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The Effect of Driving Style on Responses to Unexpected Vehicle Cyberattacks

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Abstract: Vehicle cybersecurity is a serious concern, as modern vehicles are vulnerable to cyberattacks. How drivers respond to situations induced by vehicle cyberattacks is safety critical. This paper sought to understand the effect of human drivers' risky driving style on response behavior to unexpected vehicle cyberattacks. A driving simulator study was conducted wherein 32 participants experienced a series of simulated drives in which unexpected events caused by vehicle cyberattacks were presented. Participants' response behavior was assessed by their change in velocity after the cybersecurity events occurred, their post-event acceleration, as well as time to first reaction. Risky driving style was portrayed by scores on the Driver Behavior Questionnaire (DBQ) and the Brief Sensation Seeking Scale (BSSS). Half of the participants also received training regarding vehicle cybersecurity before the experiment. Results suggest that when encountering certain cyberattack-induced unexpected events, whether one received training, driving scenario, participants' gender, DBQ-Violation scores, together with their sensation seeking measured by disinhibition, had a significant impact on their response behavior. Although both the DBQ and sensation seeking have been constantly reported to be linked with risky and aberrant driving behavior, we found that drivers with higher sensation seeking tended to respond to unexpected driving situations induced by vehicle cyberattacks in a less risky and potentially safer manner. This study incorporates not only human factors into the safety research of vehicle cybersecurity, but also builds direct connections between drivers' risky driving style, which may come from their inherent risk-taking tendency, to response behavior to vehicle cyberattacks.

Keywords: vehicle cyberattacks; driving behavior; driving simulation; DBQ; sensation seeking

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1. Introduction

1.1. Vehicle Cybersecurity and Human Factors

The last few decades have witnessed a transition of automotive systems from electromechanical to electronic and software-driven systems [1]. Today's vehicles are important to society and are examples of a cyber-physical system because of their integration of computational components and physical systems [2,3]. As increasingly more vehicles are connected to the Internet, cyberattacks against modern vehicles are said to be inevitable [3,4]. It is reported that the frequency and cost of cyberattacks continue to grow exponentially worldwide [5,6]. As a consequence, cybersecurity is one of the highest priorities for industry, academia, and government [5].

Cyberattacks can be passive, with no system damage, or active, with damage being fatal to the system or the entire network [2,6]. For example, a vehicle cyberattack or a vehicle system error can: (1) cause false or misleading information to be displayed to the driver [7], (2) cause driver distraction [7], (3) show erroneous output on the human–machine interface

(HMI) of the vehicle system [8], and (4) obstruct traffic by commanding compromised vehicles under their control to benefit the attacker [9]. Resultantly, vehicle cyberattacks can lead to outcomes ranging from minor comfort restraints to actual crashes [10,11]. It has already been reported that hackers are able to manipulate and control certain vehicles remotely [12–14]. In July 2015, Fiat Chrysler recalled 1.4 million cars due to doubts about car software and alleged remote control [1].

Vehicle cyberattacks differ from common vehicle failures in that they are more likely to be sudden without salient signals for the driver to notice [3]. Researchers have suggested that a key feature of vehicle cyberattacks lies in their unpredictability, which leads to a belief that there might not exist a one-size-fits-all solution to prevent vehicle cyberattacks [11].

In regard to traffic safety, the three main components are drivers, vehicles, and the driving environment [15]. Efforts should accordingly also be devoted to these three aspects to tackle the safety issue under the context of vehicle cyberattacks. Therefore, the role of vehicle systems and drivers shall both be considered and treated equivalently critical for vehicle cybersecurity studies [16]. Researchers and designers have been actively studying the potential access points of vehicle cyberattacks and the vulnerability of vehicle systems and connections from a technological perspective, hoping to design future vehicle systems in a safer way against cyberattacks [14]. Yet, there lacks an understanding of drivers' response behavior to vehicle cyberattacks, even though previous research has stressed the important role of human drivers when vehicle cyberattacks occur [3]. That is, the component of "driver" is understudied. What human factors underlie drivers' safe and unsafe response behavior in such an environment needs to be uncovered and better understood [17].

1.2. Self-Reported Risky Driving Behavior

Many factors pertaining to human drivers can affect driving safety, such as being inexperienced, risky driving behavior, and driver error [18,19]. It is believed that drivers often engage in behaviors that pose a risk to both themselves and to other road users [20]. Researchers have developed tools to measure such risky driving behaviors, among which a widely used instrument is the Driver Behavior Questionnaire (DBQ) [20–23]. In addition to the DBQ, drivers' personalities have been a subject of interest in exploring what may affect a driver's behavior [24,25]. It is suggested that personality traits are an important influence on both risk perceptions and driving behavior and that they are closely linked with risky driving behaviors [26,27]. One personality trait that has received considerable attention is sensation seeking [28]. As human factors are very broad topics [3], in this paper, we solely focused on the role of one's self-reported risky driving behavior assessed by the Driver Behavior Questionnaire and sensation seeking in how they respond to vehicle cyberattacks.

1.2.1. The Driver Behavior Questionnaire (DBQ)

The DBQ is a survey that measures three self-reported risky and aberrant behaviors in driving: (1) *errors*—misjudgments or failures of observation that could be hazardous to others, (2) *lapses*—attention and memory failures that can cause embarrassment but are unlikely to have an impact on driving safety, and (3) *violations*—deliberate contraventions of legally regulated or socially accepted behaviors associated with safe vehicle operation [17,29]. One main reason that researchers have expressed interest in the DBQ is the frequently reported relationship between DBQ scores and risky driving behavior [17]. For example, in a previous driving simulator study exploring the impact of personal traits on driver behavior, it was found that drivers with higher DBQ-Violation scores tended to brake less heavily [30,31]. Others found that drivers with high DBQ-Violations scores drove faster and demonstrated more lane changes in a highway setting [17,30]. However, there is also little published information on the relationship between DBQ scores and actual driving behavior that may bear some relationship to crash risk [17]. In the context of a driver encountering vehicle cyberattacks, specifically, research data are extremely limited regarding how DBQ scores are associated with how one responds to a vehicle cyberattack.

1.2.2. Sensation Seeking

Sensation seeking is a personality characterized by "the need for varied, novel, and complex sensations and experiences and the willingness to take physical and social risks for the sake of such experiences" [32,33]. Researchers have found that individuals high in sensation seeking appear to be drawn to activities that are high in risk, such as reckless driving [34,35]. It is suggested that sensation seeking is a potent predictor of a wide array of problem behaviors and that high sensation seekers are more likely than their low sensation-seeking counterparts both to try and repeat risky activities [35,36]. Sensation seeking has also been linked with traffic crash involvement [37]. Researchers have pointed out that it is significantly related to aberrant driver behavior, such as driving while intoxicated, speeding, and low seat belt usage [28,37]. In general, the association between sensation seeking and risky driving behavior has been constantly reported by traffic safety professionals and researchers [28]. However, there is also growing evidence showing that sensation seeking may moderate the manner in which drivers respond to other factors such as perceived risk [28]. Some researchers showed that high sensation seekers performed better on focused attention tasks [37]. When one encounters unexpected driving situations caused by vehicle cyberattacks, the attention needed to notice and observe what might be happening, as well as maintain safe driving, is expected to be substantial. Whether drivers with high sensation seeking would perform better under a cybersecurity event remains unknown. That is, although sensation seeking is believed to be associated with various risky driving behaviors, its effect in the context of a more specific driving situation (i.e., vehicle cyberattacks) needs to be further assessed. Sensation seeking is operationally defined in terms of scores on the Sensation Seeking Scale (SSS) [28,38]. In the present work, we employed a short version of the SSS, the Brief Sensation Seeking Scale (BSSS) [35], which measures four dimensions of sensation seeking: boredom susceptibility, disinhibition, experience seeking, and thrill and adventure seeking.

1.3. Research Gap and Objective

To date, only limited research work has been conducted to investigate how drivers respond to unexpected driving situations caused by vehicle cyberattacks, and as a result, the relationship between behavioral patterns, risky driving, and personality is not well understood. The objective of the present study was to understand the association between drivers' self-reported risky driving behavior, portrayed by the DBQ and sensation seeking, and responses to vehicle cyberattacks. We conducted a driving simulator study in which drivers experienced a series of simulated drives wherein they encountered abnormal driving situations akin to vehicle cyberattacks.

2. Materials and Methods

This research complied with the American Psychological Association Code of Ethics and was approved by the Institutional Review Board at the University of Massachusetts Amherst. This study is a continuation of a previous study [11]. In the previous phase (phase 1), we focused on gathering qualitative information concerning drivers' experience with and responses to vehicle cyberattacks. In this phase (phase 2), we quantitatively assessed drivers' response behavior to vehicle cyberattack-induced situations via a driving simulator experiment.

2.1. Participants

Thirty-two (32) participants (aged 18–26 years) were recruited from the University of Massachusetts Amherst campus and the town of Amherst using flyers and emails for this study. A power analysis showed that with a sample size of 32 and an effect size of 0.38, when setting the alpha error to 0.05, the power is 0.8. The average age of the participants was 20.5 years (SD = 1.98 years). There were 7 female participants and 23 male participants, while the remaining 2 identified themselves as "nonconforming." Only individuals with a valid United States driver's license were included in this study.

2.2. Driving Simulator and Scenarios

A fixed-based RTI (Realtime Technologies Inc.) driving simulator consisting of a fully equipped 2013 Ford Fusion surrounded by six screens with a 330-degree field of view was used for the study (Figure 1). The cab has two dynamic side mirrors, providing participants with realistic side and rear views of the scenarios. In the car, there is a fully customizable virtual dashboard and center stack. The driving environment consisted of long sections of roadway with four straight sections and four curves—a loop—with no traffic lights or stop signs and a speed limit of 35 (Figure 2). The driving environment was 2-way, 4-lane, and rural-based.

Figure 1. Driving simulator.

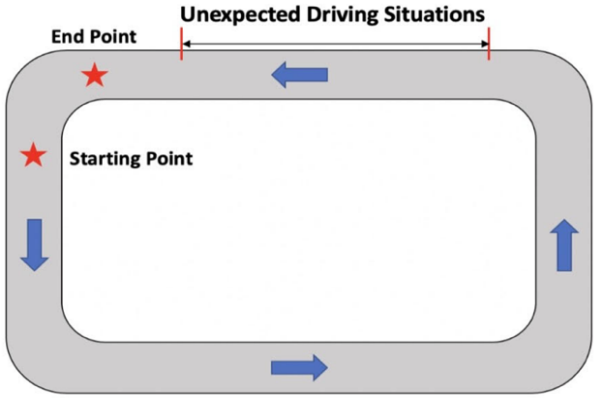

Figure 2. Road layout of driving scenario.

We implemented three vehicle cyberattacks, as suggested by the literature [3,7,8]: (1) siren—sirens similar to a police car or an ambulance start to sound while there are no vehicles in sight of the participant, (2) dashboard signs—a high-pitch beep sounds, followed by two warning signs that illuminate on the dashboard repeatedly and randomly; (3) lane change—the participant's vehicle is suddenly controlled by the experimenter and starts to repeatedly weave between lanes. These three cybersecurity events were embedded in each of the three experimental drives. The cybersecurity event always occurred in the last section of a driving scenario to ensure that participants did not become oversensitized to the appearance of hazards [11,39]. The driving scenarios were presented to all participants in the same order: siren, dashboard signs, lane change.

2.3. Procedure

Participants came to our driving simulation laboratory for one visit. After giving consent, they filled out several questionnaires about their demographics and driving history. Then half of the participants received training on vehicle cybersecurity and how

to properly respond to vehicle cyberattacks before the simulated drives (for those who received training, 3 were female, 12 were male, 1 was nonconforming; for those who did not receive training, 4 were female, 11 were male, 1 was nonconforming). We accounted for this effect by incorporating whether one received training into our analysis, and the details can be found in session *2.4*. In addition, half of the participants were notified by an in-vehicle warning signal regarding the current situation and what action they might want to take after the occurrence of a cybersecurity event. We excluded this effect of warning by averaging participants' post-cybersecurity event driving data up until the point where the warning was issued. Details regarding how we handled the effect of warnings regarding participants' physical driving behavior are given in Section 2.4 as well. Participants completed a practice drive to accustom themselves to the simulated driving environment, followed by 4 experimental drives, including a baseline drive (normal drive without any events) and 3 experimental drives in which each was associated with a cyberattack event. Their driving behavior was recorded by 2 in-vehicle video cameras and the simulator itself, yielding two sets of variables that might be of interest: driver behavior (e.g., hand and foot movements, checking side or rear mirrors) and driving data (e.g., speed, acceleration). When all drives were completed, participants again filled out a series of questionnaires, including the DBQ and the BSSS.

2.4. Variables and Data Analysis

Our dependent variables were defined and chosen to represent participants' response behavior to each of the cybersecurity events. Previous studies have used active-driving performance indicators, such as reaction time, to understand hazard response behavior [40]. Some researchers relied on drivers' visual behavior to characterize their risky driving behavior [41,42]. Others have posited that braking patterns/behaviors can be useful in inferring a driver's perceived risk [40,43]. Moreover, some have used average velocity during a driving task as a metric to quantify one's behavioral patterns regarding longitudinal controls [17,44]. In the present paper, we focused on these driving metrics as participants' response behavior to the cybersecurity events: (1) delta velocity (from driving data yielded by the simulation system), defined as the difference in velocity between after and before an event occurs and calculated by subtracting the velocity collected after the occurrence of an event by the velocity collected in a 5 s time window right before the event; (2) post-event acceleration (from driving data yielded by the simulation system), defined as the average acceleration in a 2 s time window after the occurrence of an event; and (3) time to first reaction (from driving behavior recorded by the video cameras), defined as the difference in time between the occurrence of a cybersecurity event and the first time a participant took any of these following actions: changed from 1 hand to both hands on the wheel, hovered and switched between the gas and pedal, checked the side mirrors, checked the rear mirror, looked at the dashboard, changed lanes, or pulled over. We carefully looked at the video data and chose these measures as they were observed after the cybersecurity event occurred, but they were not observed (frequently) before the event. We, therefore, believed that these behaviors would be an indicator of a driver being attentive to driving and could be incorporated to help shape participants' pattern of response behavior toward vehicle cyberattacks.

By definition, delta velocity less than 0 will indicate a decrease in driving speed after the cybersecurity event occurs; negative post-event acceleration shall suggest decelerating behavior, and shorter time to first reaction may, to some degree, indicate one being more attentive and perceiving potential risks. It should be noted that: (1) for the lane change drive, we referred participants' time to first reaction to only consider the behavior of pulling over; and (2) values for delta velocity and post-event acceleration will not exhibit any effect of warning, as data were acquired before any warnings came into play, while time to first reaction may be affected by whether a participant received warnings.

Drivers' age and gender have been shown to be related to risky driving behavior, such as accident rates [17,20,23,45]. As such, we decided to incorporate them as independent

variables. Participants' self-reported risky driving behavior was assessed by DBQ scores (i.e., 3 subscales: errors, lapses, violations) and scores to the 4 subscales of BSSS (boredom susceptibility, disinhibition, experience seeking, thrill and adventure seeking). As mentioned previously, half of the participants received training on vehicle cybersecurity and how to respond to vehicle cyberattacks before going through the drives. We, therefore, accounted for the training effect on all three response behavior metrics by including training as an independent variable, as previous research has demonstrated the positive effect of training on reducing drivers' risky behavior and crash involvement [46]. Regarding the effect of warning, as it could only possibly affect participants' time to first reaction, we included it in the analysis of time to first reaction. In addition, it is suggested that individual behavior patterns are largely determined by specific driving situations [17]. We thus performed the analysis considering the potential effect of different driving scenarios (different cyberattack-induced events) as an independent variable. The independent variables are summarized in Table 1.

Table 1. Summary and description of the independent variables.

Variable	Type	Mean		Standard Deviation	
		Female	Male	Female	Male
Driving scenario	Categorical, reference level lane change	/	/	/	/
Gender	Categorical, coded as binary with reference level female participants	/	/	/	/
Training	Categorical, coded as binary with reference level no training	/	/	/	/
Warning	Categorical, coded as binary with reference level no warning	/	/	/	/
Age	Numeric	21.0	20.4	2.19	1.90
DBQ-Errors	Numeric	1.0	0.5	1.01	0.40
DBQ-Lapse	Numeric	1.5	0.9	1.02	0.57
DBQ-Violation	Numeric	1.3	1.3	0.73	0.69
Boredom susceptibility	Numeric	3.6	3.4	0.94	0.79
Disinhibition	Numeric	3.6	3.0	0.84	1.02
Experience seeking	Numeric	3.4	3.9	1.04	0.76
Thrill and adventure seeking	Numeric	3.6	3.4	1.38	1.10

As an exploratory process, we first built univariate linear regression models between each of the independent variables (i.e., driving scenario, gender, training, warning (only for time to first reaction), age, the 3 subscales of the DBQ, the 4 subscales of the BSSS) and each of the response behavior metrics (i.e., delta velocity, post-event acceleration, time to first reaction) to check whether any significant relationships exist. If so, the significant independent variables would be entered into a larger linear regression model together for each dependent variable. Resultantly, 3 large statistical models corresponding to the 3 response behavior metrics were built, and the results were further investigated. The statistical significance level (α) was set to 0.05. All analyses were performed using the programming language R [47].

3. Results

3.1. Delta Velocity

Driving scenario, training, DBQ-Errors, and DBQ-Violation were shown to be statistically significantly associated with delta velocity and then included in a larger multiple

linear regression model. Because there was multicollinearity detected in the model, we further assessed the correlation between the independent variables along with their variance inflation factor (VIF) and decided to remove DBQ-Errors from the model.

Table 2 presents the results of the multiple regression. When accounting for the effect of the other independent variables, driving scenario, training, and DBQ-Violation scores all had a significant impact on participants' delta velocity. Specifically, when compared with the lane change drive, participants were associated with a significantly higher delta velocity in the siren drive (β = 3.39, $p < 0.001$) and the dashboard signs drive (β = 4.30, $p < 0.001$). Combined with the visualization in Figure 3, this indicates that participants tended to increase their speed right after the cybersecurity event occurred (note that a value of 0 indicates no speed change for delta velocity between after and before the cybersecurity event) in both the siren and dashboard signs drives relative to the lane change drive, in which they generally reduced speed. Similarly, participants who received training appeared to be more likely to reduce their speed ($\beta = -1.59$, $p = 0.021$) after the cybersecurity event occurred compared with those who did not receive training. Moreover, participants with higher DBQ-Violation scores were more likely to increase their speed after the occurrence of the cybersecurity event compared with their low-score counterparts (Figure 4).

Table 2. Multiple regression results on delta velocity.

Variable	Coefficient	Standard Error	t-Value	Pr (>|t|)
Driving scenario	β = 3.39 (siren)	0.821	4.129	<0.001 *
(ref = lane change)	β = 4.30 (dashboard signs)	0.814	5.284	<0.001 *
Training (ref = no training)	$\beta = -1.59$	0.680	−2.341	0.021 *
DBQ-Violation	β = 1.34	0.489	2.735	0.008 *

Note: * indicates statistical significance.

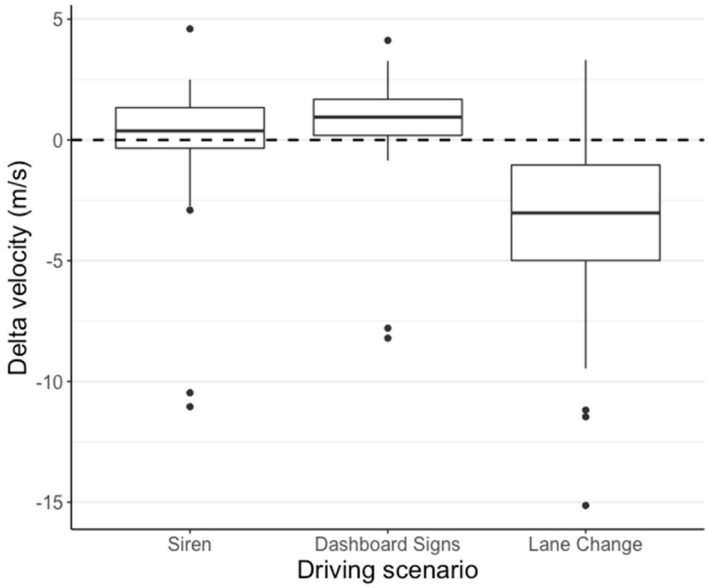

Figure 3. Effect of driving scenario on delta velocity; the dots represent outliers.

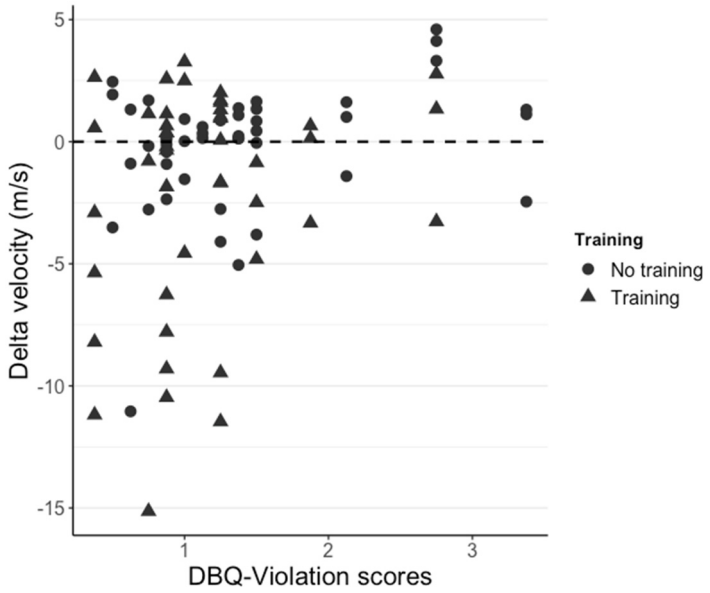

Figure 4. Effect of training and DBQ-Violation scores on delta velocity.

3.2. Post-Event Acceleration

Driving scenario, participants' gender, DBQ-Violation scores, boredom susceptibility, and disinhibition were shown to have a significant univariate relationship with post-event acceleration. Because there was a multicollinearity issue, we followed the same procedure as mentioned above. Boredom susceptibility was excluded from the larger model, and the multiple linear regression results are detailed in Table 3.

Table 3. Multiple regression results on post-event acceleration.

Variable	Coefficient	Standard Error	t-Value	Pr (>|t|)
Driving scenario	$\beta = 0.22$ (siren)	0.140	1.564	0.122
(ref = lane change)	$\beta = 0.63$ (dashboard signs)	0.139	4.518	<0.001 *
Gender (ref = female)	$\beta = 0.30$	0.137	2.173	0.033 *
DBQ-Violation	$\beta = 0.30$	0.084	3.528	<0.001 *
Disinhibition	$\beta = -0.24$	0.061	−3.876	<0.001 *

Note: * indicates statistical significance.

Compared with the lane change scenario, participants were associated with a significantly higher post-event acceleration in the dashboard signs drive ($\beta = 0.63$, $p < 0.001$). From the visualization presented in Figure 5, we see that participants were more likely to have accelerating behavior after the cybersecurity event in the dashboard signs drive compared with the lane change drive. It should be noted that negative post-event acceleration indicates decelerating behavior. Male participants were more likely to have a statistically significantly higher post-event acceleration relative to female participants ($\beta = 0.30$, $p < 0.033$). The direction of effect of DBQ-Violation is opposite to that of disinhibition: participants with higher DBQ-Violation scores tended to have significantly higher post-event acceleration than those with lower scores ($\beta = 0.30$, $p < 0.001$); those with higher disinhibition portrayed by the BSSS were more likely to have lower post-event acceleration compared with their low-score counterparts ($\beta = -0.24$, $p < 0.001$). From the visualization presented in Figure 6, female participants were more likely to decelerate after the cybersecurity event relative to males; higher disinhibition was associated with decelerating behavior after the cybersecurity event; higher DBQ-Violation scores were associated with less decelerating behavior after the cybersecurity event.

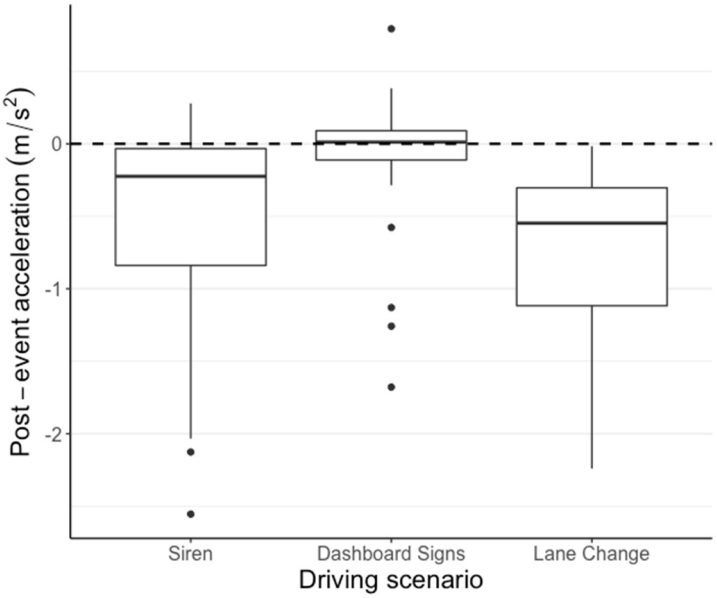

Figure 5. Effect of driving scenario on post-event acceleration; the dots represent outliers.

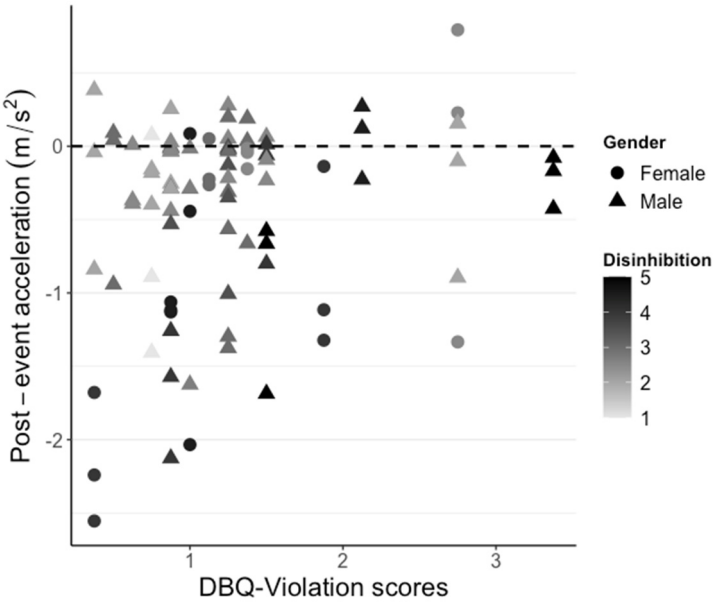

Figure 6. Effect of gender, DBQ-Violation scores, disinhibition on post-event acceleration.

3.3. Time to First Reaction

Only driving scenario and training had a statistically significant univariate association with time to first reaction. They were then entered into a multiple regression model, the results of which are presented in Table 4. Participants had a significantly shorter time to first reaction in both the siren drive ($\beta = -18.96$, $p < 0.001$) and the dashboard signs drive ($\beta = -15.71$, $p < 0.001$) compared with the lane change drive. Participants who received training were more likely to have a shorter time to first reaction relative to those who did not receive training ($\beta = -8.93$, $p = 0.023$).

Table 4. Multiple regression results on time to first reaction.

Variable	Coefficient	Standard Error	t-Value	Pr (>|t|)
Driving scenario	$\beta = -18.96$ (Siren)	4.719	−4.018	<0.001 *
(ref = lane change)	$\beta = -15.71$ (dashboard signs)	4.719	−3.33	<0.001 *
Training *(ref = no training)*	$\beta = -8.93$	3.864	−2.311	0.023 *

Note: * indicates statistical significance.

4. Discussion

The DBQ has been constantly reported by traffic safety professionals and researchers to be associated with risky behaviors [17]. Sensation seeking, as a measure of one facet of people's personality traits, is also linked with risky driving behavior. The two corresponding sets of scales (i.e., the DBQ and the BSSS) utilized in this paper portray one's risky and aberrant driving behavior to a great degree. While they are often studied to understand drivers' risky driving behavior, evidence regarding how they may affect detailed and actual driving behaviors under various driving situations remains limited [17]. To extend the research effort on the role of risky driving behavior in traffic safety, the present work aimed to build and understand potential associations between drivers' self-reported risky driving behavior and response behavior to an understudied domain—situations induced by vehicle cyberattacks.

Regarding how one's risky and aberrant driving behavior portrayed by the DBQ affects response behavior to situations induced by vehicle cyberattacks, in this work, the violation subscale was found to be a significant factor affecting drivers' response behavior such that higher DBQ-Violation scores were associated with a smaller reduction in velocity and a higher post-event acceleration after a cybersecurity event occurred. While one may not conclude that those with higher DBQ-Violation scores would possess riskier response behavior to events induced by vehicle cyberattacks, they at least did not respond in a safer way in comparison to their low DBQ score counterparts. This might be partially explained by the definition of DBQ-Violation itself: deliberate contraventions of legally regulated or socially accepted behaviors associated with safe vehicle operation [17,29]. That is, individuals with higher DBQ-Violation scores may be more likely to violate safe behaviors when operating a vehicle. Again, considering braking behavior can be indicative of risk perception [40], the effect of DBQ-Violation might suggest that drivers with higher DBQ-Violation scores are less likely to perceive the risk associated with an unexpected cybersecurity event. In general, our findings regarding the effect of DBQ scores are in line with the relevant literature that states that higher DBQ scores are closely related to drivers' risky driving behavior [17,29].

Our results regarding the effect of one's sensation seeking on response behavior to vehicle cyberattacks suggest that when measured by the BSSS, only one's disinhibition was statistically significantly associated with how one responded to events induced by vehicle cyberattacks. We found that participants with a stronger tendency to ignore societal inhibitions (higher disinhibition scores) were associated with decelerating behavior after a cybersecurity event occurred [32] (Eachus, 2004), indicating that they were either releasing the gas pedal or applying the brakes. The findings imply that higher sensation seekers drove in a more conservative and potentially safer way in terms of accelerating behavior when unexpected and potentially hazardous driving situations occurred. While previous research work has shown that drivers' sensation seeking is associated with aberrant driving behavior and crash involvement and that high sensation seekers tend to report risky driving behaviors [34,35,37], our findings here did not establish that individuals with higher sensation seeking (specifically disinhibition) were more likely to exhibit riskier response behavior toward driving situations caused by vehicle cyberattacks. At the same time, our findings may corroborate previous evidence that high sensation seekers performed better on focused attention tasks than low sensation seekers [37,48]. Since braking behavior

is said to be useful in inferring the perceived risk [40], our findings indicate that higher sensation seekers were more likely to perceive the cyberattack risk. Given that the key to sensation seeking is believed to be "the optimistic tendency to approach novel stimuli and explore the environment" [28], the findings reported here may also be interpreted as drivers with high sensation seeking tend to drive while also exploring the surroundings, and as a result, they are more likely to notice what is happening in the environment and take appropriate actions.

The finding that female participants tended to decelerate more after the occurrence of a cybersecurity event compared to male participants may indicate that they responded to the event in a more conservative and possibly safer way. However, this could also be an indication that the unexpected event caused a stress response among female participants when compared to male participants. Future research could be directed to further investigate how gender affects (young) drivers' response behavior to vehicle cyberattacks.

From a human factors perspective, it is suggested that when faced with a stimulus, one's decision-making relies on how one perceives the current situation, working memory, long-term memory, etc. Most of the commonly focused influencing factors on one's decision-making seem to be "knowledge-based"; that is, they are related to either one's own capabilities (e.g., long-term memory) or what can be utilized from the environment to help make a decision. The significant effect of training found in the present study is evidence supporting the belief, as it can aid one's long-term memory. On the contrary, the DBQ and the BSSS, measuring one's risky and aberrant driving behavior and sensation seeking, are more related to individuals' inherent risk-taking tendencies. Toward this end, this paper is significant in that it uncovered an association between one's inherent risk-taking tendency, which is likely to be independent of any knowledge, and one's cognition and decision-making under the specific context of vehicle cyberattacks. More importantly, we demonstrated that while DBQ scores and sensation seeking are often reported to be associated with risky driving behaviors, their impact on drivers' response behavior toward vehicle cyberattacks is the opposite, with higher sensation seeking exerting a potentially positive influence. Meanwhile, previous findings have also stated that the detrimental effect of sensation seeking on driving performance can be modulated by other factors [49]. These highlight the need to consider the effect of commonly used measures in specific driving situations as well as any interacting effect with other factors on one's driving performance.

This study has its limitations. First, our sample size was relatively small (N = 32), and participants were recruited from a geographically narrow area. The findings reported here might not be generalizable. Second, order effects might not be fully accounted for in the analysis, as the order in which the drives were presented to the participants was not counterbalanced. However, we suspect the effect of being subtle, given that the different driving scenarios and participants were never told if they were driving properly after each drive. Third, although driving scenario was incorporated as an independent variable in our analysis, the event presented in the siren drive might be weaker than that in the dashboard signs drive and the lane change drive, the effect of which may not have been fully captured. Last, the dependent variables chosen here are not safety critical. Future research could assess the effect of sensation seeking on drivers' response behavior to a broader spectrum of events/driving situations induced by vehicle cyberattacks and might consider using the full SSS to portray individuals' sensation seeking.

5. Conclusions

This study sought to build and understand the association between human drivers' self-reported risky and aberrant driving behavior and their response to vehicle cyberattacks. It was found that higher DBQ-Violation scores were associated with a less safe response and that higher sensation seeking (measured by disinhibition) was associated with decelerating behavior after vehicle cyberattacks occurred. Drivers' risk-taking tendencies might play a role in affecting how they respond to unexpected and potentially hazardous situations. However, such tendencies might exert different impacts on one's driving behavior de-

pending on the specific driving situations. Future research efforts should further assess the effect of the DBQ and sensation seeking on driving behavior, not only the response behavior toward vehicle cyberattacks but also a broad spectrum of specific and actual driving behaviors that could be risky.

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