Evaluation of Autonomous Vehicles and Smart Technologies for Their Impact on Traffic Safety and Traffic Congestion

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James Miles, California State University, Long Beach

Thomas Strybel, California State University, Long Beach

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16. Abstract

Over the next several decades, highly automated driving systems (HADS) will become increasingly common on our roads, greatly reducing traffic accidents and road congestion. However, for the foreseeable future, the human driver will be required to take control when automation fails. Therefore, it is critical to understand how take-overs from HADS affect driver performance and whether driver take-over performance will affect crash rates rate and related issues of congestion. We review extant research on driver take-over performance, identifying key factors influencing driver performance. We then develop a virtual-reality driving simulator designed to evaluate specific differences in driver performance during take-overs from HADS versus current full-manual driving. In a study using this simulator, we find no clear difference in driver performance during obstacle avoidance maneuvers and identify several benefits that HAD take-overs provide to driver performance.

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About the Pacific Southwest Region University Transportation Center

The Pacific Southwest Region University Transportation Center (UTC) is the Region 9 University Transportation Center funded under the US Department of Transportation's University Transportation Centers Program. Established in 2016, the Pacific Southwest Region UTC (PSR) is led by the University of Southern California and includes seven partners: Long Beach State University; University of California, Davis; University of California, Irvine; University of California, Los Angeles; University of Hawaii; Northern Arizona University; Pima Community College.

The Pacific Southwest Region UTC conducts an integrated, multidisciplinary program of research, education and technology transfer aimed at *improving the mobility of people and goods throughout the region.* Our program is organized around four themes: 1) technology to address transportation problems and improve mobility; 2) improving mobility for vulnerable populations; 3) Improving resilience and protecting the environment; and 4) managing mobility in high growth areas.

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Disclosure

Dr. James Miles (PI) and Dr. Thomas Strybel (co-PI) conducted this research titled, "Evaluation of Autonomous Vehicles and Smart Technologies for Their Impact on Traffic Safety and Traffic Congestion" at California State University, Long Beach. The research took place from 2-1-19 to 1-31-20 and was funded by a grant from the METRANS in the amount of $100,000. The research was conducted as part of the Pacific Southwest Region University Transportation Center research program.

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Abstract

Over the next several decades, highly automated driving systems (HADS) will become increasingly common on our roads, greatly reducing traffic accidents and road congestion. However, for the foreseeable future, the human driver will be required to take control when automation fails. Therefore, it is critical to understand how take-overs from HADS affect driver performance and whether driver take-over performance will affect crash rates rate and related issues of congestion. We review extant research on driver take-over performance, identifying key factors influencing driver performance. We then develop a virtual-reality driving simulator designed to evaluate specific differences in driver performance during take-overs from HADS versus current full-manual driving. In a study using this simulator, we find no clear difference in driver performance during obstacle avoidance maneuvers and identify several benefits that HAD take-overs provide to driver performance.

Evaluation of Autonomous Vehicles and Smart Technologies for Their Impact on Traffic Safety and Traffic Congestion

Executive Summary

1. Over the next several decades, highly automated driving systems (HADS) will become increasingly common on our roads, greatly reducing traffic accidents and road congestion. However, for the foreseeable future, the human driver will be required to take control when automation fails. The current report describes the design and data collection criteria in a driving simulation determining specific driver performance costs associated with driver take-overs from automation when compared to manual, non-automated driving performance. Data analysis details driver performance during obstacle avoidance events, subjective workload measures, and how performance is related to individual differences including trust in automation.

2. Key points of this Report:

   - A review of current research on take-overs from HADS found few research articles that directly compare driver performance following take-overs from HADS to current fully-manual driving. We further identify several critical factors that affect driver performance during HADS takeovers, including workload, take-over design elements, and driver characteristics such as age and sensation-seeking.
   - We design a virtual reality highway driving simulator that provides a fully actualized, high-fidelity testbed for examining impacts of HADS on driver take-over performance. The simulator provides clear, intuitive measures of driving performance as well as workload during manual and take-over driving and attitudes toward automated driving systems
   - Using the simulator, we conduct a study directly comparing driver performance in obstacle avoidance maneuvers following HADS take-overs and fully-manual driving. Results indicate a consistent benefit to obstacle avoidance performance following take-overs from automation when compared to fully-manual driving. This somewhat surprising result is likely related to the benefit of the take-over request (TOR) alert as well as the reduced driver workload in the Take-Over condition. Vehicle speed may have played a role in the observed better performance in the take-over condition – drivers opted to increase speed in the Manual condition but maintained the speed of the automated vehicle following take-overs. Practice did not have an overall effect on avoidance maneuvers in either the Manual or Take-Over conditions

3. Conclusion:
    - Our results indicate that driver take-overs from automation may lead to a performance benefit in some cases, further supporting the adoption of highly automated vehicles on the roadways in the upcoming decade.

Introduction

Highly Automated driving systems (HADS) will strongly impact driving safety and traffic flow within the next several decades. The expectation is that such technologies will be largely beneficial, with decreases in human error, reduced crash rates and more efficient traffic flow (Fagnant & Kockelman, 2015). Rough estimates of the benefits to HADS implementation over the next decade are profound. Between 5% and 20% penetration of highly automated vehicles by 2025 could lead to worldwide economic benefits of between $200 billion and $1.9 trillion due to reductions in congestion (Manyika et al, 2013) as well as significant drops in accident rates – in fact, it has been projected that full adoption of HADS could lead to crash rate comparable with those in aviation (less than 1%), which already uses highly automated navigational systems Even with increases in car automation, for the foreseeable future, it is anticipated that human driver take-over will serve as a backup when HADS fails. Recent results of autonomous vehicle testing indicate a significant need for driver intervention. Waymo, Google's self-driving car project, reported the need for human intervention of the automated vehicle every 5600 miles (Waymo Team, 2018), and Uber's self-driving car required intervention an average of every 13 miles (Bowden, 2018). Although this technology will continue to improve, driver take-overs from ADS will be commonplace even with the former estimate.

Decades of human factors research in other task domains such as aviation has shown that human performance on monitoring tasks (also called "vigilance") is very poor and a source of stress and workload (e.g., Galister, Doley, Masalonis, & Parasuraman, 2001). Although the benefits to HADS implementation can be substantial, human driver monitoring of and take-over from HADS can create new sources of human error and must be considered when predicting future automotive accident rates and related traffic congestion. In other words, it is necessary to consider any potential attenuation of HADS benefits stemming from increases in human-driver errors that follow HADS implementation and take steps to prevent these errors from occurring.
Therefore, we report here on a one-year project examining the consequences of highly automated vehicles to human drivers when the automation hands back control of the vehicle to the driver (take-overs). Specifically, we reviewed existing research on operator inattention, situation awareness and trust in automation, and their potential impacts on driver performance. We summarize this review in this report – further details are provided in technical reports (Miles, Strybel & Chompff, 2019; Miles, Strybel, Chompff, & Bai, 2019). From this review we developed a virtual reality driving simulator for investigating driver performance in HADS automobiles. Finally, we ran a driving simulation to identify driver performance costs as the level of automation increased from manual to fully automated driving. We found that take-over performance does not significantly differ from traditional driving, and that there are several benefits to take-overs related to obstacle avoidance.

Literature Review

The Society of Automotive Engineers (SAE) categorized levels of automation by the amount of engagement required of the human operator (see Table 1). As automated vehicles (AVs) increase in their level of automation, it is expected that human operator participation in the driving task will be minimized and common sources of human error will be reduced.

Whereas LO-0 through LO-2 require some amount of continuous driver input, LO-3 through LO-5 involve automated driving systems are capable of fully performing the driving task and only vary in the requirements for human-driver interventions. These levels, which are considered highly automated driving systems (HADS) are the focus of the current report.

Table 1. SAE Internationally levels of automation (adapted from Kyriakidis et al, 2019)

Monitoring of driving environment	Level of automation (LO)	Description	Example
Human driver	0: Driver Only	The human driver performs all aspects of the dynamic driving task	Most cars - more recent cars may offer driver alerts, but are still 100% on the driver for all driving tasks
	1: Assisted automation	A driver assistance system performs either steering or acceleration/deceleration, while the human driver is expected to carry out the remaining aspects of the dynamic driving task	Available since around 2007. Basic control of either steering or pedals, may perform adaptive maneuvers such as adjusting speed for curves.
	2: Partial Automation	One or more driver assistance systems perform both steering and acceleration/deceleration, while the human driver is expected to carry out all remaining aspects of the dynamic driving task	Available since around 2014. Car will do most of simple driving task on highways, but driver takes over for stop-and-go traffic, car accidents, and passing other cars.
Automated driving system	3: Conditional Automation	An automated driving system performs all aspects of the dynamic driving task (in conditions for which it was designed), but the human driver is expected to respond appropriately to a request to intervene	Available since 2018. Hands-off and foot-off driving under all standard highway situations, but driver will be required to take over driving if automation fails.
	4: High Automation	An automated driving system performs all aspects of the dynamic driving task (in conditions for which it was designed), even if the human driver does not respond appropriately to a request to intervene	Projected 2021. Controls all aspects of driving in specific scenarios, may request driver assistance in some situations (car accidents, construction), but will keep control if driver does not act (e.g., slow down and pull to the road side)

	5: Full Automation	An automated driving system performs all aspects of the dynamic driving task under all roadway and environmental conditions	Projected mid-late 2020s. Controls all aspects of driving in all situations without any need for driver (Unlikely that LO-5 cars will have driver controls).

LO-3 systems will likely be the predominant HADS in the near future (5 years to decades from now; Kyriakidis et al, 2019). It is likely that LO-3 will remain the maximum level of automation until technological problems are overcome and legal liability is worked out. On the highways, LO-3 automation will initially be mixed with lower levels of automation. Current HADS vehicles drive alongside non-HADS cars, but it is also likely that separate lanes devoted to automated cars will be developed as HADS infrastructure is put in place (Davis, 2018; Liu & Song, 2019; Yang, Liu, Zhao & Wu, 2017).

LO-3 HADS should produce substantial reductions in driver error and consequently crash rates should markedly decline, in turn reducing congestion related to surprise traffic jams. However, human drivers will be required to assume control over a vehicle for several reasons that may be determined either by the human or the automation. The human may assume control if he/she detects a situation in which the HADS is not dealing with a traffic event in a safe or efficient manner. On the other hand, the HADS may disengage because of software or hardware failures, or encountering situations in which it has not learned to respond. In this case, the HADS must alert the human driver of the need to assume control.

Human factors experts in automated systems point out that as cars become more automated, there are increased costs to human driver's performance in situations where they must manually take control of the vehicle (Endsley, 2017; Hancock, 2014; Kaber & Endsley, 2004). Car taker-over performance is especially sensitive to human limitations, since it involves very short time periods (on the scale of just a few seconds) and small safety margins (maintaining position in a 12ft-wide highway lane) compared to other forms of take-overs from automation, such as those in aviation. Stanton et al (2001) observed that drivers using automation are more likely to be involved in a collision than those driving under fully manual control (for review, see Endlsey, 2017). Indeed, there are indications that after following a take-over from HADS, drivers show poorer lane keeping performance, shorter headways, and delayed reaction times as compared to performing fully-manual driving (e.g., de Winter et al, 2016; Gold et al, 2013; Merat et al., 2014; Radlmayr, et al, 2014; Stanton et. al, 2001). Thus, any accurate model of driving performance and crash rates must consider the tradeoffs between increased automation levels and decreased performance from the human driver.

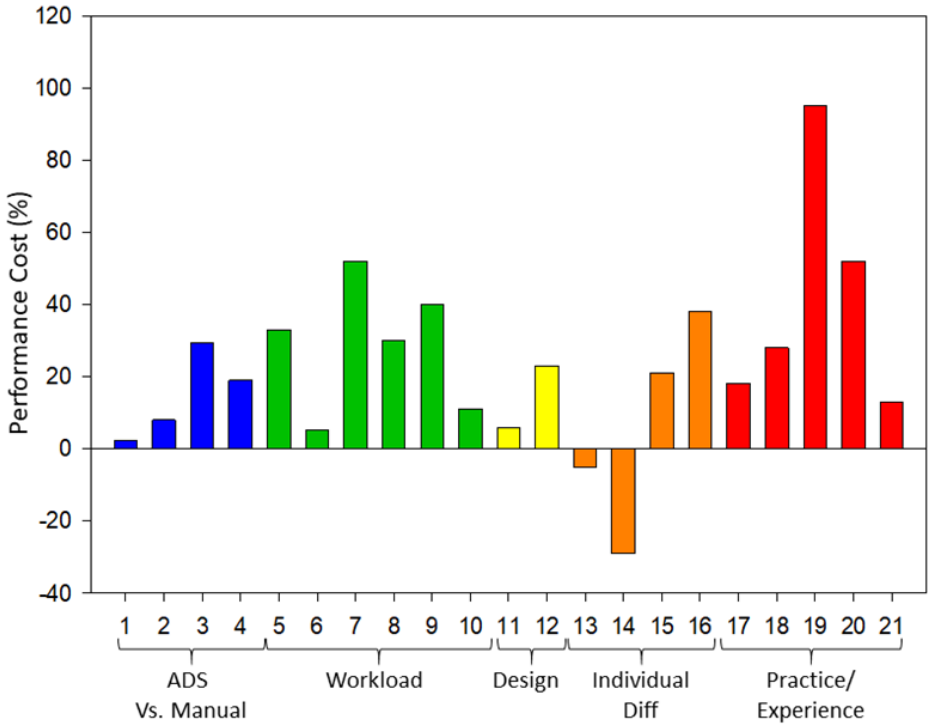
Based on a review of research related to driver take-overs from automation, we identified 22 representative articles in which specific changes in take-over performance could be determined. We categorized this research into 5 factors affecting driver take-over performance:

- HADS vs. fully-manual (no HADS) driving
- Workload (Secondary Tasks)

- Take-over Design elements
- Individual Differences
- Practice/Experience

Figure 1 summaries the changes in performance observed in all the studies we report. Each number along the x-axis represents a different article (see in Appendix A for references). Performance-cost change is calculated as the change in performance from the expected "easier" to "harder" conditions. The actual type of performance measure (generally either take-over time, braking time, or steering correction) varied across studies.

Figure 1. Estimated percent driving performance costs associated with driver take-overs from HADS. More details on each numbered study can be found in the Appendix A.



HADS vs. Manual Driving

Few research studies have directly compared purely manual driving and take-over performance in isolation, without additional factors involved, making it difficult to gauge the specific take-over costs.

The first challenge when comparing fully manual (LO-0) and ADS (LO-3) take-over performance is determining the proper comparison. One solution is to include warning alerts to upcoming obstacles in both manual and ADS conditions and measuring response times from the alert to the initiation of a corrective response (either braking or steering responses). In the 3 studies we examined that included clear comparisons between fully manual and HADS performance, two of the studies found performance differences between manual and HADS responses (2.4% and 8%

performance reductions with HADS). A third and fourth study found a much more substantial performance cost when using HADS (29.4% and 19%, respectively). The latter studies also included secondary tasks to increase workload in both the HADS and manual conditions, which may have had a more substantial effect on HADS responses compared to manual driving responses.

Workload and Secondary Tasks

In the reviewed studies, workload manipulations led to some of the highest performance costs to HADS take-over. Out of the 6 workload-related studies that included quantifiable measures of performance changes, 4 found performance costs of 30% or greater when workload was increased (Eriksson & Stanton, 2017; Hancock et al., 1999; Zeeb, Buchner & Schrauf, 2016; Louw, Merat & Jamson, 2015). These studies involved workload manipulations that involved distraction by reading e-mails or books from electronic devices, which is likely to be a common while HADS is engaged. The greatest cost (52%) was found when the distraction was highly salient and occurred at the same time as the take-over (Hancock et al., 1999). Workload costs were smaller when engaged in conversational tasks (approx. 5%; Gold, Körber, Lechner & Bengler, 2016), or when watching videos (11%; Yoon & Ji, (2019).

Take-over Design Elements

A recent review of take-over request lead times by Eriksson and Stanton (2017) found no consistent lead time used across studies, which ranged from about 1s to 15s. However, the most commonly used lead times were around 3 seconds. Not surprisingly, increasing lead time generally led to better take-over performance by the driver. For example, when take-over performance was examined at several different lead times (4, 6, or 8 seconds), take-over performance improved as lead time increased, with 8s lead time performance no different from fully manual driving performance (Damböck et al., 2012).

Takeover requests can be made via the visual, auditory, or tactual, modalities, or consist of some combination of modalities. Drivers take over faster with any takeover-request combination that includes auditory cues (e.g. auditory only, visual-auditory, tactile-auditory) than without an auditory cue, and drivers rate the usefulness, safety and effectiveness of multimodal alerts containing auditory cues highest (Roche et al., 2018).

Individual Traits

In addition to the design of the HADS take-over system and immediate workload demands, take-over performance will also be determined by individual traits of the driver.

A wide range of cognitive research show steady declines in fluid intelligence with advancing age (Salthouse 1996; Salthouse & Miles, 2002). By itself, this would indicate that older adults would find it more difficult to maintain situation awareness during HADS driving and have slowed responses to take-over events. However, the 2 studies of age and HADS take-overs we found indicate either no difference between young and old take-over performance (Körber, Gold,

Lechner, & Bengler; 2016) or even better take-over performance in older vs. younger adults (Clark & Feng, 2017).

Need for stimulation, or sensation-seeking, refers to the tendency to seek out novel, varied, complex, and intense sensations/experiences (Zuckerman, 1994). Rudin-Brown & Parker (2004) suggest that individuals that are high in sensation-seeking are more likely to engage in other tasks while HADS is engaged, making them less prepared to take over control of the vehicle if a take-over request occurs. In the two studies we reviewed related to need for stimulation, average take-over performance was 29.5% worse for individuals high in the need for stimulation vs. those low in the need for stimulation.

Practice/Experience

Most drivers have yet to experience HADS driving, and it is unlikely that most drivers will receive training with HADS before they hit the roadways. Therefore, an obvious sources of ADS take-over costs may be related to driver inexperience. In the studies reviewed, practice/expertise had some of the most dramatic effects on HADS take-over performance. For example, Payre, Cestac, & Delhomme, (2016) found a 28% performance improvement on the second vs. first take-over event, indicating that even a small amount of practice with HADS take-overs can improve driver experience. The benefit of just 1 take-over event was especially beneficial to drivers with no familiarity with HADS (Hergeth, Lorenz, & Krems; 2017). Additional training with either fixed base or VR simulators resulted in significant benefits to take-over performance (97%-100% improvement; Sportillo, Paljic & Ojeda; 2018).

To summarize, a qualitative examination of takeover performance effects indicates:

- Worse driver performance following take-over of HADS vs. fully-manual driving (an average 14.7% decline).
- Worse take-over performance with increased workload created by the introduction of secondary tasks (average 28.5% decline)
- Smaller take-over performance effects related to the type of take-over alert (performance effects between 5.8% and 23% depending on alert type)
- Individual differences in take-over performance are less clear and are somewhat contrary to expectations: age may improve takeover performance in some situations (18% better performance for older vs. young adults); need for stimulation reduces performance (average 29.5% performance decline with high need for stimulation)
- Worse take-over performance with no experience with the HADS (average 41.4% decline).

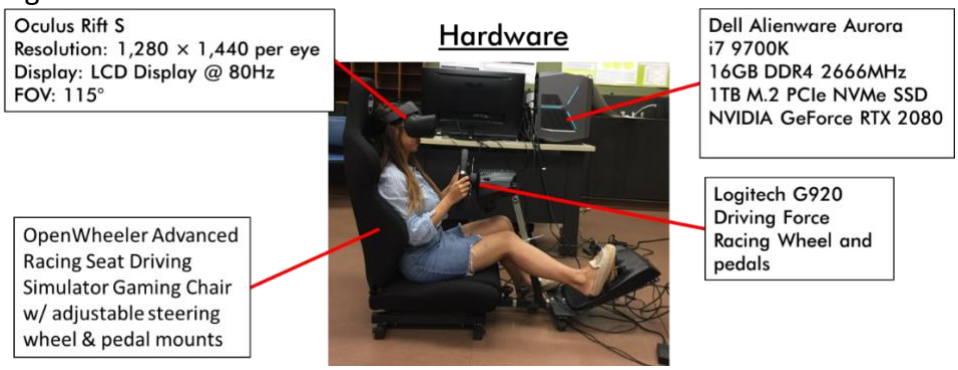
Methodology

Equipment

Equipment used includes a desktop computer with an Intel i9 9900k processor, Nvidia 2080 ti graphics card, standard mouse and keyboard, 27-inch monitor, and Microsoft Windows 10

operating system. The VR and driving equipment include an Oculus Rift S VR Head-mounted display, Logitech G9200 steering wheel, Unity3D software, and Easyroads3D Unity asset.

Figure 2: Simulation Hardware



As shown in the Figure 2, each participant comfortably sat in an adjustable bucket seat with a steering wheel bracket attachment, adjusted their seating position towards the gas and brake pedals (right-knee bent greater than 120 degrees in resting position), then donned the Oculus Rift S HMD for proper fitment and clear VR display.

Virtual Environment

Car Interior

In the virtual environment, participants were seated in the driver's seat of a 4-door sedan with a fully detailed interior (see Figure 3). The interior included a fully functional dashboard including analogue speedometer and tachometer. The steering wheel provided rotational feedback to movement of the wheel in the real world (i.e., moving the real-world steering wheel led to congruent movements of the virtual steering wheel). Steering and brake pedals were also visible in the foot well. The vehicle also had functional rear and side-view mirrors.

Figure 3: View from inside vehicle

Driving Track

Participants drove eight track scenarios, four in the Manual condition and four in the Take-Over condition. The tracks consisted of three-lane highway roads and were 12m wide. Prior to an initial practice track, participants received the following instructions:

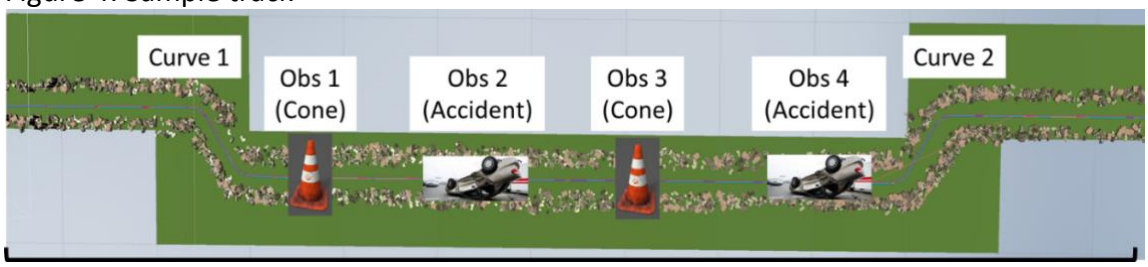
"In this experiment, you will perform a simple driving task in virtual reality (VR). On some trials, you will do all of the driving and occasionally avoid an obstacle in the road. You should try to

maintain highway driving speeds. On other trials, the car driving will be fully automated. However, occasionally, the automation will turn off (an alarm will sound) and you will need to quickly take over control of the car and avoid an obstacle. You will start with some practice driving to get used to the driving environment. If you have any questions, please ask the experimenter now."

Participants were also verbally instructed to maintain the vehicle at a highway speed of 80 miles per hour.

A practice track was run prior to the eight test tracks. The practice track was approximately 9 miles in road length and took 6 minutes to complete. All test track scenarios were approximately 17.5 miles in road length and took 12 minutes to complete. In each track two S-curves occurred, requiring the driver to change lateral position in order to stay in the center lane. Each S-curve was rated at 60 mph or 2500 feet in radius per turn in accordance with Maximum Comfortable Speed on Horizontal Curves (Caltrans Highway Design Manual 2018, p. 200-215). The order of test tracks as well as the driving condition (Manual or Take-Over driving) were counterbalanced across participants. A sample track is shown In Figure 4.

Figure 4: Sample track



Participants were instructed to drive in the center lane and maneuver around three types of obstacles: reduced speed s-curve (left-right or right-left), orange traffic cone, or an overturned vehicle.

Driving events

On each of the 4 Manual Driving and 4 Take-Over Driving tracks, there were 2 different event types, cones, accidents and curves that occurred twice in each track:

Obstacles (cone in center lane)

Each traffic-cone obstacle would appear in the center lane approximately 6 seconds (approximately 215m) ahead of the participant vehicle, assuming a vehicle velocity of 80 mph.

Obstacles (Overturned car in center lane)

Overturned vehicles, similar to cones, appeared in the center lane 6 seconds (approximately 215m) ahead of the participant vehicle when traveling at 80 mph.

Vehicle traffic

All track scenarios contained 10 additional vehicles (also 4-door sedans) to simulate highway traffic, with most traffic vehicles within viewing distance of the participant's vehicle. Traffic

vehicles maintained a distance from the participant's car to prevent any driver-initiated maneuvers to avoid traffic.

Driving Condition

Manual Driving

On 4 of the tracks, the participant had complete control over driving the entire track, and was instructed to maintain the car in the center lane except when avoiding obstacles (cones or overturned vehicles) located in the center lane.

Take-Over Driving

On 4 of the tracks, the car was in a fully automated, self-driving mode. Six seconds, approximately 215m in distance, prior to driving events (one of each event type), a take-over request (TOR) indicated that the participant should immediately take control of the vehicle. The TOR was both visual and auditory in nature. At the onset of a TOR, the center of the car steering wheel changed from green to red, indicating the car was now in manual (non-automated) mode. In conjunction with this change from green to red, a brief, repeating auditory tone was presented. Two seconds after the vehicle passed the driving event (the obstacle), the car returned to the automated self-driving mode as indicated by the light at the center of the steering wheel turning from red to green. The remaining 2 obstacles were handled by the automation (no TOR issued).

Data Recording

Recording Vehicle Position

Vehicle position was recorded every 20ms, resulting in approximately 300,000 measures for each driver. The following performance measures were subsequently determined:

- Lateral position: Position of the center of the vehicle relative to the center of the middle lane
- Road progression: How far the vehicle was along the roadway
- Speed: Speed of vehicle in mph

Analysis of Avoidance Maneuvers

For each obstacle event in the driving task, vehicle position was calculated as lateral deviation from the center of the middle lane starting 350m prior to the obstacle until 350m after passing the obstacle.

For each specific obstacle event (cone in road and car accident), the following data (Table 2) were determined based on lateral position, distance from obstacle, and time course of the maneuver.

Table 2. Detailed description of each of these measures and how they were calculated are provided below.

Measure	Abbreviation	Meaning
Initial Distance to Contact	DTC_{init}	Distance from obstacle when avoidance manuever began in meters (m)
Initial Time to Contact	TTC_{init}	How long before obstacle contact the avoidance maneuver began in milliseconds (ms)
Completed Distance to Contact	DTC_{comp}	Distance from obstacle when vehicle was sufficiently moved so that it would avoid the upcoming obstacle in meters (m)
Completed Time to Contact	TTC_{comp}	How long before obstacle contact that the vehicle was sufficiently moved to avoid the upcoming obstacle in milliseconds (ms)

Initial Distance To Contact (DTC_{init}) And Time To Contact (TTC_{init}):

Initial distance to contact (DTC_{init}) and initial time to contact (TTC_{init}) indicate the respective distance from the obstacle and time until contacting the obstacle when an avoidance maneuver was initiated.

Two criteria were used to determine the initiation of the obstacle avoidance maneuver:
Final direction change – The point from which all movement was in the direction of the avoidance maneuver (from the center lane to either the left or right lane).

Sustained acceleration – For some obstacle events, participants were already gradually moving toward the side of the maneuver before the appearance of the obstacle. In these cases, final direction change was not an appropriate way to determine the onset of the maneuver. Instead, onset of the maneuver was determined as the point at which the speed of movement toward the obstacle increased to 1m/s, or 2.2 mph.

The speed of the vehicle at the time of the initiation of the obstacle maneuver was also analyzed.

Completed Distance To Contact (DTC_{comp}) and Time to Contact (TTC_{comp})

The obstacle maneuver was considered completed when the vehicle had moved laterally to a sufficient degree to avoid the upcoming obstacle (i.e., the vehicle fully crossed into the left or right lanes from the center lane, either 2.85m to the left or right from the center).

Completed distance to contact (DTC_{comp}) and completed time to contact (TTC_{comp}) are the vehicle's distance from the obstacle and time until contacting the obstacle after the obstacle avoidance maneuver was completed. DTC_{comp} and TTC_{comp} represent when the vehicle had been sufficiently maneuvered around the obstacle.

The speed of the vehicle at the completion of the obstacle maneuver was also analyzed.

Workload

After each of the 8 tracks, participants completed a paper-based NASA Task Load Index (TLX) workload scale (see Appendix B). NASA-TLX consists of 6 subscales measuring different subjective dimensions of workload: Mental Demands, Physical Demands, Temporal Demands, Frustration, Effort, and Performance. NASA-TLX also included an initial weighting of these dimensions. Developed in 1986, NASA-TLX is a very well accepted measure of workload and has been translated into over 12 languages – a review by Hart (2006) found over 550 studies in which the scale is used, and there are over four thousand citations to the scale.

A single workload score is calculated from NASA-TLX following each track by measuring the percent rating (0-100) on each dimension and calculating the average across all dimensions. Higher values indicate increased subjective mental workload.

Driver opinions of automation

After completing the final (8th) track, participants completed a Trust in Automation questionnaire adopted from Jian et al. (2000) using a 6 choice Likert-type scale (see Appendix B). The 6-choice scale was selected to prevent neutral responses, requiring participants to select either positive or negative responses. The questionnaire is designed to measure specific attitudes about automation including trust (items 2-5) and overall view of automation (items 9-12). Several additional questions were included that were specific to the current simulation, including:

- How much did the simulator feel like a car on the road?
- How concerned would you be about driving or riding in a vehicle with self-driving technology such as what you experienced in this experiment?
- Highly-automated vehicles such as in the experiment will have a harmful or injurious outcome.

Each question was rated on a 6-point forced choice Likert-like scale from 1(low or highly disagree) to 6(high or highly agree).

Correlative analysis

A correlative analysis explored any relations between measures of workload, opinions of automation, and driver performance on the tracks to determine whether these factors predict successful performance on driver events (obstacles and curves) in both the Manual and Take-over conditions.

Experimental Results

A total of 37 individuals participated in the experiment. Four participants did not complete the experiment – 2 ended after the first practice track because of minor dizziness related to the VR simulator and 2 because of unrelated illness (flu and back pain). An additional participant did not follow instructions, staying on the left or right side of the roadway rather than at the center throughout most Manual condition trials; therefore, their data was removed from the final data analysis. Demographic information for the remaining 32 participants is shown in Table 3. No participants were excluded based on their demographic characteristics.

Table 3: Summary of participant demographic information

Subject	Age	Sex	Ethnicity	Driving Experience	Miles Driven/Year	Simulator Experience	Get VR Simulator Sickness	Play Video Games	Color Blind
1	21	M	Hispanic	5yr	10000	n	n	y	n
2	24	m	Hispanic	6yr	15000	n	n	n	n
3	19	f	Hispanic	3yr	300	n	n	n	n
4	20	f	White	4yr	10000	n	n	n	n
5	25	f	Asian	9yr	8000	y	n	n	n
6	23	m	White	8yr	20000	n	n	y	n
7	28	f	Hispanic	10yr	13000	n	n	n	n
8	21	f	Hispanic	3yr	15000	n	n	y	n
9	22	f	Hispanic	5yr	15000	n	n	n	n
10	26	m	Hispanic	8yr	15000	n	n	n	n
11	22	f	Asian	4yr	20000	y	n	n	n
12	39	m	White	23yr	15000	y	n	n	n
13	22	f	White	5yr	2000	n	n	n	n
14	22	f	White	5yr	10000	n	n	n	n
15	22	m	White	4yr	2000	n	n	n	n
16	21	m	Hispanic	4yr	25000	n	n	y	n
17	20	m	Hispanic	1yr	1000	y	n	n	n
18	21	f	Asian	4yr	10000	n	n	n	n
19	23	f	Hispanic	6yr	3000	n	n	n	n
20	28	m	Hispanic	10yr	12,500	n	n	y	n
21	27	m	White	11yr	13000	n	n	y	n
22	22	f	Hispanic	5yr	6000	n	n	y	n
23	23	m	Hispanic	7yr	10000	n	n	n	n
24	21	f	White	4yr	1500	n	n	n	n
25	28	m	White	10yr	10000	n	n	y	n
26	26	m	White	10yr	15000	n	n	y	n
27	21	f	Hispanic	4yr	2000	n	n	n	n
28	28	m	N/A	11yr	33000	n	n	n	n
29	21	f	Pacific Is.	3yr	5000	n	n	n	n
30	28	m	Asian	8yr	10000	y	n	y	n
31	29	m	White	14yr	10000	y	n	n	n
32	25	f	Asian	10yr	10000	n	n	n	n

Demographics of were representative of young-adult drivers in the Los Angeles area. Participant characteristics are summarized below:

- Age: Mean = 24 years (19yr-39yr), SD = 4.0yr
- Gender: 50% male, 50% female
- Ethnicity: 43.8%% Hispanic, 34.4%% White, 15.6%% Asian, 3.1% Pacific Islander

- Driving experience: Mean = 7 years (1yr - 23yr), SD = 4.24yr
- Drive/Yr: Mean = 10,853 (300mi – 33000mi), SD = 7270mi

Wrong-Lane Driving and Crashes

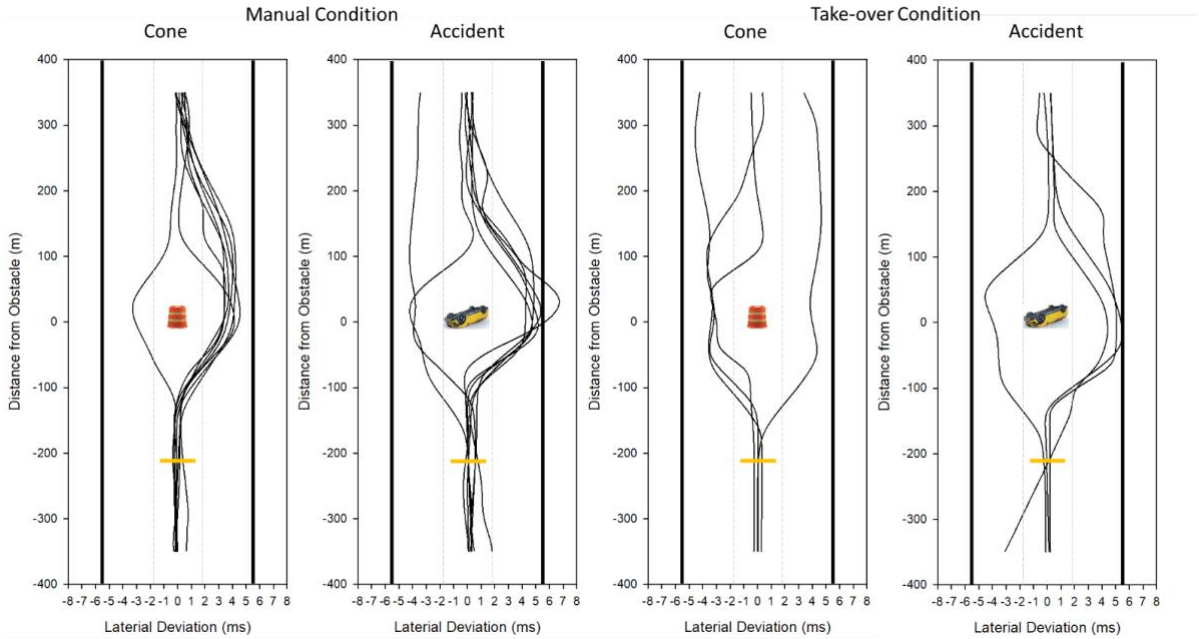
Participants made very few crashes (contact with the obstacles). In total, out of 768 obstacle maneuvers across all 32 participants, there were 9 crashes, or a total crash rate of 1.2% during obstacle avoidance maneuvers.

In the Manual driving condition, there were a large number of wrong-lane driving maneuvers, in which the participants opted to drive in the left or right lane prior to the obstacles, despite being instructed to maintain the vehicle in the center lane. In total, participants were in the wrong lane prior to 18% of obstacle maneuvers. Crashes and wrong lane driving maneuvers were excluded from the following analyses of initiations and completions of obstacle avoidance maneuvers.

Initiation and Completion of Avoidance Maneuver

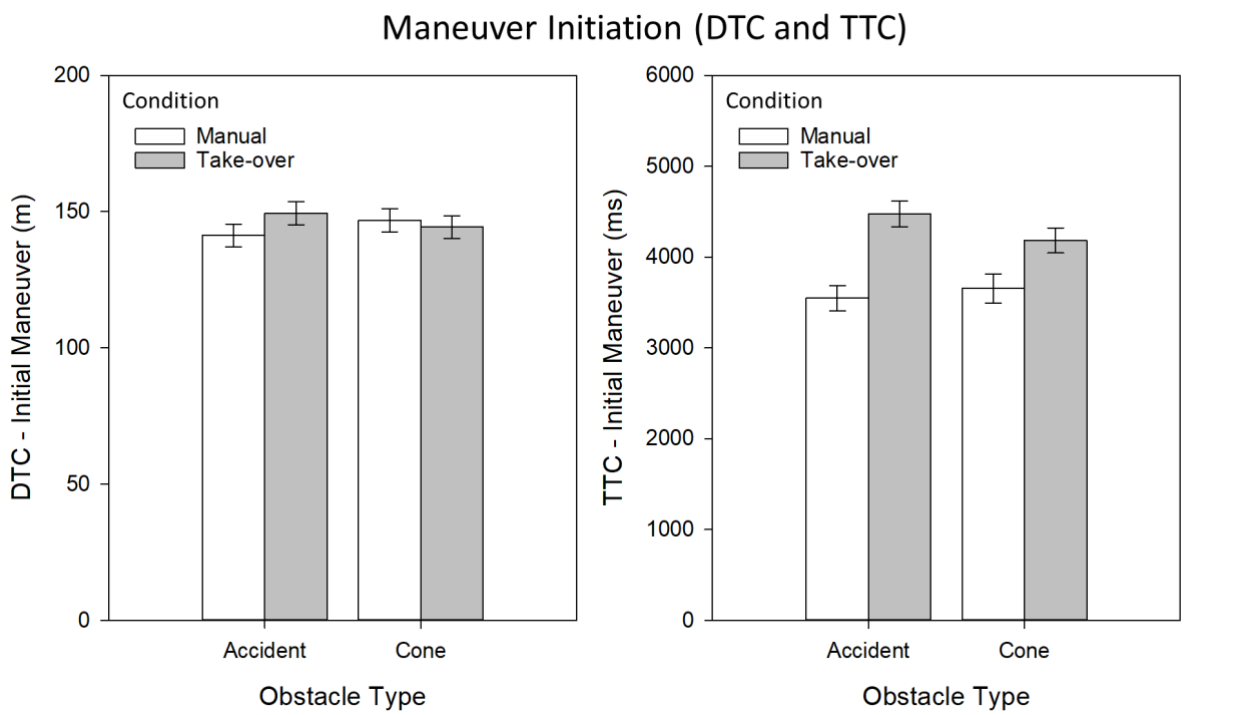
For each participant, 8 cone and 8 accident obstacle maneuvers were recorded in the Manual condition (2 in each of the 4 Manual condition blocks) and 4 cone and 4 accident obstacle maneuvers were recorded in the Take-over condition (1 in each of the Take-over condition blocks). Obstacle maneuvers for obstacle types and condition are shown for 1 participant in Figure 5. Negative distances from obstacle indicate that the vehicle was approaching the obstacle and positive distances indicate that the vehicle passed the obstacle. Lateral deviation is how far the vehicle was to the left or right of the center of the middle lane. These data were used to calculate the distance from the obstacle (Distance to Contact; DTC) and time to obstacle (Time to Contact; TTC) when the obstacle maneuver was initiated and completed. Yellow bars indicate when the obstacle appeared as well as the onset of the take-over request (TOR) in the Take-Over condition.

Figure 5



Distance and Time to Contact in maneuver initiation

Figure 6

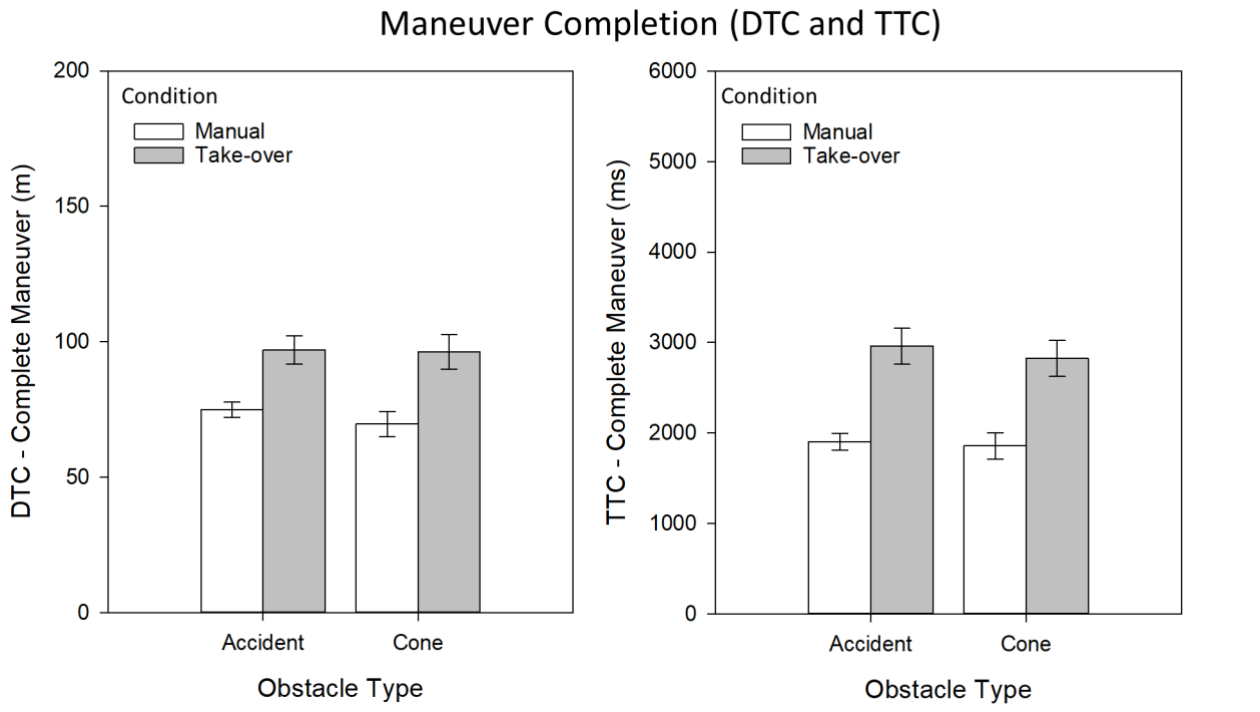


Initial maneuver data for DTC_{init} and TTC_{init} were subjected to a repeated measures ANOVA with the factors of Obstacle Type (Accident or Cone) x Condition (Manual x Take-over). Significance levels were set at $p < .05$. P-values indicate the likelihood that the difference between conditions was due to chance (not a real difference). A p-value less than .05 means that, given the data, there is less than a 5% chance that the observed effect is not really there – if p is greater than .05, then the assumption is made that the examined effect was not significant. This is a common conservative threshold used in behavioral research. As shown in Figure 6, for DTC_{init}, the distance of the obstacle at initiation of the obstacle avoidance maneuver was not different for Manual and Take-over trials, and no difference for accident vs cone obstacles, *p's* > .38.

For TTC_{init} , the time between initiation of the avoidance maneuver and obstacle contact was greater in the Take-over condition than the Manual condition, $F(1,31) = 44.32$, $p < .001$, indicating that avoidance maneuvers were initiated with more time to spare in Take-over trials than Manual trials. There was no difference in TTC_{init} for accident vs cone obstacles, $F(1,31) = .74$, $p = .40$. However, the difference in TTC_{init} for Manual vs Take-Over conditions was slightly smaller for cones than accidents, $F(1,31) = 4.25$, $p = .05$.

Distance and Time to contact in maneuver completion

Figure 7

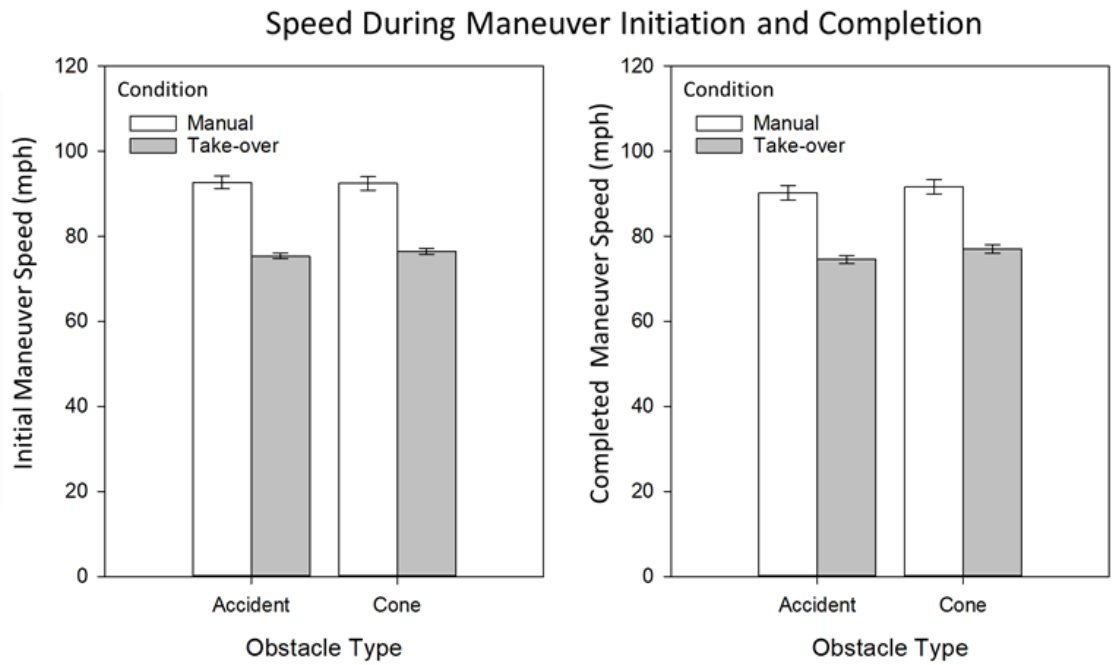


Distance to contact (DTC_{comp}) and time to contact (TTC_{comp}) for maneuver completion (when the vehicle had been maneuvered far enough to avoid the upcoming obstacle) are shown in Figure 7. An ANOVA with the factors of Obstacle Type (Accident or Cone) x Condition (Manual x Take-over) indicates that participants in the Take-Over condition were farther away from the obstacle when the obstacle avoidance maneuver was completed compared to the Manual condition, $F(1,31) = 31.47$, $p < .001$. There was no difference in DTC_{comp} for obstacle type and no interaction between Condition and Obstacle Type, p's > .36.

Consistent with DTC_{comp} , TTC_{comp} was greater in the Take-over condition than in the manual condition, indicating that avoidance maneuvers were completed with more time left before obstacle contact, $F(1,31) = 52.61$, $p < .001$. There was no difference in TTC_{comp} for accident vs cone obstacles and no interaction between the factors, *p's > .39*.

Vehicle speed at maneuver initiation and completion

Figure 8

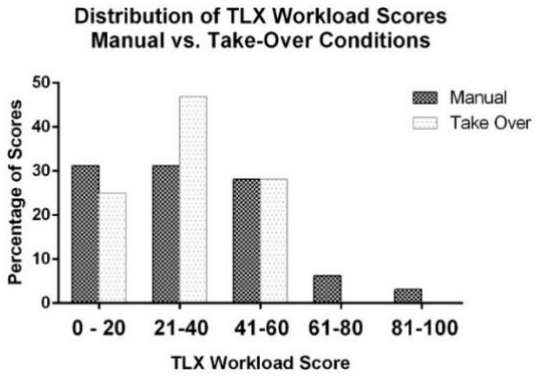


ANOVAs of vehicle speed at the initiation and completion of obstacle avoidance maneuvers found that vehicles were going significantly faster in the Manual compared to the Take-over condition, $F(1,31) = 151.92$, $p < .001$. Vehicle speed was also faster in the Manual condition than the Take-over condition at completion of the obstacle maneuver, $F(1,31) = .76$, $p = .39$ (see Figure 8). There was no difference in vehicle speed for the Obstacle type and no Obstacle Type x Condition interaction at obstacle avoidance maneuver ignition or completion, *p*'s > .15. Note also, that differences in speed between initial and completed maneuvers were minimal.

Workload Measures

Figure 9 summarizes reported NASA TLX workload rating frequencies for participants in the Manual and Take-Over conditions. Self-reported workload ranges from 0 (lowest) to 100 (highest).

Figure 9

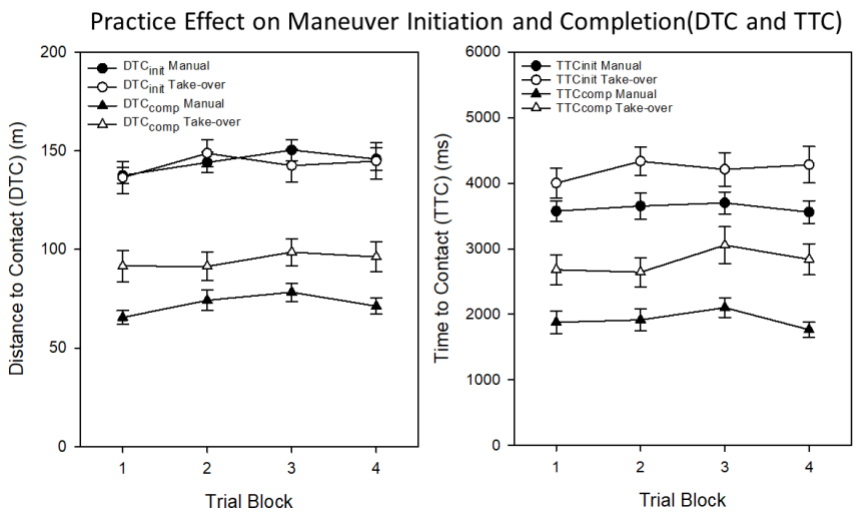


Average reported workload was relatively low. In a meta-analysis of TLX scores for driving, Grier (2015) reported that the 50th percentile TLX score was 42. In this simulation, although workload was higher in the Manual (*M* = 34%, *SD* = 20.2%) compared with the Take-over condition (*M* = 28%, *SD* = 13.5%), this difference was not significant, $t(32) = 1.90$, $p = .07$. Note, however, that the variability of the workload scores was higher in the Manual Condition.

Practice effects on maneuver performance and subjective workload

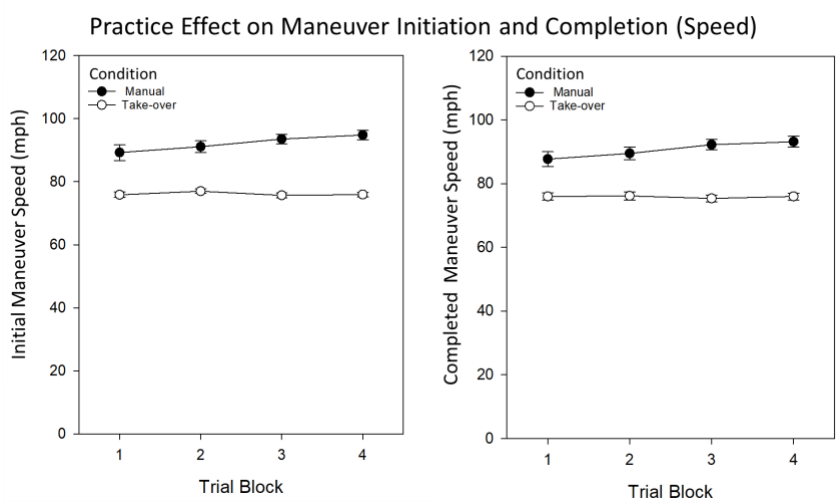
Since each participant performed 4 trial blocks in the Manual and Take-Over conditions, analyses were conducted across trials blocks to determine if there were any practice effects on obstacle maneuver performance or workload rating.

Figure 10



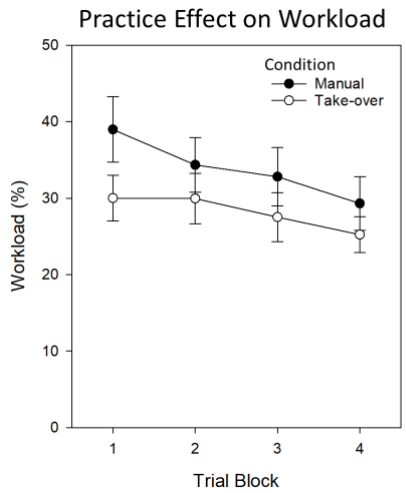
Practice effects for obstacle avoidance maneuver performance are shown in Figure 10. An ANOVA of Condition x Block found no change in distance from contact (DTC) at the initiation of the obstacle avoidance maneuver, $p > .61$, nor at the completion of the maneuver, $F(3, 90) = 2.16$, $p = .10$. Likewise, no practice effect was found for time to contact (TTC) at the initiation, $p > .77$, or completion of the maneuver, $F(3, 90) = 2.18$, $p = .11$.

Figure 11



Vehicle speed at the initiation of obstacle avoidance maneuvers (Figure 11) did increase linearly across trial block for the Manual Condition, $F(1,30) = 9.45$, $p = .004$, but not for the Take-over condition, $p > .42$. For vehicle speed at the completion of obstacle maneuvers, the Manual Condition again showed a linear increase in speed, $F(1, 30) = 12.74$, $p < .001$, and the Take-Over condition did not, $p > .89$.

Figure 12



As shown in Figure 12, workload rating was lower as trial block progressed, likely due to increased familiarity with the task, $F(1,30) = 11.56$, $p = .002$. This decline in workload was not different in the Manual and Take-over conditions, $F(1,30) = 1.20$, $p = .28$.

Opinions of Automation

Table 4 provides a summary for each of the questions on the Opinions of Automation questionnaire. Each item was rate on a forced-choice Likert scale between 1 (strongly disagree/negative) and 6 (strongly agree/positive). Of note, participants on average agreed that the simulator felt like a car on the road ($M = 4.16$). Views of automation were for the most part neutral, with an average score of 3.44 on item 4 ("I would like to have a highly-automated system in my car."), a score of 3.03 on item 12 ("Automation will free me of much of the routine parts of driving so I can concentrate on "managing" the drive.") and a score of 3.10 on item 16 ("I would like to have a highly-automated system in my car.").

Table 4: Summary of ratings from Opinions of Automation Questionnaire

Question #	Question	Mean (SD)	Median	Lower Limit	Upper Limit
1	How much did the simulator feel like a car on the road?	4.16(.99)	4.00	2.00	6.00
2	The system is dependable.	3.63(1.26)	3.50	1.00	6.00
3	The system is reliable.	3.75(1.27)	4.00	1.00	6.00
4	I can trust the system.	3.44(1.50)	3.00	1.00	6.00
5	How concerned would you be about driving or riding in a vehicle with self-driving technology such as what you experienced in this experiment?	2.75(1.24)	3.00	1.00	5.00
6	Highly-automated vehicles such as in the experiment will have a harmful or injurious outcome.	3.56(1.22)	3.50	2.00	6.00
7	The idea of fully automated driving is fascinating.	4.88(1.50)	5.00	1.00	6.00
8	Manual driving is enjoyable.	5.00(1.05)	5.00	1.00	6.00
9	Highly automated driving will be enjoyable.	3.63(1.30)	4.00	1.00	6.00
10	Highly automated driving will be easier than manual driving.	4.27(1.46)	5.00	1.00	6.00
11	What is your general opinion regarding autonomous and self-driving vehicles?	3.80(1.45)	4.00	1.00	6.00
12	Automation will free me of much of the routine parts of driving so I can concentrate on "managing" the drive.	3.03(1.35)	3.00	1.00	6.00
13	I will make fewer errors in a highly-automated vehicle than in my current vehicle.	3.37(1.13)	3.50	1.00	5.00
14	Automation will not reduce the workload, because there will be more to monitor.	3.70(1.26)	4.00	1.00	6.00
15	In a highly-automated vehicle, I will feel more like a "button pusher" than a driver.	4.53(1.20)	5.00	2.00	6.00
16	I would like to have a highly-automated system in my car.	3.10(1.52)	3.00	1.00	6.00

Correlative Analysis

Pearson correlations of avoidance maneuver performance measures, workload, and ratings of opinions of automation are shown in Table 5.

Table 5: Correlations between avoidance maneuver performance measures and workload, ratings of opinions of automation, and demographic information. All correlations that were significant ($p < .05$) are bolded. A single asterisk indicates a significance of $p < .05$. Double asterisk indicates $p < .01$.

	Manual Condition						Take-Over Condition					
	Initial			Completed			Initial			Completed		
Question	DTC	TTC	Speed	DTC	TTC	Speed	DTC	TTC	Speed	DTC	TTC	Speed
1	-0.04	.26	**-.45***	-.11	.23	**-.39***	-.05	.22	**-0.40***	.20	-.18	-.29
2	-0.03	-.04	-.02	-.22	.10	.04	-.06	-.09	.34	-.07	-.11	.24
3	-.17	.04	.00	-.22	.07	.04	-.14	.01	.29	.03	-.18	.21
4	-.09	-.09	.20	-.14	.00	.23	-.05	-.10	**0.37***	-.07	-.09	.25
5	-.12	.00	.14	.08	-.12	.14	.01	.00	-.09	.07	-.06	-.16
6	-.15	.31	**-.37***	-.08	.20	**-.40***	-.06	.21	-.26	.02	.06	-.25
7	-.07	-.03	.19	.12	-.17	.09	**.37***	**-.42***	-.03	**0.37***	**-0.36***	.12
8	-.28	.13	-.01	-.23	.14	.02	-.19	.14	.05	.01	-.15	.11
9	-.13	-.07	**.39***	.34	**-.39***	.26	.17	-.20	.15	.21	-.17	.01
10	-.11	-.18	**.53****	**.37***	**-.52***	**.44***	-.03	-.16	.32	.10	-.15	.28
11	-.11	-.12	**.36***	.24	-.32	.30	.13	-.26	.28	.15	-.19	.28
12	.10	-.25	**.44***	.28	-.30	.34	.16	-.31	**0.41***	-.03	.04	.33
13	.25	-.28	.35	**.61****	**-.55****	.27	.20	-.19	.03	.33	-.26	-.04
14	.20	-.07	-.22	-.10	.16	-.18	.12	-.01	-.23	.04	.00	-.22
15	.03	-.09	.18	.03	-.09	.20	.10	-.14	.14	.14	-.14	.19
16	-.03	.02	-.02	.04	-.03	.00	.01	.05	.05	.02	-.03	-.05
Workload Manual	-.14	.25	-.23	-.09	.13	-.26	-.10	.26	-.35	.07	.02	-.27
Workload Take-Over	-.04	.30	**-0.46***	-.23	**0.39***	**-.48****	.04	.15	**-0.35***	-.10	.19	-.35
Age	-.06	-.10	.25	-.07	-.02	.17	.08	-.11	.05	-.12	.14	.02
Driving Exp	-.04	-.10	.23	-.12	.02	.17	.08	-.10	-.03	-.12	.13	-.02
Miles/Yr	-.14	.05	.17	.08	-.13	.07	.21	-.24	.00	.07	.02	.08

Items 9-12 on the Opinions of Automation questionnaire are related to how positively automation is perceived. Positive correlations between these items and speed indicate that participants with more positive views of automation tended to drive faster at the initiation of obstacle avoidance maneuvers in the Manual Condition.

Also noteworthy, workload measures in the Take-Over condition were negatively correlated with vehicle speed; participants experiencing high workload may have slowed the vehicle to better handle obstacle avoidance maneuvers. There were no significant correlations between obstacle maneuver performance and either age, driving experience (driving exp.), or miles driven per year (Miles/Year).

Finally, significant correlations were also found between workload ratings and opinions of automation. As summarized in Table 6, items 2-5 on the Opinions of Automation questionnaire were strongly negatively correlated with workload ratings for the Take-Over condition. These items are also correlated with one another and are related to subjective trust in automation. The

negative correlations may indicate that when general trust in automation is high, participants spent less time monitoring the automation, leading to lower workload ratings.

Table 6: Correlations between workload, ratings of opinions of automation, and demographic information. All correlations that were significant ($p < .05$) are bolded. A single asterisk indicates a significance of $p < .05$. Double asterisk indicates $p < .01$.

Question	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	WL(M)	WL(T)	Age	Drv Exp
1. Sim Feels like car or road																				
2.System Dependable	.20																			
3. System Reliable	.21	**.93****																		
4. Trust System	.04	**.80****	**.79****																	
5. Not concerned with system	.09	**.39***	**.43***	**.61****																
6. Automation harmful	.19	-.30	**-.37***	**-.49****	**-.52***															
7. Automation fascinating	-.05	.13	.10	.20	.35	-.15														
8. Driving enjoyable	.29	.18	.23	.22	-.17	.11	-.21													
9. Automation enjoyable	-.13	-.06	.03	.15	**.49****	-.24	**.49****	-.23												
10. Automation easier	-.33	-.07	-.01	.10	.36	-.29	.22	-.22	**.73****											
11. Opinion of automation	-.21	.04	.11	.29	**.48****	-.382*	.652**	-.20	**.69****	**.56****										
12. Automation freeing	-.28	.05	.03	.25	**.39***	**-.38***	**.44***	**-.49****	**.69****	**.55****	**.55****									
13. Automation fewer errors	-.05	-.01	.04	.03	**.39***	-.06	.16	**-.47****	**.57****	**.57****	.32	**.49****								
14. Automation reduce work	.25	.22	.15	-.15	-.24	.32	-.29	.00	**-.38***	**-.46***	**-.64****	-.32	.03							
15. Automation button pusher	.17	.01	.05	.15	.07	-.14	.12	-.01	-.12	-.01	.06	.11	.02	-.27						
16. Want automated vehicle	-.20	.12	.09	.15	-.04	.10	-.20	.11	.08	.05	-.06	-.09	-.03	.09	**-.56****					
Workload Manual (WL(M))	.17	-.33	-.26	**-.38***	-.28	.18	-.13	-.24	-.02	-.03	-.21	-.12	.07	.13	-.02	-.04				
Workload Take-Over (WL(T))	.05	**-.40***	**-.40***	**-.61****	**-.54****	.34	-.12	-.22	-.32	**-.46***	-.26	-.33	-.29	.28	-.33	.00	**.56****			
Age	-.21	.06	.15	.11	.19	**-.39***	.17	.03	.11	.02	.15	.16	-.01	-.01	.17	**-.41***	-.27	-.21		
Driving Experience	-.19	.02	.10	.06	.21	**-.40***	.18	.05	.13	.05	.14	.15	.05	.02	.10	**-.38***	-.24	-.19	**.96****	
Miles Driven/Year	-.21	-.24	-.13	-.13	.17	-.15	.521**	-.402*	.375*	.35	**.50****	**.38***	.20	**-.44***	.29	-.35	-.08	-.09	.35	.35

Summary

The table below summarizes the main differences in obstacle maneuver performance in the Manual and Take-Over driving conditions. Percent differences are changes from the Manual to the Take-Over Conditions.

Table 6

	Manual	Takeover	Difference (%)
Initial			
DTC	144m	147m	2.08%
TTC	3599ms	4310ms	19.76%
Speed	93mph	76mph	-18.28%
Completed			
DTC	72m	97m	34.72%
TTC	1878ms	2880ms	53.35%
Speed	91mph	76mph	-16.48%

Overall, participants performed safer obstacle avoidance maneuvers in the Take-Over condition, as indicated by farther distance to contact (DTC) and longer time to contact (TTC) for both maneuver initiations and completions. It is likely that the better performance observed following take-overs than manual driving is related to the following factors:

1) Vehicle speed was on average around 17% slower when performing obstacle avoidance maneuvers after a take-over from automation than in fully manual driving. Although participants were instructed to maintain a speed of 80mph throughout the driving track, they had more control over the vehicle in the Manual condition and opted to drive at higher speeds. There are several reasons that this may have been the case. First, since the track was of fixed length, drivers may have opted to driver faster to complete the task more quickly. Second, recent research indicates that drivers may underestimate vehicle speed in virtual environments compared to the real world (Hurwitz, Knodler & Dulaski, 2005). This is likely the case because of the reduced visual information in virtual environments, which makes it more difficult to gauge speed and distance. Additionally, the lack of gravitational forces and haptic feedback from the vehicle may also play a role in speed underestimation.
2) In Take-Over trials, participants received a take-over alert (TOR) tone alerting them that the vehicle has shifted to manual mode. Since all take-over occurred immediately prior to an obstacle, participants may have also used the TOR as an alert to prepare for an obstacle maneuver.
3) The Manual driving condition likely led to greater driver fatigue. When in the Take-over condition, participants could largely ignore the road environment until the TOR indicated the need to intervene. This possibility is partially supported by workload rating, which,

although not significantly different between the conditions, were slightly higher in the manual condition.

Correlative analyses did not find a clear relation between maneuver performance and either workload or opinions of automation. However, reported workload was related to several ratings of trust in automation. Higher trust in automation led to lower reported workload in the Take-over condition.

Conclusions

Recommendations and Implementation

In this report, we performed a review of current knowledge of driver performance following take-overs from HADS, developed a virtual reality highway driving simulator to further test driver take-over performance, and conducted a simulator study comparing human driver performance on obstacle avoidance maneuvers following take-overs from HADS versus current all-manual driving. Although previous work has found performance costs during take-overs, especially with the inclusion of other factors such as secondary tasks and inexperience, we found no driver performance cost following takeovers when compared to current, all-manual driving. Rather, our results indicate several features of automation take-overs that potentially benefit driver performance, including:

- Take-over requests (TORs) are likely to occur when an emergency driving maneuver is required – therefore TORs may also act as a more general alert for the human driver to prepare for a vehicle maneuver
- Since automated driving systems maintain the vehicle in a safer state, such as lower speed and less lane deviation, the vehicle will be in a better initial state when action from the human driver is required
- Automated driving systems will reduce driver fatigue, leaving the human driver more capable of responding to road conditions following take-overs.

Limitations and Future Directions

There are several limitations in scope to the current study which require further investigation in order to more precisely anticipate the influence of driver take-overs on vehicle performance:

- There are likely individual differences in take-over performance that were not measured in the current study including age, experience with technology, and cultural background. Such demographic factors likely influence performance when transition from automated systems as well as reported workload and opinions of automation.
- In the current study, we measured driver performance based on obstacle avoidance maneuvers. Other common driver actions such as lane keeping, braking actions, and vehicle following may be more or less likely to elicit driver errors following takeovers.
- Although we did not find a clear relation between trust in automation and performance, lower reliability of automated driving systems may affect driver responsiveness in take-over situations. For example, in the current study, TORs always occurred prior to obstacle

avoidance maneuvers. If TORs occurred more frequently and without a clear reason, drivers may become more complacent and less responsive in take-over events.

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Data Management Plan

Products of Research

Our research generated demographic, survey, and behavior data related to driver performance on a simulated highway environment. Data was collected from 36 individuals, that were predominantly undergraduate and graduate students at California State University Long Beach. All identifying information has been removed from the data.

Specifically, data in the selected repositories includes:

- Demographic data related to participant characteristics, including age, gender, ethnicity, and driving experience.
- Subjective reports of participant trust in automation adopted from Jian et al. (2000) using a 6 choice Likert-type scale. The questionnaire is designed to measure specific attitudes about automation including trust (items 2-5) and overall view of automation (items 9-12).
- Subjective reports of participant workload. Participants completed a paper-based NASA Task Load Index (TLX) workload scale (see Appendix B). NASA-TLX consists of 6 subscales measuring different subjective dimensions of workload: Mental Demands, Physical Demands, Temporal Demands, Frustration, Effort, and Performance. NASA-TLX also included an initial weighting of these dimensions. A single workload score is calculated from NASA-TLX following each track by measuring the percent rating (0-100) on each dimension and calculating the average across all dimensions. Higher values indicate increased subjective mental workload.
- Driver performance measures when performing obstacle avoidance maneuvers on a simulated highway. Specific performance measure for each obstacle maneuver are provided in the repository including vehicle state at the initiation and completion of maneuvers.

Data Format and Content

CSV files are provided. The first file contains all demographic and trust ratings for each participant. The second file contains subjective workload ratings for each participant. The third file contains a driver performance measures including vehicle states at the initiation and completion of all obstacle maneuvers.

Data Access and Sharing

The research data from this project are deposited in the Dataverse data repository to ensure that the research community has long-term access to the data.

Link to data: https://doi.org/10.7910/DVN/BWCCET

Reuse and Redistribution

In addition to the research community, we expect these data will be used by practitioners and policymakers. Users of field data should acknowledge and/or offer co-authorship to the investigators who collected the data.

Appendices

Appendix A

HADS vs. Manual						
Article #	Article Citation	Participants	Driving Task	Factor(s) Tested	Results	Effect on Performance
1	de Winter, J. C., Stanton, N. A., Price, J. S., & Mistry, H. (2016)	N: 51 Male: 31 Female: 20 Age: 18y-53y	Manual vs. HADS avoiding object collision (pedestrian or dog)	Manual vs. HADS	**Braking Response Times (BRT)** Manual: 3740ms HADS: 3830ms	2.4% performance decrement in HADS vs manual
2	Gold, C., Damböck, D., Bengler, K., & Lorenz, L. (2013)	N: 32 Male: 24 Female: 8 Age: 19y-57y	Manual vs. HADS with alert to obstacle (construction)	Manual vs. HADS	**Intervention (BRT or lateral RT)** Manual: 3800ms HADS: 4100ms	8% performance cost to HADS compared to manual
3	Radlmayr, J., Gold, C., Lorenz, L., Farid, M., & Bengler, K. (2014)	N: 48 Male: 38 Female: 10 Age: M = 33.5	Driving manual or HADS w/ N-back	Manual vs. HADS	**Time of Task (TOT)** Manual:1,835 ms HADS:2,375ms	29.4% performance decrease from manual to HADS
4	Stanton, Young, Walker, Turner & Randle (2001)	M: 20 Male: 20 Age: 21y-31y	Driving Manual or HADS, responding to braking car	Manual vs. HADS	**Lateral Lane Deviation** Manual: 2.1m HADS: 2.5m	19% performance decrease from manual to HADS

Workload						
		Participants	Driving Task	Factor Tested	Results	Effect on Performance
5	Eriksson, A., & Stanton, N. A. (2017).	N: 26 Male: 16 Female: 10 Age: 20y-52y	HADS take-over with secondary task (reading)	Secondary task or no secondary task	**TOT:** No secondary task: 4,567ms Secondary Task: 6,061ms	33% Performance decrement with secondary task
6	Gold, C., Körber, M., Lechner, D., & Bengler, K. (2016).	N: 72 Male: 58 Female: 14 Age: 19y-79y	HADS take-over with different traffic densities and a secondary twenty questions task TQT).	Secondary Task: TQT or no TQT	**TOT:** No TQT: 3.10s TQT: 3.26s	5.2% Performance Decrement with secondary task
7	Hancock, P. A., Simmons, L., Hashemi, L., Howarth, H., & Ranney, T. (1999)	N: 10 Male: 5 Female: 5 Age: 26y – 46y	Presence of in-vehicle distractor on braking response at traffic light	In vehicle distractor or no distractor	**BRT:** No distractor: 610ms Distractor: 930ms	52% performance decrement with distractor
8	Zeeb, K., Buchner, A., & Schrauf, M. (2016).	N: 79 Male: 44 Female: 35 Age: M = 39.5	HADS take-over with wind gusts and secondary task (emailing, reading news,	Secondary task or no secondary task	**Lateral Lane Deviation:** No Secondary Task: .2 m Secondary Task: .26 m	30% Performance decrement with secondary task

			watching video)			
9	Louw, T., Merat, N., & Jamson, H. (2015)	N: 16 Male: 8 Female: 8 Age: 19y-26y	Obstacle avoidance under manual, HADS alone, or HADS with secondary task	Manual Driving HADS alone HADS with secondary task (reading)	**Lateral acceleration (object avoidance):** Manual: $1.31ms^{-1}$ HADS Alone: $1.84ms^{-1}$ HADS with secondary task: $2.22ms^{-1}$	40% performance decrement from manual to HADS alone, additional 21% decrement with secondary task
10	Yoon, S. H., & Ji, Y. G. (2019)	N: 27 Male: 17 Female: 10 Age 24y-38y	3 HADS Take-overs on a 15km track, using 55 in. display	Visual attention required for secondary task - Entertainment console (low) - Smartphone (low) - Video (high)	**TOT:** Low attention:1.6s High Attention: 1.80s	11% Performance Decrement with secondary task
Design Elements						

	Article Citation	Participants	Driving Task	Factor Tested	Results	Effect on Performance
11	Melcher, V., Rauh, S., Diederichs, F., Widlroither, H., & Bauer, W. (2015).	N: 40 Male: 23 Female: 17 Age: 19y-53y	HADS take-over while playing mobile phone game.	Mobile phone did or did not included redundant alert signal for take-over request	**TOT:** Phone alert:3430ms No Phone Alert: 3631 ms	5.8% Performance Decrement without phone alert vs. with alert
12	Walch, M., Lange, K., Baumann, M., & Weber, M. (2015)	N: 30 Male: 21 Female: 9 Age: M = 24.9	HADS take-over with or without a warning before take-over request	Take-over request 4 or 6 seconds before take-over, with or without hazard alert 2 seconds prior to TOR	**TOT:** No hazard alert: 2,506ms Hazard alert: 2028ms	23% Performance decrement with alert vs. no alert
Individual differences						
	Article Citation	Participants	Driving Task	Factor Tested	Results	Effect on Performance
13	Körber, M., Gold, C., Lechner, D., & Bengler, K. (2016)	N: 72 Male: 58 Female:14: Young: 36 Old: 36 Young Age: M = 23.3y Old Age: M = 66.8y	Take over time for older v. younger drivers in no, medium, or high traffic density and with/without secondary task	Young or Old Drivers With or without secondary twenty questions (TQT) task	**TOT:** Young w/o secondary task: 3.14ms Young w/secondary task: 3.37ms Old w/o secondary task: 3.08ms	5% performance decrement in young vs old 7% secondary task cost in young 1.6% secondary task cost in old

					Old w/ secondary task:3.13ms	
14	Clark, H., & Feng, J. (2017)	N: 35 Young = 17 Old = 18 Young Age: 18y-35y Old Age: 62y-81y	Take-over time for young vs. old drivers	Young vs. Old Drivers Optional secondary task	**TOT:** Young:2.2ms Old: 1.7ms	29% performance decrement for young vs. old
15	Rudin-Brown, C. M., & Parker, H. A. (2004)	N: 18 Male: 12 Female: 4 Age: 21y-34y	Reaction to obstacle (brake light) in individuals with low and high sensation seeking (SS)	Low and high SS individuals with and without ACC	**Lane position variance (SD)** Low SS w/o ACC: 31cm Low SS w/ ACC: 31cm High SS w/o ACC: 34cm High SS w/ ACC: 41cm	0% performance decrement for low SS from w/o to w/ ACC 21% performance decrement for high SS from w/o to w/ ACC
16	Zeeb, K., Buchner, A., & Schrauf, M. (2015)	N: 89 Male: 54 Female: 35 Age: 20y-72y	The effect of driver attentional focus on braking to obstacle (construction site)	Low, Medium, and High risk drivers (defined by gaze location and duration toward roadway)	**BRT:** Low: 1,630ms Medium:1860 ms High: 2310ms	14% performance decrease from low to medium risk 24% performance decrease from medium to high risk
Practice/Expertise						
	Article Citation	Participants	Driving Task	Factor Tested	Results	Effect on Performance

17	Larsson, A. F., Kircher, K., & Hultgren, J. A. (2014)	N: 31 Male: 24 Female: 7 Age: M = 50y	Braking time to traffic cut-in with various levels of car automation	Manual driving vs. HADS (adaptive cruise control + assisted steering) No experience vs experience with automated driving	**BRT:** Novice Manual:1.38 ms HADS: 3.45ms Experienced Manual: 1.34ms HADS: 3.09ms	18.2% performance decrease to Novices vs. Experienced18 %
18	Payre, W., Cestac, J., & Delhomme, P. (2016)	N: 69 Male: 37 Female: 32 Age: 20y-75y	Practice effect on TOT	First vs. second take-over	**TOT** First:8.7s Second:6.8s	28% performance improvement from first to second take-over
19	Sportillo, D., Paljic, A., & Ojeda, L. (2018)	N: 60 Male: 30 Female: 30 Age: 22y-71y	Training using a manual, fixed based, or VR driving simulator	Training scenarios: UM = User Manual FB = Fixed Base LVR = Light Virtual Reality	**TOT** UM: 6660ms FB: 3410ms VR: 3320ms	95% improvement in FB vs. UM 3% improvement in VR vs FB
20	Hergeth, S., Lorenz, L., & Krems, J. F. (2017)	N: 110 Male: 81 Female: 29	Familiarity with take-over responses	No Familiarization vs highly familiar	**TOT** No familiarization	52% performance benefit to highly familiar vs no familiarity

		Age: 20y-59y		(descriptions and experience) 1st vs 2nd take-overs	1st take-over: 3500ms No familiarization 2nd take-over: 2300ms Highly familiar 1st take-over: 2300ms Highly familiar 2nd take-over: 2100ms	in first take-over 9% performance benefit to highly familiar vs no familiarity in second take-over
21	Young, M. S., & Stanton, N. A. (2000)	N: 32 Age: M = 22.3	Driving Expertise (Learner's permit or full driver's license) using ACC or HADS (ACC + AS) Must brake to avoid collision.	Learner vs. Expert ACC vs. HADS	**BRT:** Learner ACC: 2300ms Learner HADS: 2420ms Expert ACC: 2120ms Expert HADS: 2480ms	14% better overall performance in ACC vs. HADS 13% better expert than learner performance in ACC 2.4% better learner than expert performance in HADS

Appendix B

Informed Consent

Informed Consent Form

Measuring performance costs associated with takeovers from automated driving systems

Purpose of Research
The purpose of this study is to investigate driver performance immediately after taking over control from a self-driving vehicle.
Specific Procedures to be Used: The experiment will be conducted using a virtual reality headset. You will be asked to sit in a seat similar to a driver's seat in a car that has a steering wheel and gas and brake pedal attached. When you put on the VR headset, you will be in the viewpoint of a driver behind the wheel of a car driving along a highway. On some trials, the car will be in manual mode and you will do all the driving. In self-driving mode, the car will do all of the driving, but may occasionally alert you to take over full control of the car. After each trial, you will fill out a short questionnaire about your experience. At the end of the driving part of the experiment, you will be asked to fill out another questionnaire related to your opinions of automated vehicles.
Duration of Participation and Compensation The experiment will last approximately 1 hours. You will receive 1 credit hour towards your SONA research requirement for your participation.
Benefits to the Individual There are no direct benefits to you as a participant, but you may learn about how driver performance in highly automated cars can be affected by their trust in automation, and how driving performance changes when taking over control from a self-driving car.
Risks to the Individual Minimal: The risks are not greater than those ordinarily encountered in daily life (e.g., playing a game on a computer). There is a chance of fatigue and a risk of confidentiality breach. In order to mitigate these risks, you will be provided with rest break opportunities every 6 minutes. There is also a small change of dizziness that can be caused by the virtual reality environment. For confidentiality, consent forms will be separated from data, so no names will be attached to the data, and have the right to skip questions or withdraw with no penalty.
Confidentiality The subject information entered into the computer will NOT contain your name or student ID or social security number. Your participation will be logged separately in order to give you the appropriate course credit for your participation. Your personal information will not be associated with your data.
Voluntary Nature of Participation Your participation in this research project is completely voluntary. If you do agree to participate, you can withdraw your participation at any time without penalty.
Human Subject Statement: If you have any questions about this research project, contact James Miles at (434) 242-5309. If there are concerns about the treatment of research participants, contact the office of Office of University Research, CSU Long Beach, 1250 Bellflower Blvd., Long Beach, CA 90840; Telephone: (562) 985-5314 or email to research@csulb.edu.
BY SIGNING BELOW, YOU ACKNOWLEDGED THAT YOU HAVE HAD THE OPPORTUNITY TO READ THIS CONSENT FORM, ASK QUESTIONS ABOUT THE RESEARCH PROJECT AND ARE PREPARED TO PARTICIPATE IN THIS PROJECT.

_____ _____
Participant's Signature Date

_____
Participant's Name

_____ _____
Researcher's Signature Date

Demographic Questionnaire

DIRECTIONS: Please answer each question as accurately as possible by checking the correct answer or filling in the space provided.

1) **What is your current age?** _____

2) **What is your gender?** _____

3) **I identify my ethnicity as:**

   ☐ **Asian**

   ☐ **Black/African**

- ☐ **Caucasian**
- ☐ **Hispanic/Latinx**
- ☐ **Native American**
- ☐ **Pacific Islander**
- ☐ **I prefer not to answer**
- ☐ _____

4) Do you currently have an active driver's license?

☐ **Yes** ☐ **No**

5) How many years of driving experience do you have? _____

6) How many times per week do you drive? _____

7) On average, how many miles do you drive per year? _____

8) Have you ever participated in an experiment involving a driving simulator?

☐ **Yes** ☐ **No**

9) If you have used a driving simulator before, did you experience simulator sickness?

☐ **Yes** ☐ **No**

10) Do you regularly play video games involving driving?

☐ **Yes** ☐ **No**

11) Are you colorblind?

☐ **Yes** ☐ **No**

Workload Questionnaire

Participant ID _____

Road # _____ **M/A** _____

NASA TLX Workload Scale

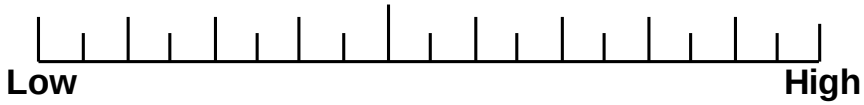
RATING SCALE DEFINITIONS

Title	Endpoints	Descriptions
MENTAL DEMAND	*Low/High*	How much mental and perceptual activity was required (e.g., thinking, deciding, calculating, remembering, looking, searching, etc.)? Was the task easy or demanding, simple or complex, exacting or forgiving?
PHYSICAL DEMAND	*Low/High*	How much physical activity was required (e.g., pushing, pulling, turning, controlling, activating, etc.)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious?
TEMPORAL DEMAND	*Low/High*	How much time pressure did you feel due to the rate or pace at which the tasks or task elements occurred? Was the pace slow and leisurely or rapid and frantic?
EFFORT	*Low/High*	How hard did you have to work (mentally and physically) to accomplish your level of performance?
PERFORMANCE	*Good/Poor*	How successful do you think you were in accomplishing the goals of the task set by the experimenter (or yourself)? How satisfied were you with your performance in accomplishing these goals?
FRUSTRATION LEVEL	*Low/High*	How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?

NASA TLX RESPONSE FORM

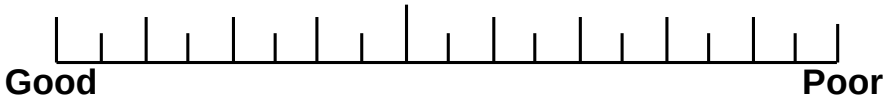
MENTAL DEMAND

PHYSICAL DEMAND

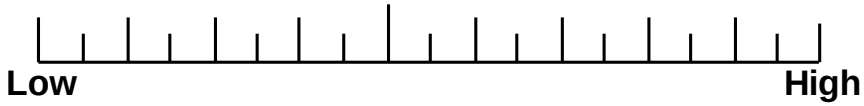


TEMPORAL DEMAND

PERFORMANCE



EFFORT



FRUSTRATION

Effort **or** **Performance**	**Temporal Demand** **or** **Frustration**
Temporal Demand **or** **Effort**	**Physical Demand** **or** **Frustration**
Performance **or** **Frustration**	**Physical Demand** **or** **Temporal Demand**
Physical Demand **or** **Performance**	**Temporal Demand** **or** **Mental Demand**

Frustration **or** **Effort**	**Performance** **or** **Mental Demand**
Performance **or** **Temporal Demand**	**Mental Demand** **or** **Effort**
Mental Demand **or** **Physical Demand**	**Effort** **or** **Physical Demand**
Frustration **or** **Mental Demand**	

Opinions on Automation

Trust in Automation Questionnaire (NOTE: More questions on the back of the page)

Please answer the following questions related to your experience with the automated car in the experiment:

1) How much did the simulator feel like a car on the road?

1 2 3 4 5 6

Not at All Very Much

2) The system is dependable.

1 2 3 4 5 6

Strongly Disagree Strongly Agree

3) The system is reliable.

1 2 3 4 5 6

Strongly Disagree Strongly Agree

4) I can trust the system.

1 2 3 4 5 6

Strongly Disagree Strongly Agree

5) How concerned would you be about driving or riding in a vehicle with self-driving technology such as what you experienced in this experiment?

1 2 3 4 5 6

Strongly Concerned Strongly Unconcerned

6) Highly-automated vehicles such as in the experiment will have a harmful or injurious outcome.

1 2 3 4 5 6

Strongly Disagree Strongly Agree

Please answer the following questions related to your general opinion on driving:

7) The idea of fully automated driving is fascinating.

1 2 3 4 5 6

Strongly Disagree Strongly Agree

8) Manual driving is enjoyable.

1 2 3 4 5 6

Strongly Disagree Strongly Agree

9) Highly automated driving will be enjoyable.

1 2 3 4 5 6

Strongly Disagree Strongly Agree

10) Highly automated driving will be easier than manual driving.

1 2 3 4 5 6

Strongly Disagree Strongly Agree

11) What is your general opinion regarding autonomous and self-driving vehicles?

1 2 3 4 5 6

Strongly Unfavorable Strongly Favorable

12) Automation will free me of much of the routine parts of driving so I can concentrate on "managing" the drive.

1 2 3 4 5 6

Strongly Disagree Strongly Agree

13) I will make fewer errors in a highly-automated vehicle than in my current vehicle.

1 2 3 4 5 6
Strongly Disagree Strongly Agree

14) Automation will not reduce the workload, because there will be more to monitor.

1 2 3 4 5 6
Strongly Disagree Strongly Agree

15) In a highly-automated vehicle, I will feel more like a "button pusher" than a driver.

1 2 3 4 5 6
Strongly Disagree Strongly Agree

16) I would like to have a highly-automated system in my car.

1 2 3 4 5 6
Strongly Disagree Strongly Agree

Debriefing form

1. What is the general aim of this research? The experiment in which you have participated is investigating how drivers focus their attention when in manual driving and automated driving situations. We also want to understand how trust in automation can be gained or lost depending on the vehicle's speed and performance. We also want to learn how mental workload is affected while transitioning between manual and automatic driving conditions. This study falls in the general area of trust in automation and human performance, which is basic research that can be applied to the area of Human Factors, or designing for human use.

2. Is this correlational or experimental research? What are some of the variables of interest? This is experimental research. We are examining attention in automated and manual cars. The variables of interest are the whether driving is fully manual or involves a self-driving car, whether you successfully use attention to detect targets in the car and environment.

3. What topic in psychology does this research illustrate? It is most closely related to the topics of situational awareness and attention vigilance, which generally involve your ability to stay focusses on driving, even when the car is doing all of the driving for you.

4. Where can I learn more about this type of research? The following articles describe research on attention and automation:

Stockert, S., Richardson, N. T., & Lienkamp, M. (2015). Driving in an increasingly automated world – approaches to improve the driver-automation interaction. *Procedia Manufacturing, 3*, 2889 – 2896. Doi: 10.1016/j.promfg.2015.07.797

Zeeb, K., Beuchner, A., & Schrauf, M. (2015). What determines the take-over time? An integrated model approach of driver take-over after automated driving. *Accident Analysis and Prevention, 78*, 212-221. http://dx.doi.org/10.1016/j.aap.2015.02.023

5. Which faculty member is supervising the research and how can I contact him? This research is being conducted by Dr. James Miles, Assistant Professor in the Department of Psychology at California State University, Long Beach. If you would like to know more about this

research, contact Dr. Miles at 562-985-5030. You can also e-mail Dr. Miles at jim.miles@csulb.edu.

6. How long has the investigator been studying this specific topic? How does this experiment fit into their program of research? Dr. Miles has been studying response-selection processes for over ten years. He has published numerous articles on the topic. His current interests include how response selection is influenced by stimulus modality, age, and instruction.

Much research in psychology depends on participation by individuals like you. We are very grateful for your help. Also, please do not discuss this experiment with other potential participants because this might jeopardize the research. Thank you again for your participation in this study.

IRB approval

CALIFORNIA STATE UNIVERSITY, LONG BEACH

OFFICE OF RESEARCH & SPONSORED PROGRAMS

DATE:	September 2, 2019
TO:	James Miles, PhD
FROM:	CSULB IRB
PROJECT TITLE:	[1483897-1] Measuring performance costs associated with takeovers from automated driving systems.
REFERENCE #:	20-044
SUBMISSION TYPE:	New Project
REVIEW TYPE:	Exempt Review
ACTION:	APPROVED under 45 CFR 46 Exempt Category 104 (d) (3).
APPROVAL DATE:	September 1, 2019

This is to advise you that the Institutional Review Board for the Protection of Human Subjects (IRB) of California State University, Long Beach, has reviewed your protocol application.

Approval is effective beginning September 1, 2019 and conditional upon your willingness to carry out your continuing responsibilities under University policy:

1. If you need to make changes/revisions to this approved project, you must submit a Request for Amendment to an Approved Protocol form in addition to any documents affected by the requested change. Submit these documents as a subsequent package to your approved project in IRBNet. You are not allowed to implement any changes to your research activities prior to obtaining final approval of your Amendment from the CSULB IRB.
2. You are required to inform the Director of Research Integrity and Compliance, Office of Research & Sponsored Programs, via email at ORSPCompliance within twenty-four hours of any adverse event in the conduct of research involving human subjects. The report shall include the nature of the adverse event, the names of the persons affected, the extent of the injury or breach of confidentiality or data security, if

any, and any other information material to the situation.

3. Maintain your research records as detailed in the protocol.

Should you have any questions about the conduct of your research under this protocol, particularly about providing informed consent and unexpected contingencies, please do not hesitate to call the Office of Research & Sponsored Programs at (562) 985-8147. We wish you the best of success in your research.

This letter has been electronically signed in accordance with all applicable regulations, and a copy is retained within California State University, Long Beach Institutional Review Board's records.

1250 Bellflower Blvd., Long Beach, CA 90840 Ph. (562) 985-8147 Fax. (562) 985-8665