CRISP Type 2: Collaborative Research: Towards Resilient Smart Cities

Submitted by:
Virginia Tech Transporatation Institute
February 28, 2020

Submitted to:
Dr. Walid Saad, Department of Electrical and Computer Engineering, Virginia Tech

VIRGINIA TECH

EXECUTIVE SUMMARY

The goal of the Critical Resilient Interdependent Infrastructure Systems and Processes (CRISP) collaborative research project is to address the fundamental challenge of the vulnerability of smart city infrastructure. CRISP is pursuing a coordinated and interdisciplinary approach that relies on machine learning, operations research, behavioral economics, and cognitive psychology to lay the mathematical foundations of resilient smart cities. The anticipated results will break new ground in the understanding of synergies between cyber-physical infrastructure and resilient resource management, thus catalyzing the global deployment of smart cities.

The current study was an extension of the overall CRISP project and was conducted on the Virginia Smart Roads Highway section. This is a 2.2-mile controlled-access test track owned by the Virginia Department of Transportation and operated by the Virginia Tech Transportation Institute. The test vehicle that was used by the participant was an Infiniti Q50 that was retrofitted with additional hardware (e.g., differential Global Positioning System) to allow the vehicle the ability to operate under automated conditions.

The design for this study consisted of a between-subjects experimental design. The primary independent variable was the between-subjects factor "operating condition" that dictated the method of driving control through two levels: manual operation or automated operation. Participants in the manual condition controlled the test vehicle using standard vehicle controls (i.e., steering wheel and pedals). Participants in the automation condition had the automated driving features of the test vehicle activated for them, which then controlled the vehicle. Thirty-two participants were randomly binned into one of these driving control conditions. The experimental implementation involved a sudden lane deviation that all participants experienced. This lane deviation happened at the end of the experiment using inconspicuous controls operated by the experimenters in the backseat of the test vehicle. Participants also completed four secondary tasks during the study using a mounted tablet: perform a calculation, type an email, find an address, and find a movie playing at a specific time in a local theatre.

Results suggested that participants in the automated condition had slower corrective steering reaction times than those in the manual condition. This could be explained by the participants in the automated condition not having their hands on the wheel, requiring them to cover a longer distance to reach the wheel. In contrast, those in the manual condition already had their hands on the wheel, meaning that the sudden lane deviation would be perceived and reacted to faster.

All participants used the steering wheel as corrective input after the lane deviation. Only one-third of participants (N = 11) reacted by applying the brake. Analyses showed that braking or not braking was not influenced by the operating condition.

Limitations of the current study include minimal exposure to the automated driving features that could hinder the trust participants had in the test vehicle and their subsequent reaction times. Additionally, the presence of researchers in the test vehicle could have put undue stress on the participant during trials. While this study provides some initial guidance, future research using naturalistic methods that incorporate longitudinal study designs to alleviate these limitations may provide additional insight.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ACC	adaptive cruise control
ADAS	advanced driver assistance systems
ADS	automated driving systems
CI	critical infrastructures
CRISP	Critical Resilient Interdependent Infrastructure Systems and Processes
D-GPS	differential Global Positioning System
DAS	data acquisition system
DDT	dynamic driving task
HMI	human-machine interface
OEDR	object event detection and response
RTI	request to intervene
TTC	time-to-collision
VTTI	Virginia Tech Transportation Institute

CHAPTER 1. INTRODUCTION

Realizing the vision of truly smart cities is one of the most pressing technical challenges of the coming decade (Saad, 2017). The success of this vision requires synergistic integration of cyber-physical critical infrastructures (CIs) such as smart transportation, wireless systems, water networks, and power grids into a unified smart city. Smart city CIs have significant interdependence, sharing resources such as energy, computation, wireless spectrum, users and personnel, and economic investments. As such, they are prone to correlated failures occurring due to day-to-day operations, natural disasters, or malicious attacks. Protecting tomorrow's smart cities from such failures requires resiliency in the processes that manage common CI resources. These processes must be able to adaptively and optimally reallocate resources to recover from failure.

Smart cities are the future of major metropolitan areas. They can be described as the synergistic integration of cyber-physical CI (e.g., automated driving systems [ADSs], electric grid; Saad, 2017). Each CI modality has the potential for failure due to adverse events, such as equipment malfunction or human error but also if individual failures are not contained or extreme events, such as natural disasters, power outages, or cyberattacks, are not prepared for. Having resiliency across modalities is paramount to ensure that a weak link does not act as a potential target or unnecessary danger (Brown, Carlyle, Salmeron, & Wood, 2005).

ADSs are a smart city modality that will have a high degree of interaction with residents and will interface with a number of other CI modalities. With such a high level of human interaction, they could become a target for technological attacks intended to cause motor vehicle crashes and loss of life. Because other CI modalities may rely on data shared from ADSs, technological attacks on these vehicles have the potential to propagate failures into other components of the system (e.g., smart infrastructure).

The goal of the Critical Resilient Interdependent Infrastructure Systems and Processes (CRISP) collaborative research project is to address this fundamental challenge. CRISP is pursuing a coordinated and interdisciplinary approach that relies on machine learning, operations research, behavioral economics, and cognitive psychology to lay the mathematical foundations of resilient smart cities. The anticipated results will break new ground in the understanding of synergies between multiple cyber-physical infrastructure and resilient resource management, thus helping to move forward the global deployment of smart cities.

The current study examined the effects of a simulated hacking of a vehicle (i.e., vehicle forced to run off-road) on participant reactions in a vehicle operated either manually or under automated conditions. The following chapters explain the method for the current study, provide results of the experiment, and discuss how these results inform the overall CRISP effort.

CHAPTER 2. METHODOLOGY

2.1 TEST TRACK

Testing took place on the Virginia Smart Roads, highway test bed, which is a 2.2-mile long controlled-access test track (see Figure 1). The sudden lane deviation event (i.e., lateral steering input) took place at a location where there is additional paved space to the right of the normal lane (see Figure 2; red arrows indicate path of sudden lane deviation).

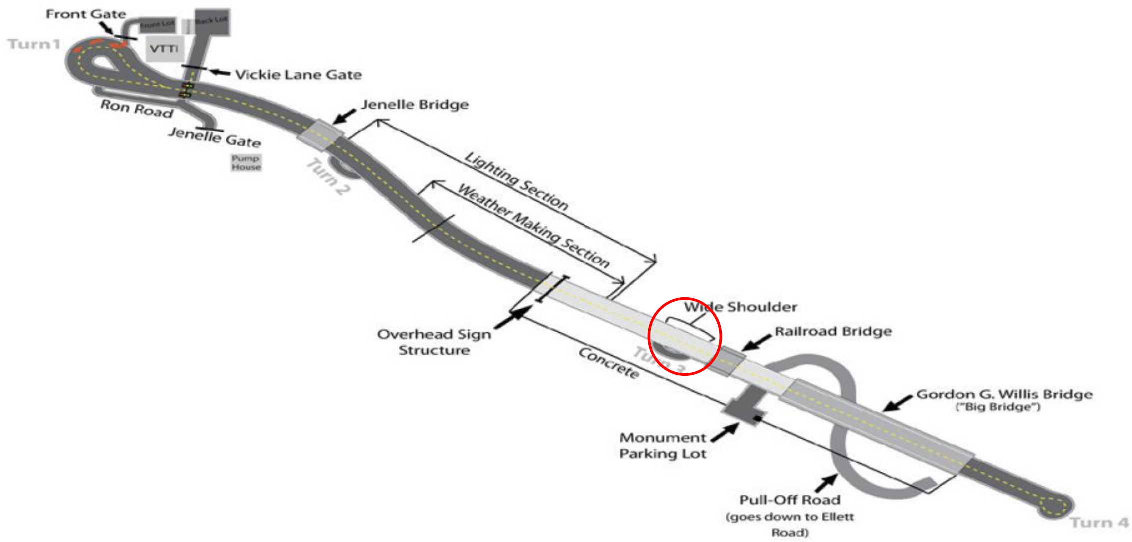

Figure 1. Map of Virginia Smart Road with extended shoulder marked.

Figure 2. Extended shoulder for lane deviation.

2.2 VEHICLES

Two vehicles were used for this experiment: an Infiniti M35 and an Infiniti Q50. The M35 was used as the lead confederate vehicle that simulated ambient traffic, and the Q50 (Figure 3) as the test vehicle that participants used.

Figure 3. Test vehicle (Infiniti Q50).

2.3 VEHICLE INSTRUMENTATION

The M35 (lead confederate vehicle) did not require any instrumentation for this experiment.

The Q50 (test vehicle) used a combination of manufacturer original equipment and retrofitted systems. The retrofitted features included the automated control features, data collection, and redundant manual operated steering controls in the backseat. The test vehicle came equipped with a camera aligned behind the rearview mirror that allowed lateral control of the vehicle through lane line identification. A differential Global Positioning System (DGPS; Figure 4) was also used to control the longitudinal and lateral movement of the test vehicle during automation (further discussion of automated driving features in section 2.3.1).

Figure 4. In-vehicle DGPS unit.

In addition to the longitudinal and lateral automated driving features, the experimenter had access to manual operated steering controls in the backseat (see Figure 5) to engage and disengage these features. With the safety key turned to the “on” position, automation was engaged using the green “Resume” button and disengaged with the red “Cancel” button. The “Master Kill” button turned off all power to the automated driving features in case of a safety-critical event (i.e., loss of vehicle control).

Figure 5. Automation control box.

A human-machine interface (HMI) showed when automation was active by displaying a green “A” (see Figure 6; note, the “System Active” text and “System NOT Active” text were added to the figure for clarity in this report but were not actually present in the HMI display). In addition, an auditory alert consisting of a power-up noise and message stating “automated control engaging” was played when the automation was activated. When the automation was turned off, the green “A” was cleared from the display and a power-down noise followed by a message stating “automated control disengaging” was used to alert the participant of the change in system status

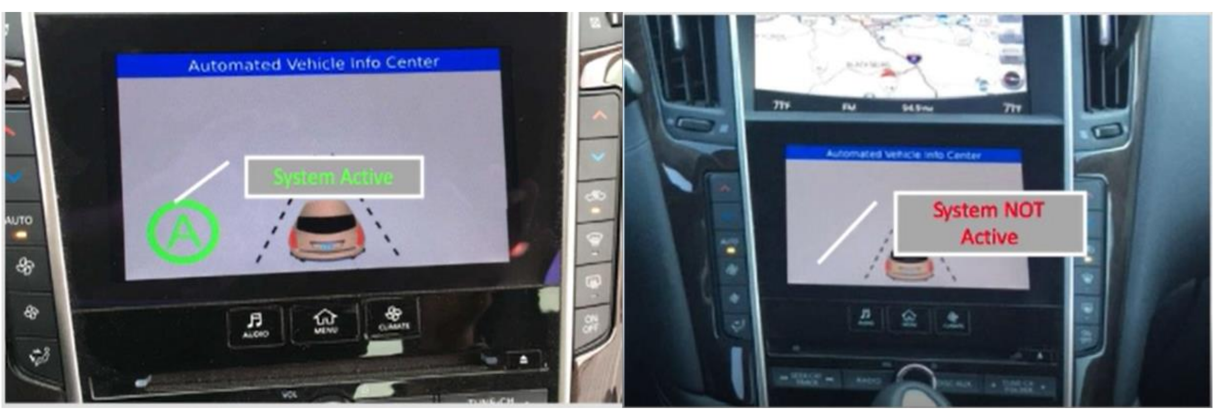

Figure 6. HMI for participant vehicle.

For data collection, the test vehicle was instrumented with the Virginia Tech Transportation Institute’s (VTTI’s) data acquisition system (DAS; see Figure 7), which collects a wide range of data. Various inputs to the flex-DAS include an inertial measurement unit,, and six camera streams (front view, rear view, over the shoulder, feet, face, and backseat; see Figure 8). The test vehicle was also retrofitted with an SMS radar mounted on the front bumper.

Figure 7. VTTI DAS.

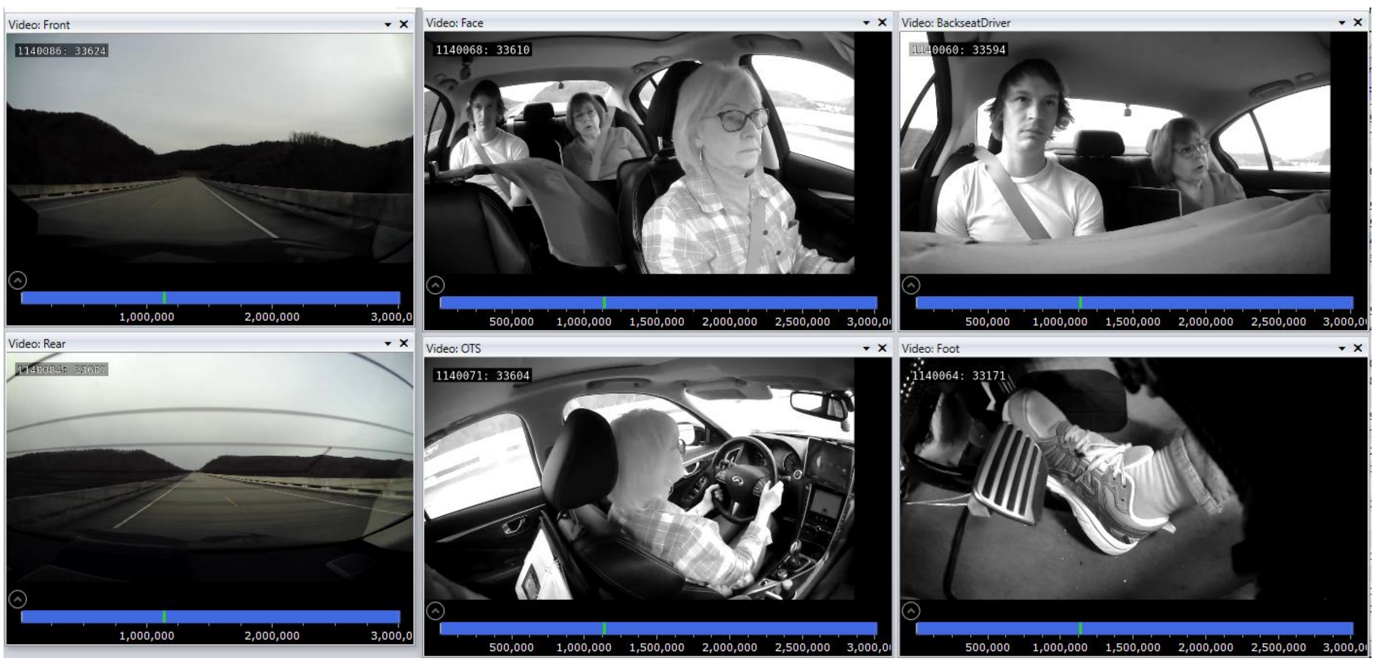

Figure 8. Vehicle camera instrumentation (researchers shown).

To initiate the sudden lane deviation, experimenters had access to redundant steering controls located in the backseat of the test vehicle (see Figure 9). In addition to the steering wheel, a brake lever was also available for use in a potential safety-critical events (e.g., wildlife, loss of vehicle control, participant not reacting).

Figure 9. Redundant steering controls.

2.3.1 Automated Lateral and Longitudinal Control Features Summary

The test vehicle had standard advanced driver assistance system (ADAS) features that control various aspects of the dynamic driving task (DDT). Longitudinal movement could be controlled by the adaptive cruise control (ACC) and lateral control by lane keeping with the forward-facing camera positioned behind the rear-view mirror. Applying SAE (2018) definitions to these features categorizes them as level 1 when operated separately and level 2 under simultaneous operation.

For the purposes of this experiment, the standard features were not capable of maneuvering around the turnarounds found at each end of the test track. For this reason, the test vehicle was retrofitted with DGPS to help maneuver these turnarounds. During testing, it was determined that the standard camera system would maintain the test vehicle’s lane position on the straightaways, then transition to following DGPS waypoints through the turnarounds. These systems were used in conjunction with other retrofitted systems (e.g., programmed brake/acceleration pedal input) that controlled the acceleration and deceleration of the vehicle.

An automated feature orientation video shown to participants told them that they were responsible for monitoring the system for safety by responding to requests to intervene (RTIs; i.e., an automation disengaged message) and that they did not need to have their hands or feet actively controlling the test vehicle. The video explained that the automated driving features controlled both the test vehicle’s longitudinal and lateral movement.

In fact, the test vehicle was not equipped with the hardware needed to perform some of these tasks. Instead, these were actually performed by the rear seat safety driver and lead confederate vehicle driver. The test vehicle, when automation was engaged, essentially operated on a recording that VTTI’s hardware team developed. That is, the test vehicle would run the test track loop the same way each session (e.g., accelerating/decelerating in the same locations at the same velocity). This was useful for keeping automation exposure consistent across participants, but posed some setbacks. Although this arrangement managed the longitudinal and lateral control of the test vehicle, it was not dynamic in its action. That is, if a vehicle, object, or animal moved in front of the test vehicle, it would not detect it or slow down and would continue running the recording that had been programmed. To give the illusion that the automated driving features were as capable as described, the 3-second gap between the test vehicle and lead confederate vehicle was managed by the lead confederate vehicle driver, not the test vehicle. Object event detection and response (OEDR) was performed by the rear seat safety driver, who had access to redundant steering and braking controls and could react if necessary.

For these reasons, the test vehicle, from the participant's perspective, could be defined as operating with SAE level 3 driving automation systems where lateral and longitudinal control were performed by sensors and OEDR was performed inconspicuously by the rear seat safety driver.

2.4 EXPERIMENTAL DESIGN

This study was designed to replicate an external hacking of the test vehicle that would cause it to run off-the-road independent of input from the driver. This study was performed using a between-subjects design. All participants completed one driving session where they experienced the sudden lane deviation. During the drive, participants also completed four secondary tasks (e.g., Web browsing, email; tasks explained in the following section).

2.4.1 Independent Variable

This research design included one independent variable:

> *Operating condition* – The test vehicle had the ability to operate in automation with level 3 driving automation systems and to operate manually. If participants where in the automated condition, they were shown a video detailing the longitudinal and lateral control features. Once the automation was activated, participants were reminded that they did not need to have their hands or feet active while driving.

2.4.2 Dependent Variables

This research design included six dependent variables:

> *Task (1,2,3,4) Completion Time* (in seconds*)* – This was defined as the total time the participant took to complete the given tablet tasks. A separate variable also indicated whether the task was successfully completed.

> *Steering Initial Reaction* (in seconds) – This was defined as the difference in time between when the participant started to reach for the steering wheel (i.e., lifting hand towards the wheel) and when the sudden lane deviation was initiated.

Steering Corrective Reaction (in seconds) – This was defined as the difference in time between the participant providing corrective input to the steering wheel (i.e., steering toward roadway) and when the sudden lane deviation was initiated.

Braking Initial Reaction (in seconds) – This was defined as the difference in time between when the participant started to move a foot toward the brake pedal and when the sudden lane deviation was initiated.

Braking Corrective Reaction (in seconds) – This was defined as the difference in time between the participant providing corrective input to the brake pedal (i.e., maximum pressure on the pedal) and when the sudden lane deviation was initiated.

Swerve Distance (in meters) - This is the distance that the vehicle swerved during the lane deviation. This was calculated by taking the difference between the maximum deviation from the Smart Road centerline (lane deviation) and the participant's baseline lane position (average lane position from previous laps).

2.5 PROCEDURE

2.5.1 Participants

Participants were recruited through social media advertisements, email, and phone calls throughout Southwestern Virginia by VTTI's recruitment group. Thirty-two participants met the inclusion criteria for this study (i.e., 18 years of age or older, held a U.S. driver's license for 2 or more years, had not previously participated in a deception study). Participants were equally distributed across the gender (16 male; 16 female) and age group ranges (i.e., 18–32; 33–49; 50–65; 66–80; 8 participants in each; M_{age}= 49.72; SD_{age} = 17.21) recommended by the National Highway Traffic Safety Administration (NHTSA; NHTSA, 2013). Fifty-six percent had previous experience with crash warning systems (e.g., forward collision warning), 47% with knowledge of automated driving features (e.g., Tesla), 41% with longitudinal control features such as ACC, and 37% with lane assist that aid with the lateral control.

2.5.2 Testing Method

Participants were taken through the intake process (i.e., paperwork, vision/hearing check) once they arrived at VTTI. An experimenter then escorted the participant to the test vehicle in the VTTI parking lot. The experimenter oriented the participant to the standard features of the test vehicle (e.g., seat, mirror, steering wheel adjustment) and ensured that their seatbelt was fastened. In the test vehicle, the experimenter and a rear seat safety driver sat in the backseat. The rear seat safety driver had access to a set of redundant steering and braking controls (see Figure 9) to act as a fallback-ready user in the event of any emergency situation (e.g., loss of vehicle control, wildlife). These controls were not in sight and were not explained to the participant.

If the participant had been assigned to the automated condition, a video was played on a tablet explaining the automated driving features and capabilities. They were also told that they did not need to have their hands or feet engaged when automation was activated. After questions were answered, the participant was instructed to drive to the highway section of the Smart Roads. The test track portion was split equally into four orientation legs and four test legs. Note, one leg is defined as a one-way trip from one end of the highway to the other (i.e., two legs equal one full loop).

2.5.2.1 Orientation Legs

Each orientation lap introduced a new element of the study to allow the participant to become comfortable before actual testing:

Leg 1 – Maintain speed of 45 mph.
Leg 2 – Introduce lead confederate vehicle.
Leg 3 – Maintain 3-second following distance between participant and confederate vehicle (automation was activated if applicable).
Leg 4 – Open the Web browser on the mounted tablet.

2.5.2.2 Test Legs

During the test portion, the participant was instructed to stay in the right lane for the duration of the drive, and perform four secondary, non-driving tasks. The participant was randomly assigned to either the automated or manual operating condition. In the manual condition, participants were in full control of the vehicle using traditional controls (e.g., steering wheel, brake pedal). In the automated condition, the automated driving features were engaged, and the participant was instructed to monitor the vehicle and be prepared to take control if the automated driving features disengaged. A summary of testing procedures is as follows:

Leg 5 – Perform a calculation.
Leg 6 – Type an email.
Leg 7 – Find an address.
Leg 8 – Surprise event – Find a local movie playing at a specific time; during this task, the rear seat safety driver initiated the sudden lane deviation using the redundant steering controls (see Figure 9). This sudden lane deviation was initiated at the start of the extended shoulder (see Figure 2) and, during piloting, was determined to be performed at .6 lateral gs.

2.5.3 Debriefing

After completion of the surprise event, the experimenter instructed the participant to stop the vehicle and then proceeded with the debriefing process (i.e., revealing the true purpose of the study, signing an informed consent form). The participant, upon returning to VTTI, was then asked to complete a questionnaire. After filling out the questionnaire, the participant was then paid $60 for full participation.

CHAPTER 3. RESULTS

3.1 Data Reduction

The variables of interest were reduced and consolidated in 32 data files. These data files will be delivered on an encrypted hard drive containing a spreadsheet with human factor variable outputs and variable definitions. Video channels (i.e., over-the-shoulder and front view) will also be provided, with the participant's face masked in each. Kinematic radar data will be provided in 32 CSV files containing each participant's data (further discussed in section 3.1.3), in addition to time-to-collision (TTC) and headway plots.

3.1.1 Human Factor Variables

Human factor variables (i.e., reaction time, task completion time) were calculated by matching video timestamps to the beginning and end of specific participant actions. Viewing the video, researchers used the definitions of the variables to mark the appropriate segments of these actions. These actions ranged in movement; for example, lifting a hand to reach for the steering wheel or completing the end of a secondary task. See Figure 10 for a visual of the human factors data reduction method.

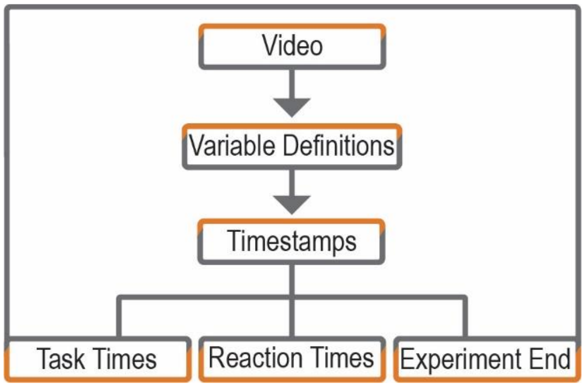

Figure 10. Human factors data reduction method.

3.1.2 GPS-based Calculations

The DGPS system available on the Smart Road allows data to be collected that is much more precise than standard GPS systems. The DGPS data include latitude and longitude values accurate to about 1–3 cm as opposed to the 2–3 m accuracy of GPS. These DGPS data points were plotted and compared to the centerline data for the Smart Road to determine how much a participant swerved during the lane deviation. The DGPS points starting at leg one until leg 4 (excluding the turnarounds) were used to calculate the average baseline lane position. Figure 11 provides a visual overlay of the DGPS calculations for one participant (the vehicle displayed in the image is not from this study). The test vehicle location is marked in blue while the Smart Road's highway centerline is in yellow, with the errant blue line onto the extended shoulder representing the lane deviation. There are blue lines on either side of the centerline as both directions of travel were used to calculate the average baseline lane position.

To determine the amount a participant swerved, the difference between the maximum deviation from the centerline and the participant's average baseline lane position in the right lane was used. For eight participants in this dataset, the average location error (i.e., DGPS accuracy error) during the surprise event was over 1.00 m. Excluding the data from those eight participants, the average location error was 0.05 m for the surprise event.

Figure 11. Centerline-to-baseline DGPS comparison and swerve mapping illustration.

3.1.3 Radar Kinematic Data

Radar, data extraction, and processing consisted of three steps: 1) epoch definition, 2) data extraction and variable calculation, and 3) validation.

Epoch definition and identification was carried out using the timestamps gathered through video reduction. The exported epochs are 20 s in length and are centered around the EventStart timestamp. The EventStart timestamp is the time associated with onset of the lane departure event. This time window was selected as it was suitable to capture the participant's response to the event, as well as the pre-event baseline driving.

The time series data for each participant's event were exported to individual CSV files. The full list of exported variables, as well as their descriptions can be found in Table 1. In addition to the measured time series variables, TTC and headway were computed from the measured radar data. The equations used to compute these were:

$$t_{TTC} = -\frac{x_{range}}{v_{lead} - v_{host}}$$

Equation 1: TTC Calculation

$$t_{Headway} = \frac{x_{range}}{v_{host}}$$

Equation 2: Headway Calculation

Table 1. Exported Variable Names, Descriptions, and Units for Each Participant's Lane Departure Event

Variable Name	*Variable Description*	*Units*
participant_id	Participant ID	
file_id	Original File ID	
timestamp_ms	Timestamp	Milliseconds
vehicle_speed_mps	Host Vehicle Speed	Meters per second
accel_x_g	Longitudinal Acceleration	g
accel_y_g	Lateral Acceleration	g
accel_z_g	Vertical Acceleration	g
brake_active	Brake Activation	Boolean
steering_wheel_angle_deg	Steering Wheel Angle	Degrees
throttle_position	Throttle Position	Percent
x_range_to_lead_m	Longitudinal Range to Lead Vehicle	Meters
y_range_to_lead_m	Lateral Range to Lead Vehicle	Meters
x_velocity_to_lead_mps	Longitudinal Velocity difference between Lead Vehicle Host (Radar)	Meters per Second
y_velocity_to_lead_mps	Lateral Velocity difference between Lead Vehicle Host (Radar)	Meters per Second
headway_s	Computed Time Headway (from radar)	Seconds
ttc_s	Computed Time to Collision (from radar)	Seconds

Once the data were exported, two separate reviewers took the exported data and compared it against the original data and the forward video to ensure that the data provided are representative of the actual events.

3.2 DESCRIPTIVE STATISTICS

Table 2 shows a summary of descriptive statistics for study variables.

Table 2. Descriptive Statistics for Study Variables

	Min	*Max*	*M*	*SD*
Age (years)	18.00	75.00	49.72	17.21
Task 1 Completion Time (s)	24.94	103.90	56.03	24.53
Task 2 Completion Time (s)	23.05	104.36	57.24	24.53
Task 3 Completion Time (s)	31.46	108.50	95.74	15.91
Steering Initial Reaction (Overall) (s)	00.14	00.67	00.44	00.14
Manual (s)	00.14	00.47	00.35	00.10
Automation (s)	00.33	00.67	00.52	00.11
Steering Corrective Reaction (Overall) (s)	00.54	01.88	00.83	00.27
Manual (s)	00.54	00.94	00.70	00.10
Automation (s)	00.53	01.88	00.96	00.34
Braking Initial Reaction (Overall) (s)	00.41	00.97	00.65	00.22
Manual (s)	00.41	00.88	00.56	00.09
Automation (s)	00.44	00.97	00.73	00.09
Braking Corrective Reaction (Overall) (s)	00.00	01.54	01.09	00.55
Manual (s)	00.75	01.35	00.95	00.23
Automation (s)	00.91	01.54	01.20	00.21
Swerve Distance (Overall) (meters)	01.31	07.90	04.83	01.60
Manual (m)	01.31	07.90	04.17	02.47
Automation (m)	03.69	07.23	05.50	02.90

Note. Braking reaction times were calculated for the 11 participants who braked. Task 4 does not have a completion time as zero participants were able to complete that task.

Table 3 shows a frequency summary of study variables, including data collected during the post-drive questionnaire. This questionnaire asked general demographic questions (e.g., age, gender, education) in addition to previous driving experience with ADAS and automated driving features.

Table 3. Frequencies of Study Variables

	Yes	No	Total
Task 1 Success Rate	28 (87.5%)	4 (12.5%)	32 (100%)
Task 2 Success Rate	28 (87.5%)	4 (12.5%)	32 (100%)
Task 3 Success Rate	11 (34.4%)	21 (65.6%)	32 (100%)
Task 4 Success Rate	0 (0%)	32 (100%)	32 (100%)
Crash Warning Systems	18 (56.3)	14 (43.8%)	32 (100%)
ACC	13 (40.6%)	19 (59.4%)	32 (100%)
Lane Assist	12 (37.5%)	20 (62.5%)	32 (100%)
Automation Knowledge	15 (46.9%)	17 (53.1%)	32 (100%)

Note. Participants did not finish Task 4 (searching for local movie) as the sudden lane deviation was initiated seconds after this task was assigned.

3.3 INFERENTIAL TESTS

Select inferential tests were run on the study data to test mean differences between groups. An independent samples *t*-test was used to analyze mean steering corrective reaction time for the manual (M = 00.70; SD = 00.10) and automated operating conditions (M = 00.96; SD = 00.34). Results suggest that the automated condition participants had significantly slower corrective steering reaction times than manual participants, $t(30) = -2.88$, $p = 0.007$; $d = 4.10$ (see Figure 12).

An independent samples *t*-test was used to analyze mean corrective braking reaction time for the manual (M = 00.95; SD = 00.23) and automated conditions (M = 01.20; SD = 00.21). Results suggest that corrective braking reaction time did not differ as a function of operating condition, $t(9) = -1.92$, $p = 0.09$ (see Figure 13). The degrees of freedom for this test is lower as only 11 out of 32 participants reacted to the sudden lane deviation, in part, by braking.

To ensure that participant braking was not a function of operating condition, a chi-squared test of independence was conducted on braking (dummy coded as yes/no) and operating condition (manual/automation). Results showed that the distribution was almost equal (five participants braked in the manual condition; six braked in the automated condition) and that this distribution was not a function of operating condition, $\chi^2(1) = 0.139$, $p = 0.71$.

Further, a two-by-two analysis of variance (ANOVA) was used to analyze if there was an interaction between gender (male/female) and operating condition (automated/manual) on corrective steering reaction times. However, the model was not significant, $F(3, 28) = 2.60$, $p = 0.07$.

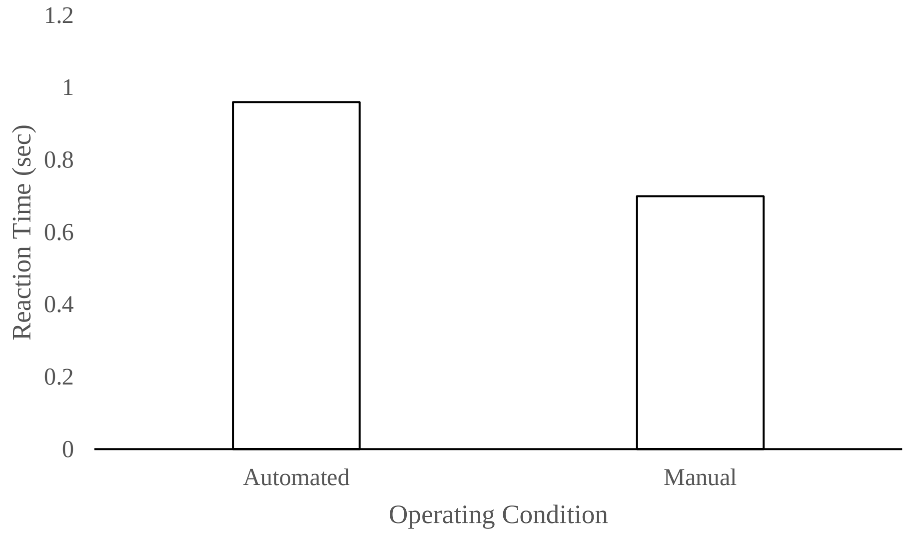

Figure 12. Corrective steering reaction between operating conditions.

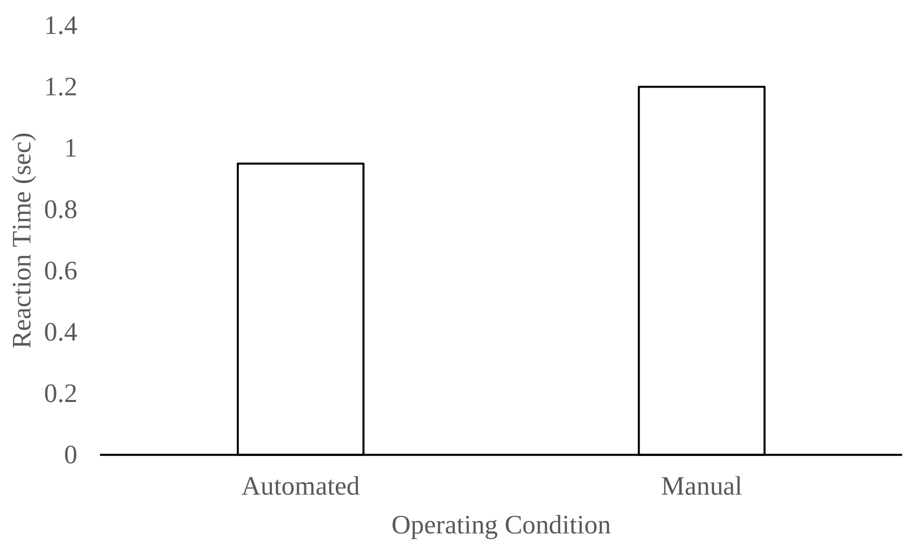

Figure 13. Corrective braking reaction between operating conditions.

CHAPTER 4. DISCUSSION

A controlled-access test track study was conducted using the Virginia Smart Roads as the test bed. An Infiniti Q50 was used as the test vehicle and was retrofitted with hardware to allow the vehicle to operate under automated conditions. Further, this vehicle had inconspicuous redundant vehicle controls located in the backseat behind the passenger's seat. These controls were used to initiate the sudden lane deviation experienced by each participant.

This sudden lane deviation was intended to simulate an over-the-air hacking of the test vehicle that would cause it to suddenly exit the current lane of travel. Results suggested that participants in the automated condition had slower corrective steering reaction times than those in the manual condition. This could be explained by the participants in the automated condition not having their hands on the wheel, requiring them to cover a longer distance to reach the wheel and, for some participants, their eyes off the forward roadway. In contrast, those in the manual condition already had their hands on the wheel, meaning the sudden lane deviation would be perceived and reacted to faster.

All participants used the steering wheel as corrective input after the lane deviation. However, only one-third of participants (N = 11) reacted by applying the brake. This could be explained by participants reacting to correct the movement error (i.e., the errant steering causing the lane deviation) by providing only the corrective input needed to address the error (Ericson, Parr, Beck, & Wolshon, 2017). Further, analyses showed that braking or not braking was not influenced by the operating condition.

Although not relevant to hypothesis testing, participant performance on the given tasks varied. The secondary tasks were implemented to simulate non-driving tasks that are people are anticipated to engage in when operating a vehicle with an automated driving system. Most participants were successful in completing task 1, calculation (87.5%) and task 2, email (87.5%) but were largely unsuccessful with task 3, finding an address (34.4%) and task 4, finding a movie (0%; happened during the sudden lane deviation). This is due to the increasing complexity of each task, compounded with extraneous factors such as unfamiliarity with operating the specific tablet provided to participants.

Limitations of the current study include participant exposure to the automated driving features of the test vehicle. Research suggests that significant driving time with automated driving features is needed to sufficiently build trust in the automated system (Hergeth, Lorenz, & Krems, 2017) beyond the approximately 30-minute drive time participants received. This could have influenced participant reactions by making them potentially hypervigilant due to unfamiliarity with the test vehicle and driving environment. A longitudinal study focusing on prolonged exposure and experience with the test vehicle could better represent the anticipated adaptation individuals have when using an automated driving feature long-term.

Having two experimenters present in the test vehicle may have placed inadvertent stress on the participant in addition to the novelty of operating a new vehicle in a novel driving environment. Performing a naturalistic driving study where the participant is able to drive comfortably in an unaltered environment could provide better insight into their true driving behavior and reaction to a surprise event.

Regarding CI resiliency, the current study suggests that drivers are resilient and, generally, could react adequately and appropriately to an unexpected event (i.e., vehicle being hacked with an abrupt steering event). Previous research suggests that driver reaction time to familiar events (e.g., forward car braking) is 2-seconds, while reacting to an unfamiliar event (e.g., roadway collapsing) is 1.53 seconds (Coley, Wesley, Reed, & Parry, 2009). The current sample has an overall mean reaction time of 0.83 (steering) and 1.09 (braking), both faster than previous research. This suggests that if a CI modality, such as a vehicle, is hacked, a driver has the potential capability to react expediently.

Overall, the current study examined driver reactions to a sudden lane deviation simulating a remote vehicle hacking. Corrective steering reaction times were slower in the automated than manual operating condition. Future studies may want to consider adding longitudinal and naturalistic driving elements to further add external validity to the context of the study environment.

REFERENCES

Brown, G., Carlyle, W. M., Salmeron, J., & Wood, K. (2005). Analyzing the vulnerability of critical infrastructure to attack, and planning defenses. *Tutorials in Operations Research*, 102 – 122.

Coley, G., Wesley, A., Reed, N., & Parry, I. (2009). Driver reaction times to familiar, but unexpected events. *TRL Published Project Report*.

Ericson, J. M., Parr, S. A., Beck, M. R., & Wolshon, B. (2017). Compensating for failed attention while driving. *Transportation Research Part F: Traffic Psychology and Behaviour*, *45*, 65-74.

Hergeth, S., Lorenz, L., & Krems, J. F. (2017). Prior familiarization with takeover requests affects drivers' takeover performance and automation trust. *Human Factors*, *59*(3), 457-470.

National Highway Traffic Safety Administration (2013). Visual-manual NHTSA driver distraction guidelines for in-vehicle electronic devices. *Docket No. NHTSA-2010-0053*. Washington, DC: United States Department of Transportation

Saad, W. (2017). CRISP Type 2: Collaborative research: Towards resilient smart cities. https://sites.google.com/site/nsfrsc/home

SAE International. (2018). J3016 taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles. https://saemobilus.sae.org/content/j3016_201401