vehicle automation was in total control (steering and cruise control to maintain speed). When automation was in control, participants were instructed to pay attention to the vehicle and roadway in case of automation failures and to practice the secondary tasks. Near the end of the scenario, an automation failure event that consisted of both cruise control and steering automation ceasing to function occurred. Approximately 3 seconds before this event, the takeover cue display indicated the need for participants to take over manual control of the vehicle. Participants were asked by the experimenters if they felt comfortable with the driving simulator controls and automation dynamics. Participants were allowed to repeat this scenario as necessary.

Participants were given a 3-minute break between the training and experimental scenarios to return physiological variables close to baseline levels. After participants completed the experimental scenario, the physiological devices were removed, and participants completed a post-experiment interview with experimenters to collect subjective feedback on their experience in the experimental environment.

Results

All data were analyzed in R Studio using between-subjects analyses of variance with cue display type and complexity as the primary variables of interest.

Participants

Twenty-four people (12 males and 12 females, mean age = 29.7 years old, standard deviation = 15.8 years, min = 18, max = 78) participated in this study. Participants were at least 18 years old with a valid driver's license. Four participants reported experience in driving simulators, four reported previous familiarity with autonomous vehicles, and two had previous experience as a driver in an autonomous vehicle. On average, participants reported 11.9 years of driving experience (standard deviation = 16.3 years).

Driving Performance

Thirteen total accidents in which participants either collided with roadway obstacles or departed from the roadway (e.g., failed to follow a curve in the road) were observed. These accidents were tallied by only seven of the 24 participants, with no participants experiencing more than two accidents. There were *no significant effects* of any independent variables on crash occurrence.

Takeover Reaction Time

Takeover reaction time was measured as the time between the start of the automation failure event and the first indication that either the steering wheel or pedals registered a change in input due to the human assuming manual control. Reaction time *did not differ significantly* across the display types (p = 0.363); however, a pattern in the results can be seen across Figure 3, Figure 4, and Figure 5, which show how Events 3 (boxes obstructing the road) and 6 (curved road), for which no takeover cues were issued, had substantially longer reaction times. This suggests that the presentation of any takeover cues (visual, auditory, or tactile) at any level of complexity (simple or complex) will lead to faster reaction times when there is a need to assume manual control of the vehicle.

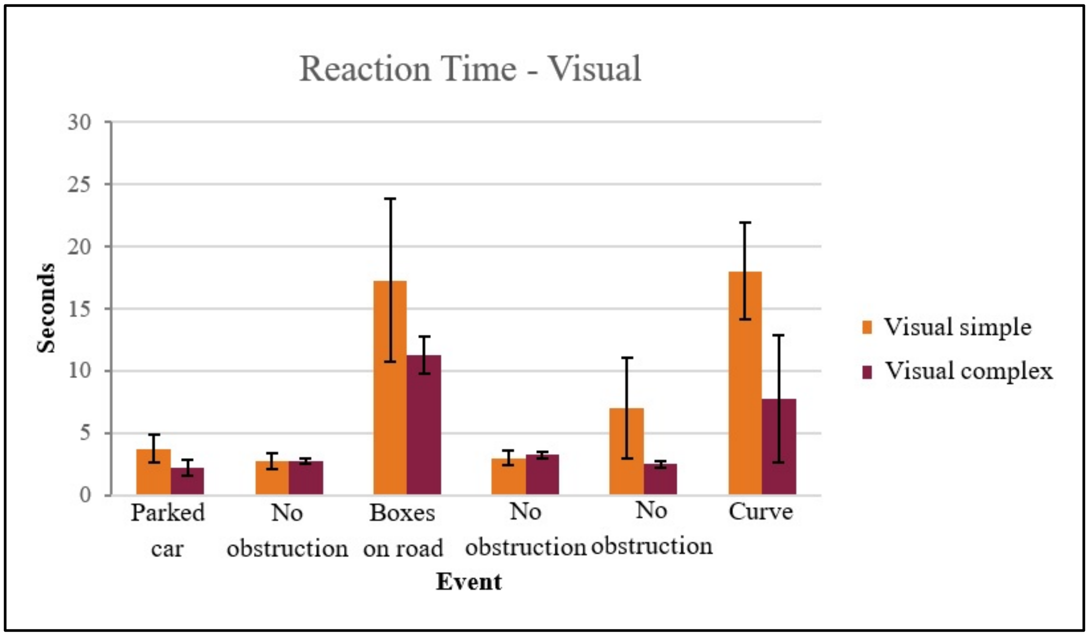

Figure 3. Graph. Reaction time (visual display). Error bars indicate the standard error.

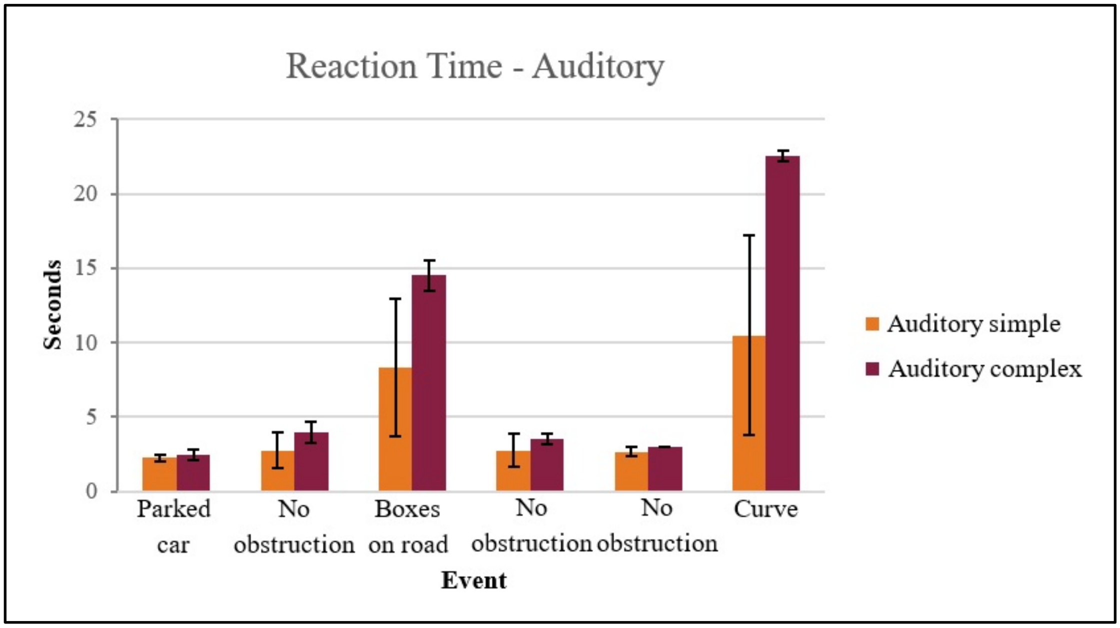

Figure 4. Graph. Reaction time (auditory display). Error bars indicate the standard error.

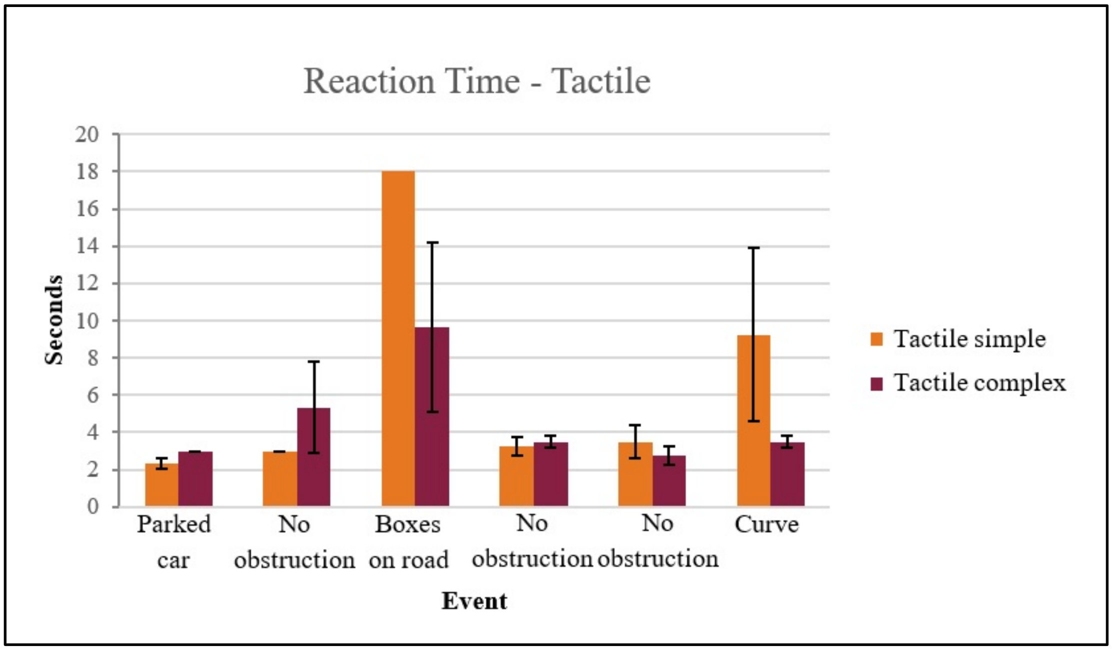

Figure 5. Graph. Reaction time (tactile display). Error bars indicate the standard error.

Secondary Task Performance

Situational awareness was assessed through secondary task performance on the chicken-counting task. Out of five possible chickens, the average number reported was 1.61, with a standard deviation of 0.87. The mental rotation game performance consisted of the percentage of correct answers. On average, participants scored 57.21% (minimum = 35.96%, maximum = 77.77%), with a standard deviation of 12.55%. There *were no significant effects* of any independent variables (display type or complexity) on the performance in either secondary task.

Physiological Measures

Physiological measures were analyzed using a within-subjects analysis of covariance (ANCOVA) with each participant's physiological baseline values as the covariate. Data from six participants were not available for analysis due to sensor malfunction and data connectivity problems. Figure 6 illustrates the results for heart rate, showing *no significant effects of any independent variable*, including display type or complexity, on heart rate measures.

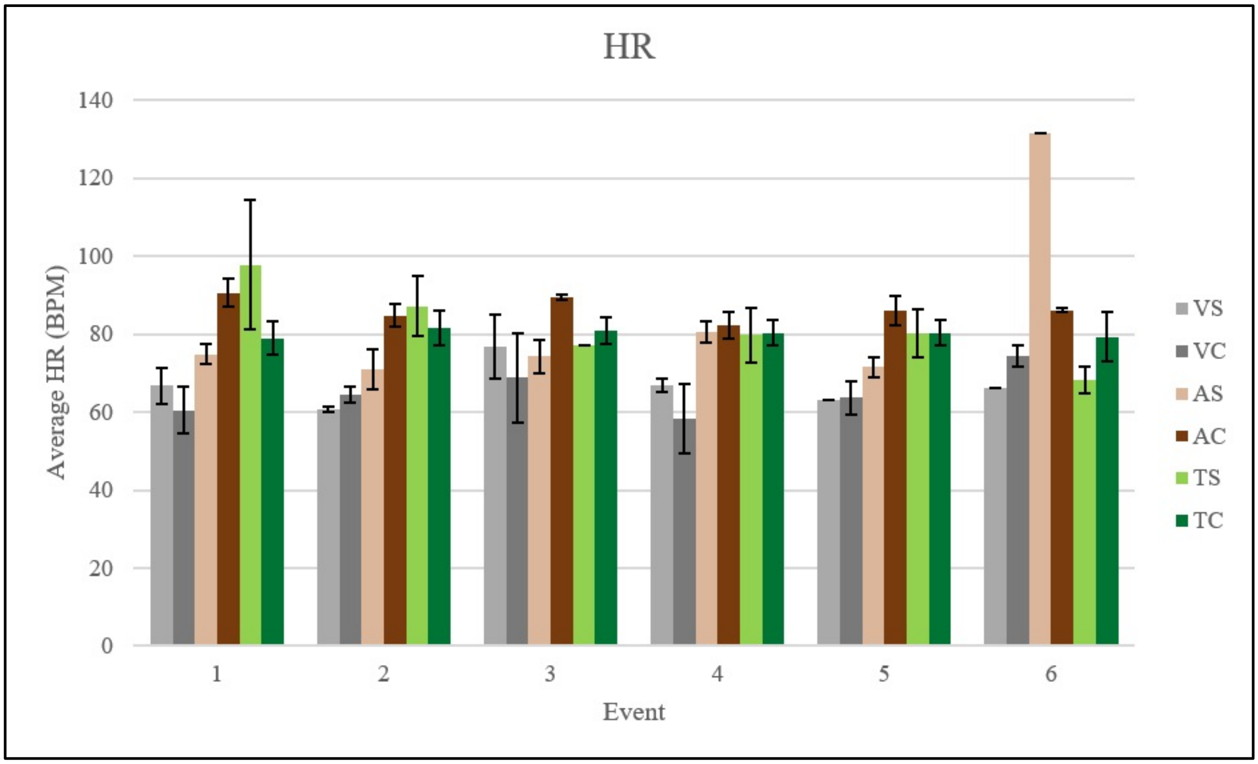

Figure 6. Graph. Average heart rate in beats per minute. Error bars indicate the standard error.

Similarly, mean electrodermal activity (EDA) measures were compared using an ANCOVA with the physiological baseline as a covariate. Figure 7 illustrates the EDA results. Although *none of the independent variables significantly impacted* the EDA measures, a trend can be seen that shows some of the lowest EDA measures overall involved participants who were presented with auditory cues. Some of the highest EDA measures are associated with tactile cues. Note, however, that these low and high patterns are also seen in the baseline (labeled as "B") results and in the segments of the experimental scenario between events (labeled as "0"), which suggests that the values are highly dependent on interindividual differences. Participants who were assigned auditory takeover cues tended to show much lower EDA baseline and experimental activity, and, similarly, participants with tactile cues showed higher levels of EDA activity in baseline and also in the experimental scenario.

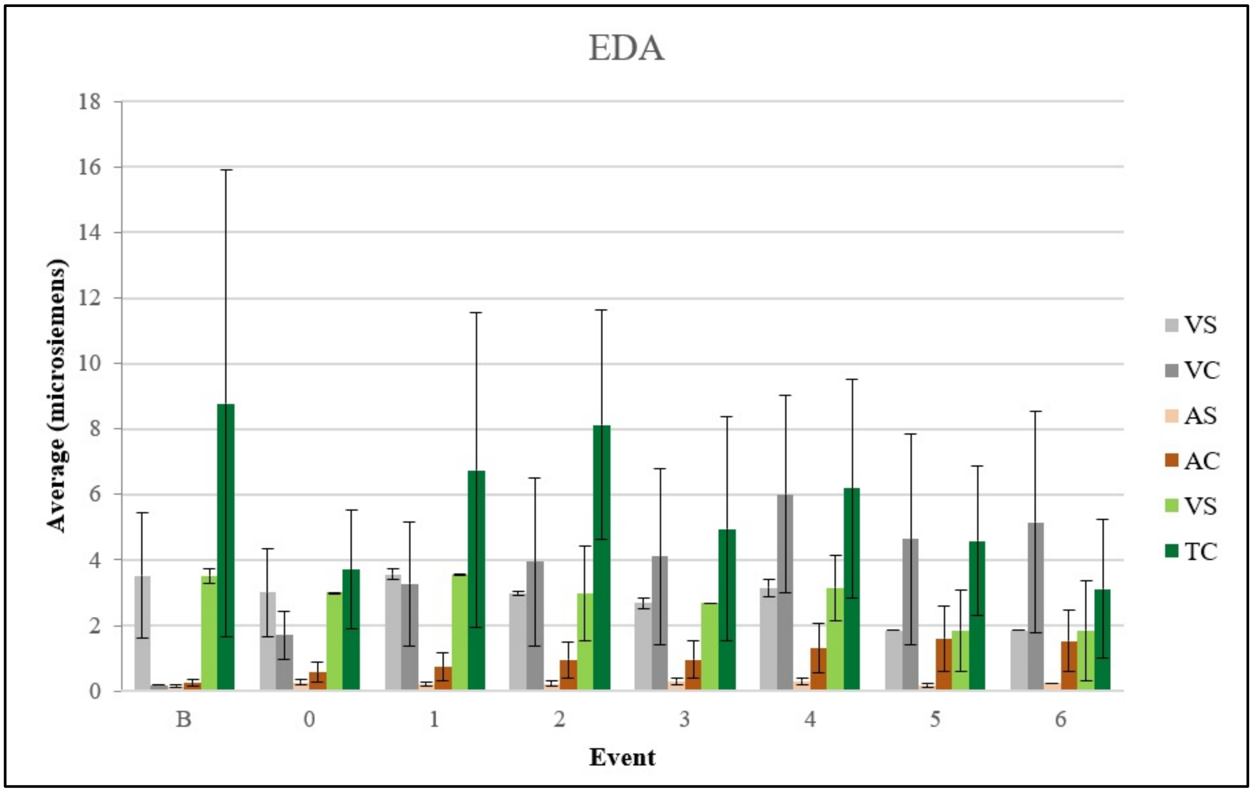

Figure 7. Graph. Electrodermal activity. Error bars indicate the standard error.

Discussion and Conclusions

This study investigated the effect of takeover cue display modality (visual, auditory, and tactile) and message complexity (simple and complex) on takeover response time behavior for a simulated partially automated vehicle task context. Driving performance, takeover reaction time, secondary task performance, and physiological data were collected and compared for the effects of cue type and complexity. These independent variables were handled as between-subjects factors, thus each participant needed only to learn to interpret and respond to one type of cue, but this also limited the ability to make firm conclusions from the results.

The general lack of significant results found in this study suggests a few things. First, it is likely that the low sample size limited the expression of any major effects of the independent variables. To reasonably scope the experience for participants while presenting novel scenario elements, the decision was made to handle the main independent variables as between-subjects variables, which makes comparison among the types and complexity levels more difficult due to the noise introduced by interindividual differences. The experiences of participants were designed to be similar, but to preserve a degree of naturalism in the driving context, a higher degree of variance could be expected among dependent measures. Unfortunately, this variance makes statistical comparisons challenging. Additionally, because interindividual differences in physiological response to task loads are expected, these factors can confound analyses of the independent variables, as the variables were handled between-subjects. Future research should reasonably emphasize *within-subjects* comparisons in the experimental and statistical models to minimize the effects of interindividual differences in performance/safety and in physiological response to changes in workload. Additionally, while the current study worked within budgetary and time constraints to complete the data collection, it did not use a formal power analysis to determine a sample size that would be sufficient for making firm conclusions.

Another methodological detail that likely reflected the results is that takeover reaction time, the measure that we most expected to differ due to display type and/or complexity, was measured from the onset of the automation failure until the first instance of takeover. Following the literature and observations from commercially available partially automated vehicles at the time of the study design, all the presented takeover cues preceded the automation failure by about 2 to 3 seconds of travel time. This lead time was more than enough to satisfy the desired purpose of alerting the driver and allowing them ample time to prepare for the takeover. This amount of lead time also is likely several times greater than any potential difference among reaction times to the cue types or complexities. Future research that involves considerably more replication and stricter control of presentation time windows could better study whether the engaged sensory channel or the complexity of a cue significantly impacts the takeover time, and whether any significant effects would be operationally relevant, given the current state of vehicle technologies.

Referring to the "complexity" of the encoded cue also may have been a bit of a misnomer in the current study, as the *complex* cues were designed to convey 1) that an automation failure is about to occur, and 2) specifically *which* automation system was predicted to fail. While there is technically more information encoded in complex cues compared to the simple cues (which only announced an impending automation failure, but not which subsystem), given the usage of the encoded information and the ample time to process it, it might have been expected that complex cues better support takeover performance than simple cues. This is because simple cues could require additional cognitive steps to determine which of the two subsystems (or if one or both) require(s) manual takeover. The complex cues, as defined in the current study, do not require these additional steps. As long as "complex" cues are sufficiently salient to capture attention, they may have advantage over the so-defined "simple" cues in the current study because they offer the additional benefit of guiding the driver response to identify and address the specific subsystem by location, at least for visual and vibrotactile cuing. Auditory cuing showed a somewhat contradictory pattern that may suggest the localization of the auditory cues (issued from speakers embedded in the simulator frame) may have been more challenging than the localization of visual or vibrotactile cues. In future research, perhaps a better way to consider the "complexity" variable from the current study might be the degree to which problem-solving during the takeover maneuver is supported by vehicle intelligence (e.g., guiding the human to the most relevant controls for handling the anticipated failure mode). In the current study, the *simple* displays would be re-classified as those at a lower level of vehicle automation—relying more on the human driver to diagnose the failure mode and decide on a course of action.

Another limitation of the current study is that false cues (i.e., issuing an alert of an impending automation failure, but then no failure is observed, or the wrong subsystem is indicated) were not included; all alerts were 100% reliable. While participants were not explicitly told of the reliability of the cues, it is reasonable that they assumed them to be 100% reliable, and thus did not need to invest mental resources in judging validity. This means that participants did not need to consider any potential *costs* to performance and safety that may arise from responding to a false cue, so they could blindly follow the message conveyed by the cue to ensure the safest/best driving performance. Future research should look at more representative degrees of validity in the automation-issued cues to determine how that affects driver trust in the automation and the degree to which drivers rely on the automation and are able to recover manually when the automation issues false cues.

Despite the lack of conclusive evidence found in this study for the effects of takeover display modality and/or complexity, there is an observable pattern that offers some evidence of the benefits of attention-directing cues to support driver awareness in partially automated vehicles. The responses to automation failures that were associated with some type of takeover cue (engaging any sensory modality, simple or complex) were clearly and considerably faster than responses to "uncued" automation failures (e.g., Event 3 and Event 6; see Figure 3, Figure **4**, and Figure **5**). Due to the nature of our experimental scenario and likely also the limitations in experimental design, a delayed response to the failure of automation systems did not lead to substantial impact on performance or safety metrics. However, it is reasonable to assume that a manual takeover time of 15 to 20 seconds is more costly to performance and riskier than a takeover time of under 5 seconds.

In conclusion, the current study offers some evidence of the benefit of issuing cues to support human situational awareness of the state of a partially automated vehicle and its interaction in the transportation system; however, firm conclusions cannot be made on the effects of cue modality or complexity. If an automated vehicle system can reliably anticipate subsystem failure modes, and communicate them reliably to the human driver, then the human-automation system can be best prepared to handle transitions of control to maintain the highest standards of driving performance and safety.

Additional Products

Education and Workforce Development Products

This work was presented at the US Science and Engineering Fair in Washington DC, April 2017.

The website documenting this project can be found at https://safed.vtti.vt.edu/projects/countermeasures-to-detect-and-combat-inattention-while-driving-partially-automated-systems/

Technology Transfer Products

The website documenting this project can be found at https://safed.vtti.vt.edu/projects/countermeasures-to-detect-and-combat-inattention-while-driving-partially-automated-systems/

Data Products

The data collected for this study have been uploaded to the SAFE-D repository here: https://dataverse.vtti.vt.edu/dataset.xhtml?persistentId=doi:10.15787/VTT1/ZXVADS

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