EXPLORING DRIVER ADAPTATION TO LOWER LEVELS OF AUTOMATION (L2) USING EXISTING NATURALISTIC DRIVING DATA

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ABSTRACT

This project evaluated driver adaptation in the hours, days, and months after the introduction of level 2 (L2) advanced driver assistance system features (i.e., the system controls lateral and longitudinal motion) into the driving task. Two existing naturalistic driving study databases were analyzed: the L2 Naturalistic Driving Study and the Virginia Connected Corridor Elite Naturalistic Driving Study. To best assess driver adaptation, the analysis identified three phases of exposure time to L2 features: Phase 1 (immediate, under 3 hours), Phase 2 (short term, 3 to 8 hours), and Phase 3 (long term, over 8 hours). The results suggested that driver adaptation was present for high-risk secondary tasks, as significant increases in engagement were observed over the three phases, but only when L2 features were active. Additionally, drivers set their vehicle speed above the speed limit more frequently between Phases 1 and 2, with higher speeds set when L2 features were active as opposed to when they were inactive. While these results may be concerning, research efforts at a larger scale are needed to determine if there is increased crash risk associated with speeding and high-risk secondary task engagement with L2 features active. We also need to better understand the impact of traffic/roadway conditions on speed selection with L2 systems.

INTRODUCTION

In the driving domain, the concept of behavioral adaptation refers to how humans respond, either intentionally or unintentionally, to the introduction of a new technology that serves a specific driver need [1]. More general theories of behavioral adaptation focus on risk-based measures, beginning with a study of changes in galvanic skin response during driving [2], which led to further investigations of behavioral adaptation and integration of the theories of risk compensation and risk homeostasis [3]. Risk compensation and risk homeostasis theories function under the principles of a perception-evaluation process: (1) people have an idea of the level of risk that they are willing to tolerate; (2) people also have a "target" level of risk at which they are most comfortable; and (3) people have a reasonably good ability to perceive their current level of risk. With the notable exception of the zero-risk theory [4], risk compensation theories neglect to explicitly consider learning and time. However, the zero-risk theory posits that drivers' target level of risk can change with learning over time, which is where driver adaptation may occur [5].

Risk allostasis theory builds on the zero-risk theory to incorporate driver perception and decision-making with the constant changes that occur in the environment (i.e., learning over time). Kinnear and Helman [5] utilized risk allostasis theory to evaluate and potentially predict behavioral adaptation for drivers using driver assistance technologies [6]. Their assessment incorporates the driver's feelings of risk, task difficulty, and workload. They maintain that with sufficient sensitivity to risk, task difficulty, and workload, risk allostasis theory predicts that any alteration of the driving task (i.e., introduction of advanced driver assistance systems [ADAS]) will result in driver adaptation that will trend toward maintaining task demand within a preferred range. In other words, as the automated driving features simplify the driving task, the driver will feel free to increase task demand in a variety of ways that could include increased speed, increased secondary task engagement, and decreased following distance. Thus, risk allostasis theory predicts that the use of driver assistance technologies would result in increased trust and reliance on these technologies. This claim was substantiated by Llaneras et al. [7], who showed that, when given the opportunity to relinquish control of lateral and longitudinal operations to a simple but reliable ADAS, most drivers will engage in moderate to complex secondary tasks and will also exhibit increased eyes-off-the-forward-road time.

While behavioral adaptation and user reliance can occur because of changes to any aspect of the roadway system, the present study is concerned specifically with how drivers initially adapt their behaviors to level 2 (L2) ADAS features, as defined by SAE International [6]. L2 system features assist the driver through a combination of simultaneous adaptive cruise control (ACC) and lane centering assistance (LCA) for longitudinal and lateral control of the vehicle, respectively, while driver constantly supports this support feature and maintains responsibility for driving. When operated without other traffic in the driver's travel lane, ACC maintains vehicle speed in a manner like that of conventional cruise control. However, if the driver approaches a slower moving or decelerating lead vehicle in their travel lane, ACC can attempt to reduce the speed of the driver's vehicle to that of the lead vehicle. In many driving situations, this results in the driver's vehicle following the lead vehicle at a prescribed following distance, or headway. Some ACC systems can also follow the lead vehicle to a complete stop; however, a constant headway operates within a speed range and is not typically maintained at very low speeds (i.e., approaching zero). Lateral features such as LC provide sustained lateral assistance using cameras to determine the location of lane lines on either side of the vehicle and can attempt to keep the driver's vehicle in the center of the travel lane. Although some systems require lane lines on both sides of the driver's vehicle to remain operational, some newer generation systems may be able to use the contrast between the road and an unpaved shoulder to define a lane boundary if a line marking is not apparent.

Both longitudinal and lateral control features are currently available on a wide variety of vehicles, and a growing number of these types of features will continue to enter the market in the near future. Figure 1 describes SAE L2 ADAS features.

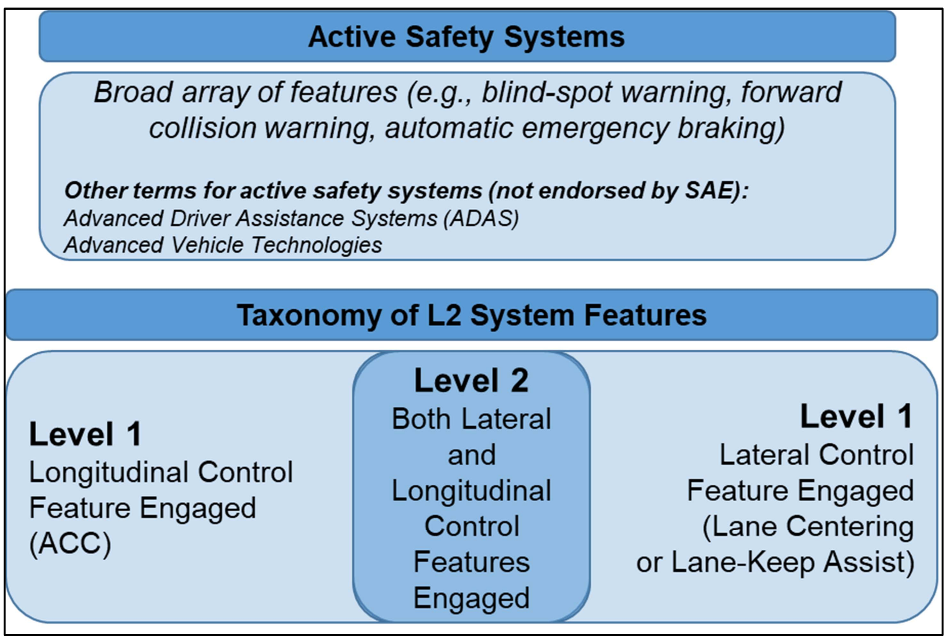

Figure 1. Definition of terminologies used to describe active safety and L2 driving system features.

Adaptation to Driving Automation Features

Although L2 system features are increasingly available in vehicles sold in the United States [8, 9], based on a 2016 survey [10], light vehicles driven in the United States were on average 12 years old. Therefore, it will likely take another decade before these systems reach substantial levels of market penetration in the United States. Given their growing availability, it is imperative that human factors researchers get ahead of this curve and develop a broad understanding of how drivers, over a range of ages and levels of driving experience, use and activate these L2 system features.

Learning theory suggests that improved performance comes with increased practice as a function of the power law of practice [11]. Figure 2 displays the pattern in which acquisition of a new skill occurs as the user gains experience. The greatest amount of new learning occurs during the early stages, when the user is initially gaining experience. Learning then follows an exponential curve, continuing but at a decreased rate [11].

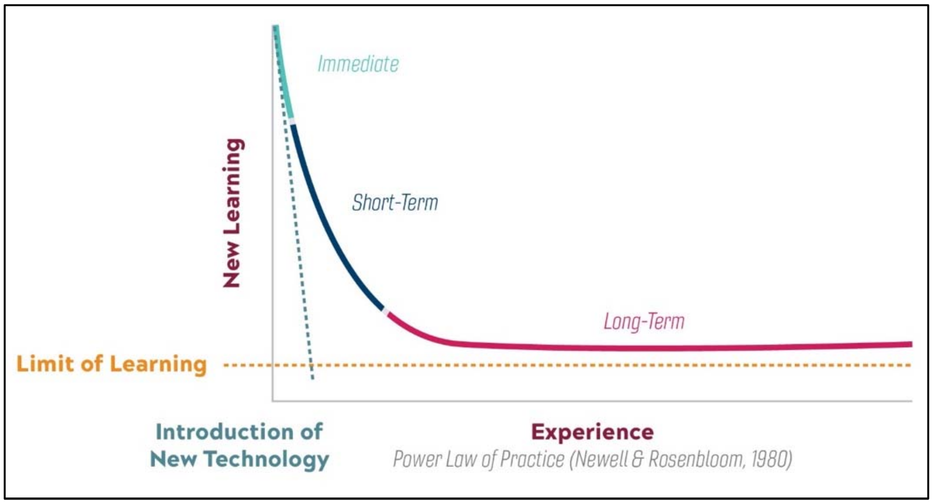

Figure 2. Depiction of immediate, short-term, and long-term phases of behavioral adaptation as plotted on a traditional learning curve (adapted from [11]).

By evaluating driver behavior for varying durations of experience with L2 system features, we can assess the moments when driver behavior may change most rapidly (immediate and short-term exposure) compared to when driver behavior may change much more slowly or when it is fairly stable after long-term use [12].

Considering this anticipated pattern of learning, we hypothesized that most behavioral adaptation to L2 system features would occur in the initial periods of use. Therefore, to gain insight into driver adaptation to L2 system features, it was necessary to observe and measure driver behavior while using these systems over time. The analysis defined three phases of exposure time to L2 features: Phase 1 (immediate, under 3 hours of L2 activation), Phase 2 (short term, 3 to 8 hours of L2 activation), and Phase 3 (long term, over 8 hours of L2 activation). There is an absence of NDS research using this approach with exposure to L2 features, so in order to select hours for the three phases, this study: (a) examined exposure data within the databases (see Method below) to observe how much drivers used L2 features and (b) sampled shorter time periods to test examine how quickly driver behavior might change.

METHOD

Overview of Naturalistic Driving Study Databases

This study evaluated driver adaptation to L2 systems using data from two naturalistic driving studies (NDSs): (1) the Naturalistic Study of L2 Driving Automation Functions (L2 NDS); and (2) the Virginia Connected Corridor 50 Elite Vehicle (VCC50 Elite) NDS.

The L2 NDS database [13] was used to assess driver adaptation to L2 system features over the course of each driver's initial 4 weeks of driving a vehicle with those features present. In the original study [13], 120 participants drove study-provided vehicles that were different from those they currently owned. Of the 120 participants, only 82 had sufficient driving time with L2 systems active (i.e., greater than 3 cumulative hours), so the analyses were based upon 82 participants. Observation from this dataset examined three phases of exposure time to L2 features: Phase 1 (immediate, under 3 hours of L2 activation), Phase 2 (short term, 3 to 8 hours of L2 activation), and Phase 3 (long term, over 8 hours of L2 activation).

The VCC50 Elite NDS database was used as a comparison group of experienced participants. In that study, 50 participants owned personal vehicles equipped with L2 system features and had driven them for several months to over a year. Of the 50 drivers in the VCC50 Elite dataset, only 33 drivers were included for sampling: drivers who owned vehicles equipped with both ACC and some form of LCA or lane keep assistance (LKA and for whom data to indicate L2 system state was available. Observations from this dataset corresponded to long-term exposure to L2 features.

L2 NDS and VCC50 Elite NDS Variables

To assess driver strategies and behaviors to maintain vehicle safety while using L2 system features, speed selection at moment of L2 feature engagement and driver engagement in secondary tasks were used for analysis. Speed selection at moment of L2 feature engagement was determined using database coding algorithms. Every time the driver engaged L2 features, the speed at which the vehicle was traveling was coded and marked, as was the posted speed limit.

The primary independent variable focused on L2 activation status, where the driving automation (i.e., the systems were both available and active) or the driver (i.e., systems were available but inactive) controlled both lateral and longitudinal motions of the vehicle. The idea of available-but-inactive is important in ensuring comparisons are reasonable. If comparisons were made between L2 usage periods and all non-L2 usage periods, any observed differences could readily be attributed to the different conditions, scenarios, and driving environments in which drivers tend to - or are permitted to - engage L2 systems. Using available-but-inactive driving epochs to provide control samples makes usage/non-usage comparisons more meaningful.

To better assess the types of behaviors that drivers engage in when using L2 features, trained data coders reviewed randomly selected matched cases (when L2 features were active) and controls (when L2 features were available but inactive) to determine prevalence of secondary task engagement. Using available data, secondary task types were grouped into those types of tasks that are high risk (e.g., texting on cell phone) or low risk (e.g., adjusting radio). High-risk tasks were those tasks that were found to be associated with increased crash risk in an analysis using the Second Strategic Highway Research Program (SHRP 2) NDS database [14]. The low-risk tasks were not found to be associated with an increase in crash risk in the same analysis. Additionally, frame-by-frame eye glance locations were recorded by trained data coders, and duration of eyes-off-road time was also calculated when L2 features were active versus when they were available but inactive.

RESULTS

Speed-Selection Behavior

Both inexperienced drivers (L2 NDS) and experienced drivers (VCC50 Elite NDS) tended to select speeds above the speed limit more frequently when L2 systems were active than when L2 systems were available but inactive. The experienced drivers demonstrated more frequent selection of speeds above the speed limit, primarily for the categories of 10 to 20 mph over the speed limit and greater than 20 mph over the speed limit compared to the inexperienced drivers. On average, drivers tended to travel 4.56 mph higher for inexperienced L2 drivers [$F(1,42,405) = 2724.83$, $p < 0.001$] and 2.66 mph higher for experienced L2 drivers [$F(1,75,208) = 452.12$, $p<0.001$], when L2 systems were active than when L2 systems were available but inactive.

The speed distributions are plotted in Figure 3 and Figure 4, in which the *x*-axes indicate speed in relation to the speed limit. Thus, 0 in the center of the *x*-axis refers to the vehicle traveling at the same speed as the posted speed limit (no difference in GPS speed and the posted speed limit). The *y*-axis represents the proportion of activations that occurred within each speed bin. Data plotted to the left of 0 indicates that the vehicle speed was slower than the posted speed limit. Data plotted to the right of 0 indicates that the vehicle speed was faster than the posted speed limit.

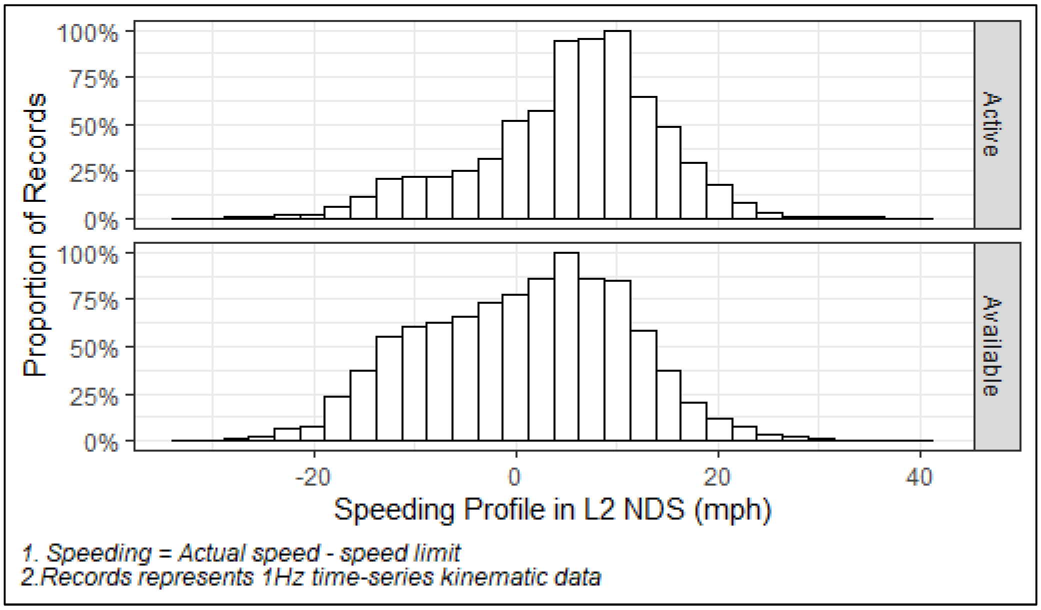

Figure 3. Inexperienced (L2 NDS of 82 drivers) driver speed selection profiles for when L2 systems were active (top) compared to when L2 systems were available but inactive (bottom).

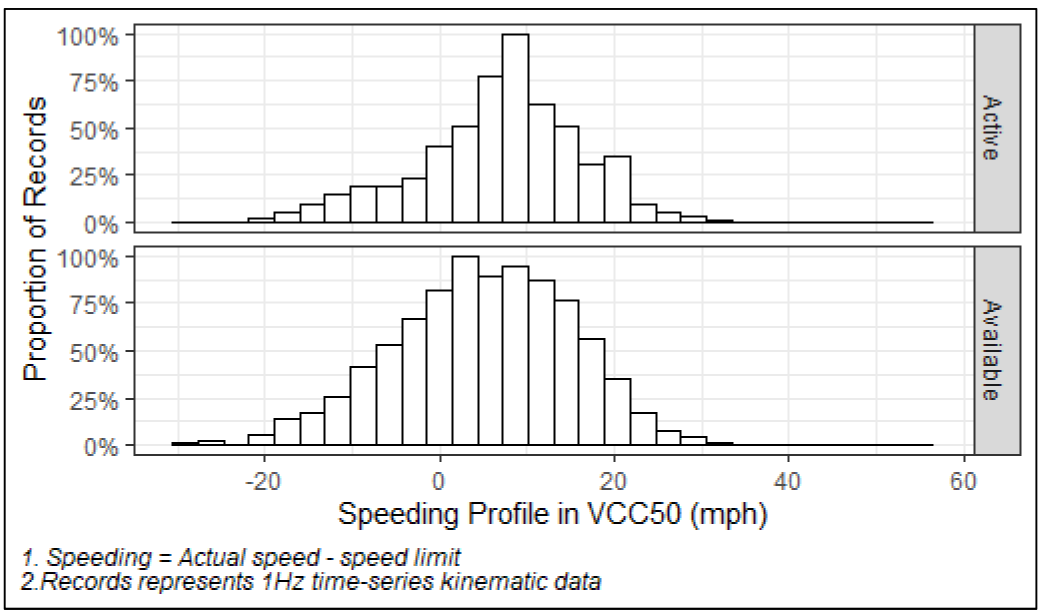

Figure 4. Experienced driver (VCC50 Elite of 33 drivers) speed selection profiles for when L2 systems were active (top) compared to when L2 systems were available but inactive (bottom).

Eye-Glance Behavior

Given that drivers were more likely to look off the forward roadway when L2 systems were active, the rest of the analyses will focus on those matched samples where drivers looked away from the forward roadway. An ANOVA was conducted to assess whether eyes-off-road glance metrics were significantly longer when L2 systems were active versus available but inactive and if eye-glance durations changed over time. Four glance metrics—the total eyes-off-road time, the mean duration of glances, the single longest glance, and the number of glances—were computed for eyes-off-road (Figure 5).

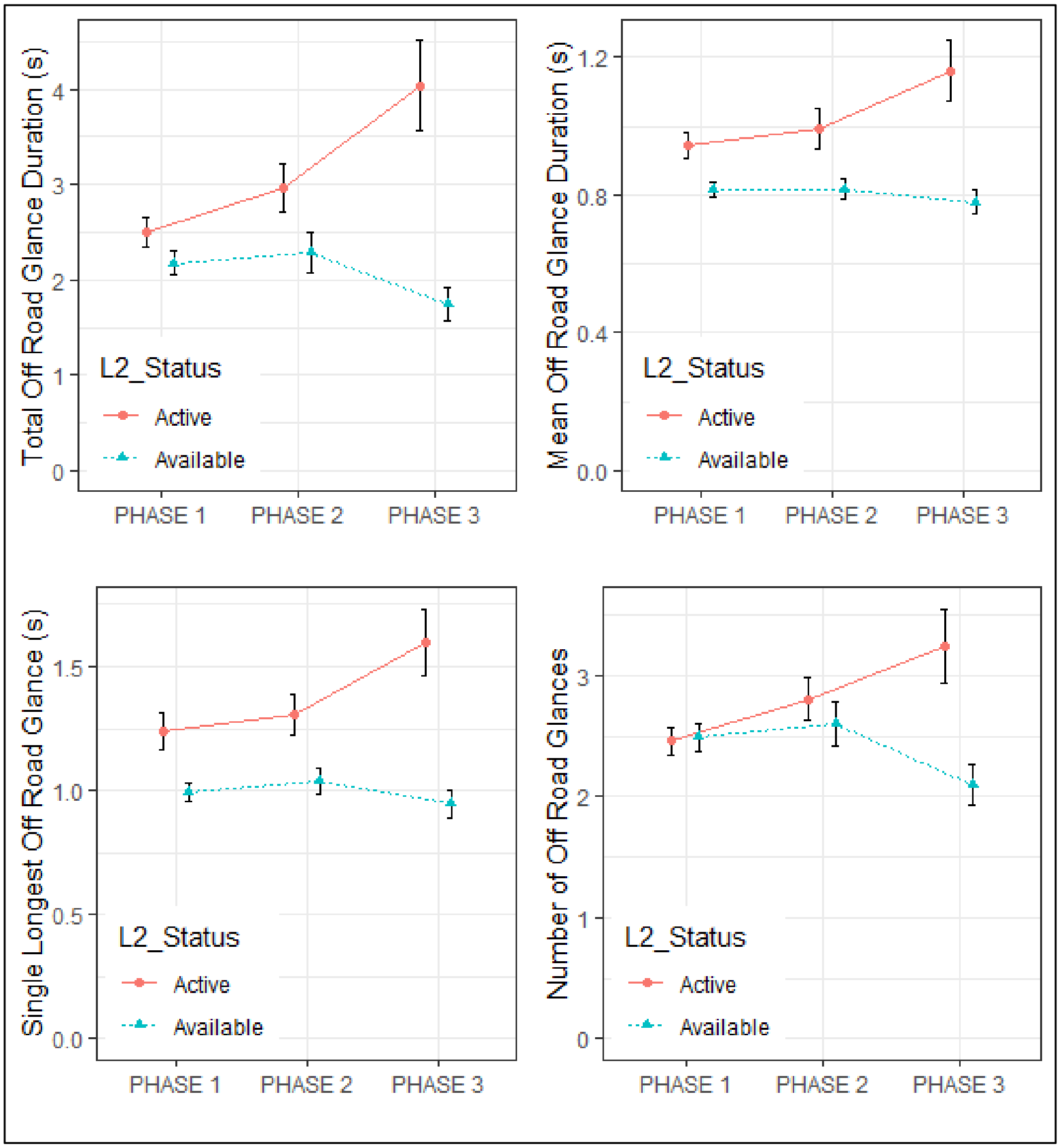

Figure 5. Total eyes-off-road time (top left), mean glance off-road duration (top right), single longest off-road glance (bottom left), and number of off-road glances (bottom right), for each exposure phase for the inexperienced drivers (L2 NDS).

Secondary Task Engagement

This study also examined the prevalence of secondary task engagement and eyes-off-road time. High-risk secondary task prevalence increased over time when L2 systems were active. High-risk secondary task prevalence decreased when L2 was available but not active. Analysis of the interaction between L2 system status and L2 exposure phase showed a statistically significant interaction (z value = -2.806, p = 0.005). As shown in Figure 6, high-risk secondary task prevalence increased over time when L2 systems were active. High-risk secondary task prevalence decreased when L2 was available but not active.

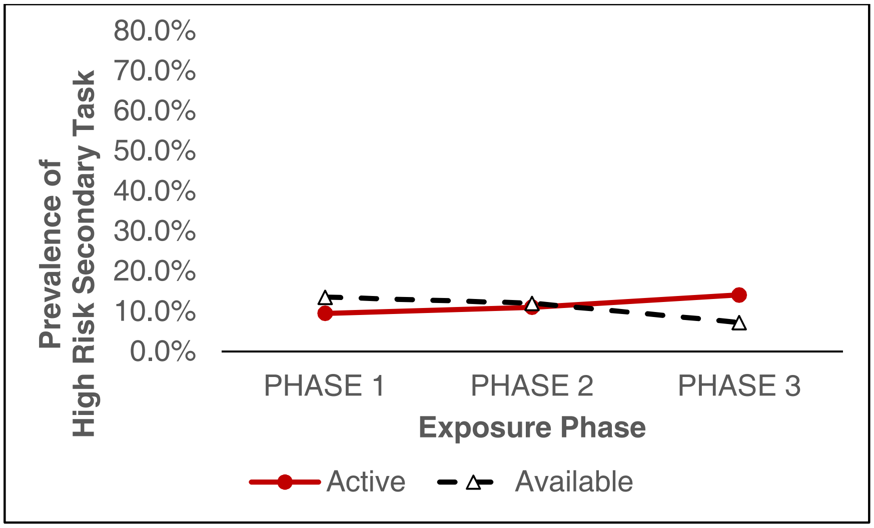

Figure 6. The interaction of L2 status by exposure phase for prevalence of engagement in high-risk secondary tasks.

CONCLUSIONS

Overall, the results from these analyses indicate that driver selection of higher speeds and high-risk secondary task engagement increased with the use of active L2 ADAS features. Eyes-off-road durations increased with use of L2 systems for both the L2 NDS drivers and VCC50 Elite NDS drivers. Regarding changes across three phases of exposure (i.e., less than 3 hours; 3 to 8 hours; 8+ hours), these findings illustrate how driver behavior changes when L2 ADAS features are used.

Regarding limitations, speed-selection is related to only one aspect of L2 control. Specifically, features are often available for independent use, such as in the form of ACC without LCA. The analyzed datasets did not have sufficient instances where L2 was available but only ACC was engaged to be included in speed-selection analysis. Therefore, it is unknown if or how much of the observed effects in speed-selection may be due to the ACC feature use versus L2 use.

This analysis also evaluated time of day, weekday versus weekend, and road type. This analysis was unable to identify a specific condition under which drivers were more likely to use L2 systems. A more nuanced, higher-level analysis involving additional data coding and/or algorithm development could identify effects of other factors.

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