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Investigating the impact of driving automation systems on distracted driving behaviors

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ABSTRACT

Driving automation systems (e.g., SAE Level 2) ultimately aim to enhance the comfort and safety of drivers. At present, these systems are able to control some portions of the driving task (e.g., braking, steering) for extended time periods, giving drivers the opportunity to disengage from the responsibilities associated with driving. In this study, data derived from two naturalistic driving studies involving automation-equipped vehicles were analyzed to evaluate driver behaviors with respect to driving automation system use, specifically distraction-related factors (i.e., secondary task engagement, eye-glance behavior, and drowsiness). The results indicate that when drivers had prior experience using driving automation systems, they were almost two times as likely to participate in distracted driving behaviors when the systems were active than during manual driving. Drivers with less experience and familiarity with driving automation systems were less likely to drive distracted when the systems were active; however, these drivers tended to be somewhat drowsy when driving with systems activated. The results provide important insights into different operational phases of driving automation system use (i.e., learning/unfamiliar vs experienced users), whereby experience results in overtrust and overreliance on the advanced technologies, which subsequently may negate some of the safety benefits of these systems. Thus, while the safety benefits of driving automation systems are evident, it is imperative to better understand the impact these advanced technologies may have on driver behavior and performance in order to evaluate and address any unintended consequences associated with system use.

1. Introduction

As transportation safety technology evolves in an effort to mitigate the more than 37,000 fatalities occurring on U.S. roadways every year (NHTSA, 2019), it is incumbent upon safety researchers and industry professionals to understand any potential detriment to the deployment of advanced-vehicle technology. Advanced driver assistance systems (ADAS) have emerged as safety systems designed to reduce driver risk (e.g., Cicchino, 2017a, 2017b, 2017c; Benson et al., 2018). These active safety systems, which include automatic emergency braking, forward collision warning, blind spot warning, and lane departure warning systems, provide transitory intervention when potentially hazardous situations are encountered. However, these systems still require the driver to actively perform the driving task; thus, they are not classified as driving automation systems (SAE International, 2018). Advanced-vehicle technologies capable of performing some or all of the driving task (i.e., simultaneous lateral and longitudinal vehicle control) on a continuous basis under the supervision of an attentive driver fall under the SAE International (2018) definition of Level 2 (L2) automation. Importantly, L2 automation is designed to assist and support a driver in performing the driving task but is not intended to replace the driver. Unfortunately, there is some evidence that driver behavior may be detrimentally impacted by the use of advanced-vehicle technologies; however, more research is needed about the possible adverse effects of driving automation systems on driver behavior (e.g., distraction and overreliance upon the system).

While studies such as Schoettle and Sivak (2015) and Blanco et al. (2016) have considered driving automation systems in relationship to driver risk, few studies have evaluated the negative effects of system use on driver behavior, and these limited studies give only a narrow view of the effects of the wide deployment of automation-equipped vehicles in the future. Several prior investigations have assessed elements of distracted driving behavior when using various automation features. For example, Llaneras et al. (2013) found that secondary task engagement

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by drivers along with the duration of driver glances off the forward roadway increased when the driver used an autonomous driving system with limited ability (i.e., a system that is capable of automated steering as well as speed and headway maintenance). Focusing specifically on adaptive cruise control (ACC), Rudin-Brown and Parker (2004) reported that drivers were better at performing a secondary task when ACC was activated, but their time required to detect a hazard was higher than when ACC was inactive. In a survey on ACC use, nearly one-third of respondents reported being comfortable participating in tasks unrelated to driving when the ACC system was activated (McDonald et al., 2018). These studies reveal potential drawbacks of driving automation system use in terms of negative effects on driver behavior and highlight the need to further understand automation/driver dynamics on a larger scale.

The current study aimed to address this gap in knowledge by assessing real-world driver behavior relative to driving automation system use based on two larger-scale naturalistic driving studies (NDSs). In an NDS, the study participants' vehicles are equipped with discreet instrumentation (cameras, sensors, radar) that collects data (e.g., vehicle parameters, driver behavior and performance) from key-on to key-off as drivers go about their normal driving routine. The resulting data furnish details regarding the behaviors of drivers, including the actions that occur before, during, and after a safety-critical event (SCE; e.g., a crash or near-crash) along with driver behavior during ordinary baseline driving when no SCEs occur (e.g., Dingus et al., 2015, 2006; Fitch et al., 2013; Klauer et al., 2010). The NDS methodology overcomes many of the limitations associated with other study types (e.g., simulator, test track, or epidemiological studies) as real-world driver behavior can be compared across events resulting in a crash and during ordinary driving. This provides researchers with the opportunity to ascertain crash risk associated with a range of driver behaviors, including drowsy driving and cognitive distraction (Dingus et al., 2019). In this work, two naturalistic driving datasets were mined and analyzed to identify any unintended consequences of driving automation systems on driver behavior with a focus on three specific distraction-related factors: secondary task engagement [STE], eye glance behavior, and drowsiness. The objective of the analyses was to improve our understanding of potential effects of driving automation system use on driver risk related to drowsiness and distraction.

The differences in the two NDSs assessed in the current study provide insight into the contrasting phases of driving automation system operation: the 'learning' (i.e., unfamiliar) phase and the experienced user phase. Thus, the results potentially reflect behavioral adaptation to driving automation technologies. Drivers who are unfamiliar with driving automation technologies are learning and testing the systems, whereas experienced users who are more familiar with driving automation systems may become over-reliant or place too much trust in the systems. Thus, unintentional dangers of driving automation system use exist for both unfamiliar and experienced users. While driving automation technologies offer important safety benefits for drivers, it is imperative that drivers remain active and engaged in the driving task. The results of this study are unique as they highlight the possible dangers present after drivers have gained experience with driving automation technologies, including when and how to use them (Dunn et al., 2019).

2. Methods

Two NDSs were assessed as part of the current research effort: 1) the Virginia Connected Corridors L2 Naturalistic Driving Study (VCC NDS) and 2) the L2 Driving Automation Functions Naturalistic Driving Study (DAF NDS). In each study, participant vehicles were equipped with driving automation systems that facilitated both lateral (i.e., lane-keep assist [LKA]) and longitudinal (i.e., ACC) maneuvers, collectively considered herein to constitute L2 automation. The vehicles in both studies were also equipped with data acquisition systems (DASs) developed at the Virginia Tech Transportation Institute (VTTI) to capture video-based driver behavior (Fig. 1) and vehicle parameters (e.g., speed, braking, GPS, lane position, and acceleration).

2.1. Participants & procedure

Fifty participants from Northern Virginia/Washington, D.C., comprised the VCC NDS cohort. As a prerequisite of study involvement, VCC NDS participants must have owned or leased an ACC-equipped vehicle, been at least 18 years old with a minimum of two years of driving experience, and frequently drove specific areas of Northern Virginia/Washington, D.C. (i.e., U.S. Routes 50 and 29 and Interstates 295 and 66). VCC NDS data collection spanned 20 months, with data collected for at least one year from every participant. Drivers participating in the VCC NDS had no training in interacting with their driving automation systems as they were presumably familiar with the vehicle's features as an owner/lessee. The responses provided by participants to a questionnaire completed upon study enrollment indicated that the VCC NDS participants were already familiar with the driving automation technologies in their vehicles and reported trusting these systems. Questions included "I am familiar with the automated system" and "I trust the automated system" with responses provided on a 7-point Likert scale from Strongly Disagree to Strongly Agree. It should be noted that the current study analyzed data from a subset of 30 participants in the VCC NDS. This was necessary to account for vehicle variability and the arrangement/design of dash icons; the method used to establish driving automation system status at any given point in a trip was dependent on the ability of a machine-learning algorithm to identify and classify dash icons. This algorithm was based on image classification using deep neural networks, specifically ResNet-18 architecture (He et al., 2015). A training set of images was created depicting dash icons that represented the driving automation system status for each vehicle make and model used in the study. The vehicles excluded from the study were the result of poor post-training accuracy of the algorithm when tested on the validation data sets, which was typically due to the presence of several dash icons at the same location or the style or size of the dash icons. The mean (±SD) age of the subset of participants was 46.5 ± 12.2 years, and of the 30 participants, 8 were female and 22 were male.

The DAF NDS involved a total of 120 participants across Washington, D.C., who were assigned a vehicle to drive (10 vehicles were used in the study) for up to four weeks each. The study was designed to balance the age and gender of participants for each vehicle. Two age groups were used, 25–39 years and 40–54 years old. Thus, each vehicle had an equal number of participants assigned from each age group and each gender (i. e., 12 participants per vehicle). Data collection lasted 16 months. Participants met the following criteria: at least 60 miles of driving per day; no suspended license within the past seven months; have not been convicted of two or more driving violations; have not been the cause of a crash in the prior three years; and own and use a Bluetooth-enabled smartphone. Participants in the DAF NDS were oriented to the vehicle's driving automation systems and received training on the use of these systems. The research team developed the training module to mimic the information drivers would receive at a dealership if they purchased a vehicle equipped with driving automation systems. Training comprised a static orientation of all vehicle features, including the location and operation of all buttons, levers, and alerts. This was followed by a test drive to ensure the participant was comfortable with the driving automation features. The training session took approximately 1.5 h. Additional details on training procedures can be found in Russell et al. (2018). Based on self-report questionnaires completed by the participants, which included questions about previous experience with driving automation systems, most of the study participants had little to no direct experience with any driving automation systems. Participants were indirectly aware of these systems, however, with 63 % reporting they had heard of an automated vehicle system of some type.

Fig. 1. Camera views captured by the DAS during the two NDSs.

2.2. Data sampling

Driving automation system status was determined via either the machine-learning algorithm outlined above or via vehicle network information (i.e., this was available on 8 out of 10 vehicles in the DAF NDS). Data were generally sampled across baseline epochs. In the VCC NDS, a matched baseline approach was used across driving automation system status, driver, weekday/weekend, time of day, and vehicle speed (20 mph or more) within a 10-s driving epoch. All baseline epochs with L2 systems activated were identified and matched with a baseline epoch with L2 systems available but not activated. The matched baseline approach resulted in a sample of 200 L2 activated epochs and 200 L2 available but not activated (i.e., no systems activated) epochs. Baseline epochs in the DAF NDS were sampled via vehicle network information (where available) or the machine-learning algorithm; 15-s baselines were sampled when the vehicle was traveling at least 40 mph on a visibly marked road. Up to 12 baseline epochs were sampled per driver of instances when L2 systems were activated and up to 12 epochs were sampled per driver when L2 systems were available but not activated (i.e., no systems activated). In practice, 12 epochs were not available for all drivers, in which case all available epochs meeting the necessary criteria were sampled.

2.3. Dependent measures

Drowsiness was assessed using percentage of eye closure (PERCLOS), whereby participants were coded as drowsy if their eyes were closed more than 12 % of the time in a one-minute epoch. “Eyes closed” is operationally defined as the eyelid being at least 80 % closed and covering the pupil. PERCLOS has been validated as a reliable indicator of driver drowsiness (Dinges et al., 1998) and has been successfully used as part of a drowsiness detection algorithm (Wierwille et al., 1994). Although these studies used three-minute epochs (i.e., PERCLOS 3) to determine driver drowsiness, a more recent study found close agreement between the odds ratio (OR) values calculated using PERCLOS 3 and PERCLOS 1 (Owens et al., 2018), suggesting that one-minute epochs are sufficient to detect drowsiness.

Eye glance behavior was considered as a distraction factor in this study as it reflects the propensity of drivers to look away from the forward roadway. Two eye glance metrics were compared during L2 activated versus no systems activated: the percentage of time that the driver’s eyes are not focused on the roadway (i.e., percentage of eyes-off-road time [%EORT]) and the percentage of eye glances lasting longer than 2 s. The 2-s timeframe was selected based on Klauer et al. (2006), who reported that a driver’s risk of a crash significantly increases when the driver looks away from the forward roadway for longer than 2 s. Similarly, Dingus et al. (2016) reported that activities that require the driver to take their eyes off the road (e.g., using a handheld cell phone to text or dial a number) increased the risk of a crash. On-road glance locations included the forward, left and right windshield. Glances to any other location (e.g., center console, interior object, passenger) were classified as off-road.

Secondary task engagement was assessed overall (i.e., the percentage of baseline epochs involving secondary task engagement of any kind) during epochs when L2 was activated compared to no systems activated. Due to the broad range of secondary tasks identified by trained data reductionists (for additional information, see Researcher Dictionary for Safety Critical Event Video Reduction Data Version 4.1, Virginia Tech Transportation Institute, 2015), the secondary tasks were categorized as visual (e.g., looking at a pedestrian), manual (e.g., holding but not using a cell phone), visual-manual (e.g., texting), or cognitive (e.g., talking to a passenger) based on the primary demands of the task. For the purposes of this analysis, the groups were collapsed to create two categories: (1) visual, manual, and visual-manual secondary tasks; and (2) cognitive secondary tasks. Additional analyses on STE can be found in Dunn et al. (2019).

Trained data reductionists view video frame-by-frame to annotate and code drowsiness, eye glance behavior and secondary task engagement. All data reductionists for both NDSs underwent identical training protocols, which included evaluations to ensure they had an accuracy rate of at least 90 % (i.e., compared to a set of events reduced and coded by an expert) before they were permitted to independently code new events. The data reduction process is also subject to regular quality-control checks to ensure continued reliability.

2.4. Statistical analyses

The current study focuses on comparing driver behavior in situations where L2 systems were activated (i.e., "L2 activated"—both ACC and LKA systems were in use) and those where no systems were activated (i. e., "no systems activated"—both ACC and LKA systems were available but not activated) within the VCC NDS and DAF NDS. Potential driver distraction was compared within each NDS between driving with L2 activated and no systems activated based on STE, drowsiness, and eye glance behavior. Due to notable differences in study design and data sampling strategy between the two studies, all statistical comparisons were kept within each NDS.

A mixed-effect logistic regression model was used to evaluate the relationship between STE and driving automation system status (i.e., active versus not active, but available). The model predicted the log odds of STE from system status; a driver-level random effect was included to account for correlations in data from the same driver. Odds ratios and 95 % confidence intervals calculated from the logistic regression model compared the estimated odds of STE in baseline epochs for active and not active driving automation systems. Beta regression models were used to assess the impact of driving automation system status on eye glance metrics. Data for Beta regression models must be within the bounds of (0, 1), not inclusive of 0 or 1. Because the current study data could include these bounds, data with these values were transformed using the method outlined by Smithson and Verkuilen (2006) and tested by Blanco et al. (2015). Beta regression models for each eye glance metric used system status as a predictor variable. The statistical significance for all analyses was evaluated at $\alpha = 0.05$.

3. Results

In the VCC NDS, L2 was activated for slightly more than 1500 h—or approximately 12 %—of the duration of the study. During the DAF NDS, L2 was activated for approximately 1,178 h—or 17 %—of the study duration. Thus, the majority of data in both NDSs were collected under manual driving conditions.

3.1. Secondary task engagement

Table 1 shows the results from the logistic regression, which indicated that the odds of STE for VCC NDS drivers were 1.5 times greater when L2 systems were activated compared to no systems activated (OR = 1.54). Results for the DAF NDS drivers, on the other hand, indicated that STE was 1.4 times more prevalent with no systems activated (i.e., under manual driving conditions) compared to L2 activated (OR = 1.38).

When looking at the frequency of STE by type, drivers in the VCC NDS were 1.8 times more likely to engage in a visual/manual/visual-manual secondary task with L2 activated than with no systems activated (OR = 1.81; 95 % CI = 1.20–2.74). In contrast, no significant difference in engagement in cognitive secondary tasks was observed between L2 activated and no systems activated in the VCC NDS. For the DAF NDS, drivers were 1.5 times more likely to engage in a cognitive task with no systems activated compared to L2 activated (OR = 1.51; 95 % CI = 1.26–1.80). Meanwhile, no significant difference in engagement in visual/manual/visual-manual secondary tasks was found between L2 activated and no systems activated in the DAF NDS.

3.2. Drowsiness

In the VCC NDS, the prevalence of drowsy driving when 0.6 % during L2 activated driving; for no systems activated, no instances of drowsy driving were detected (0% prevalence). In the DAF NDS, the prevalence of drowsy driving with L2 activated was 5.4 %, while the prevalence with no systems activated was 3.4 %.

3.3. Eye-glance behavior

For the purposes of analysis in this study, driving epochs in which the driver did not look away from the forward roadway were included in the %EORT calculation (i.e., including zero %EORT). In contrast, the calculation of the percentage of glances lasting longer than 2 s excluded zero %EORT epochs. In the VCC NDS (Table 2), participants driving with L2 activated had significantly greater %EORT and percentage of glances away from the forward roadway > 2 s than participants driving with no systems activated. In contrast, in the DAF NDS (Table 2), no significant differences were found in either metric for L2 activated vs. no systems activated.

Eye glance behavior during STE was also compared between driving with L2 activated and no systems activated. In the VCC NDS (Table 3), %EORT during STE was significantly greater for L2 activated compared to no systems activated. For the percentage of eye glances away from the road lasting longer than 2 s, the prevalence during STE was higher for L2 activated than for no systems activated, although this difference was not statistically significant. For the DAF NDS (Table 3), no significant differences were observed in %EORT or percentage of eye glances away from the road lasting longer than 2 s during STE between L2 activated and no systems activated. However, comparing eye glance behavior in both NDSs during STE to eye glance behavior during regular driving (cf. Tables 2 and 3) indicates that during STE, distracted eye glance behavior is more prevalent with L2 activated than with no systems activated.

4. Discussion

4.1. Comparison of distracted driving behaviors during driving with L2 activated vs. no systems activated

In the VCC NDS, driver use of L2 automation (i.e., simultaneous use of longitudinal and lateral automation) resulted in greater prevalence of behaviors indicative of distracted driving. Similar to the findings of Noble et al. (2021), drivers were more inclined to engage in secondary tasks and spend more time with their eyes off the forward roadway when driving automation systems were active. These results became even more pronounced when considering eye glance metrics during STE, suggesting that drivers in the VCC NDS trusted the driving automation systema to compensate for their distracted driving behaviors. These results do not necessarily mean that driving automation systems are unsafe, as drivers may activate automation features intentionally because they want to conduct a non-driving-related task; that is, drivers

Table 1
STE during baseline driving epochs with L2 activated and no systems activated in the DAF and VCC NDSs.

	ADAS Status	Number of Baselines (Total)	% with STE	OR (95 % CI)
VCC NDS	L2 Activated	200	58 %	1.54* (1.03–2.30)
	No Systems Activated	200	47 %	
DAF NDS	L2 Activated	1388	60 %	1.38* (1.16–1.64)
	No Systems Activated	1228	69 %	

Table 2
Summary of eye-glance metrics in the VCC NDS and DAF NDS.

	ADAS Status	N (incl. zero EORT)	% EORT	N (excl. zero EORT)	% of Glances > 2 s
VCC NDS	L2 Activated	195	20.3 %*	144	4.4 %*
	No Systems Activated	195	13.0 %	129	0.2 %
DAF NDS	L2 Activated	1321	16.8 %	1121	3.4 %
	No Systems Activated	1167	18.1 %	982	3.3 %

Table 3
Summary of eye-glance metrics during STE in the VCC NDS and DAF NDS.

	ADAS Status	N (incl. zero EORT)	% EORT	N (excl. zero EORT)	% of Glances > 2 s
VCC NDS	L2 Activated	114	28.8 %*	109	5.8 %
	No Systems Activated	93	18.4 %	75	0.3 %
DAF NDS	L2 Activated	791	21.1 %	727	4.4 %
	No Systems Activated	792	22.3 %	711	4.4 %

may activate L2 automation to compensate for temporary diversions of attention during STE. Regardless, engaging in distracted driving is a dangerous action even with driving automation systems activated as these systems are not intended to take the place of an attentive human driver.

On the other hand, the results from the DAF NDS were largely contrary to those of the VCC NDS. In the DAF NDS, drivers manually operating vehicles without any driving automation system activated were more prone to engaging in a secondary task; however, the analysis of the eye glance metrics revealed no difference in eye glance behavior regardless of whether the driving automation systems were activated. This result also held true for eye glance metrics recorded during STE. These results agree with those of Russell et al. (2018), who found that behaviors indicative of distracted driving were similarly prevalent during manual driving as during driving with L2 activated. This may indicate that the DAF NDS drivers did not place the same level of trust in the driving automation features as the VCC NDS drivers due to their limited experience and familiarity with the driving automation technologies.

In the VCC NDS, the baseline prevalence of drowsy driving was surprisingly low, particularly during L2 activated driving. Previous studies, including research on how underload is related to fatigue associated with passive tasks (Matthews et al., 2009) and investigations into the link between underload and automation (Young and Stanton, 2004, 2006), suggest that driver drowsiness should be more prevalent during L2 activated driving due to a substantial work underload that leads to bouts of drowsiness. In contrast, the VCC NDS results do not show evidence of such underload-related drowsiness or any negative effect of driving automation use on driver alertness. It should be noted that overall, a low prevalence of drowsy driving (0.6 %) was observed in the VCC NDS regardless of driving automation status, potentially reflecting differences between the VCC NDS drivers/trips and those in other studies. As an example, if most trips taken by VCC NDS drivers occurred in the daytime or were short-duration trips, the incidence of drowsy driving could be expected to be low. Compared to the VCC NDS, drowsiness was detected more frequently in the DAF NDS, particularly with L2 activated. These results suggest that drivers with little or no experience with driving automation system use (like those in the DAF NDS) may be affected more by drowsiness than drivers with experience using the driving automation systems (like drivers in the VCC NDS).

4.2. Behavioral adaptation to driving automation system use

As highlighted above, one of the main differences between the two NDSs analyzed in the current study relates to the drivers' experience with driving automation systems. Thus, the results provide important insights into the behavioral adaptation that occurs during different operational phases of driving automation use. The term behavioral adaptation indicates the set of behaviors that occur as an unintended outcome to a change in the road network (Organization for Economic Co-operation and Development, 1990). Researchers have postulated that behavioral adaptation contributed to driver behavioral changes after the past deployment of various measures intended to improve road safety, including seatbelts (Calkins and Zlatoper, 2001) and airbags (Peterson and Hoffer, 1994). Saad et al. (2004) introduced two phases of behavioral adaptation in response to a newly introduced technology such as driving automation systems: a learning phase followed by an integration phase. Drivers in the DAF NDS self-reported little to no prior experience with driving automation and only drove the L2-equipped study vehicles for a month; thus, the DAF NDS drivers were likely in the learning, or unfamiliar, phase of driving automation operation for the duration of their study participation. In the learning phase of behavioral adaptation, the driver begins to get acquainted with the driving automation systems, including through learning how it can be used and what its limitations are. The absence of experience may also be associated with a lack of trust in the driving automation technology. Learning can be accomplished with formal training, such as that provided to the DAF NDS participants. However, organic, real-world experience using the systems is important to provide exposure to different driving scenarios. The integration phase occurs over time as drivers gain more experience using and integrating the driving automation into their everyday driving (Saad et al., 2004). The results obtained for the VCC NDS, in which drivers were already familiarized with the driving automation features of their own vehicles, provide a snapshot of long-term adaptation and potential overreliance and overtrust effects (Dunn et al., 2019). To better understand the different operational phases of driving automation use and the effects on driver behavior in the long term, future efforts should focus on evaluating driving automation system use by drivers over even longer perioeds of time.

4.3. Limitations

While this study presents a relatively large-scale study of naturalistic driving data relative to driving automation use in comparison with other such studies, the sample size is not indicative of the U.S. population. Future studies should consider increasing the sample size. It should also be noted that driving automation system use was dependent upon the driver, not on an experimenter or other external prompt; thus, system use may have been dependent upon individual driver factors.

Drivers in the VCC NDS had an app on their smart phone that provided safety-related driving information, such as weather, traffic, and driving conditions. The data reduction process did not (and could not) distinguish between study-related app use and personal phone use. Thus, the eye glance analyses focused on eyes-off-road glances rather than non-driving-related task glances.

While NDSs allow the objective observation of driver performance and behavior, the nature of such studies precludes the use of intrusive instrumentation. As such, cognitive distraction could only be inferred from the study data and not directly measured. Refining the process of machine learning would be beneficial for future studies. For example, dash layout and automation icon appearance and location are vital to the machine-learning process; thus, vehicles with status icons that are not easy to distinguish were excluded from the current study. Finally, NDSs are dependent upon volunteer drivers. As such, a self-selection bias may exist.

5. Conclusions

A critical issue related to driving automation system use is the diversion of driver attention away from the driving task (i.e., distracted driving) while the driving automation is activated. This study analyzed data from two NDSs to evaluate driver behaviors with respect to driving automation use. The results indicate that when drivers had prior experience operating driving automation systems, they were almost two times as likely to participate in distracted driving behaviors when the driving automation was activated than during manual driving. Drivers with less experience and familiarity with driving automation systems were less likely to drive distracted when the driving automation was activated; however, these drivers tended to be somewhat drowsy when driving with driving automation activated. While the potential safety benefits of driving automation systems are undeniable, it remains critical to evaluate and address the lack of driver awareness of unintentional dangers stemming from system use. Over-trust and overreliance on driving automation may negate some of the safety benefits of these systems. In addition, removing workload from the drivers may lead to driver underload and fatigue that worsen driver performance; these effects should be further investigated in future studies.

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CRediT authorship contribution statement

Naomi J. Dunn: Conceptualization, Methodology, Investigation, Project administration, Writing - original draft, Writing - review & editing. **Thomas A. Dingus:** Conceptualization, Methodology, Supervision, Funding acquisition, Writing - review & editing. **Susan Soccolich:** Validation, Formal analysis. **William J. Horrey:** Conceptualization, Methodology, Supervision.

Declaration of Competing Interest

None.

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