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Evaluation of Models of Functional Automation and Driver Situation Awareness in Automated Vehicle Control

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ABSTRACT

The Society of Automotive Engineers (SAE, 2021) proposed a taxonomy of Levels of Driving Automation (LODA). Some research (e.g., Deng & Kaber, 2022) investigated effects of LODA on driver attention, performance and workload. The discrete nature of LODA definitions limits utility of results for systems design. We formulated an index of the rate of automation (AR) of vehicle driving functions based on elaborate task analysis and classification to stages of human information processing (Liu & Kaber, 2021). We also formulated a model of driver situation awareness (SA) based on AR index values as well as measures of driver expertise and attitudes towards vehicle automation. We showed goodness of fit of a scaled exponential function with shift to objective SA data from prior experiments and meta-analyses (Onnasch et al., 2014). Based on a new experiment, we tested the model for utility in predicting driver SA at LODA 0 (manual), 1 (driver assistance) and 4 (high driving automation). We found significant differences in SA responses among LODA (as quantified using the AR index) as well as significant effects of driver expertise. The new SA model showed superior fit to experiment data across the SAE LODA, as compared with simple linear statistical models with the AR or LODA as sole predictors. Next steps include use of the driver SA model as a design tool to prototype and test advanced driver assistance system variations to optimize driver performance based on the rate of vehicle automation (AR).

Keywords: Advanced driver assistance systems, Levels of driving automation, System automation rate, Driver situation awareness

INTRODUCTION

There are presently many different types of automated vehicles produced for personal and/or commercial use. These products integrate diverse sets of driver assistance systems, including adaptive cruise control (ACC), lane-keeping systems (LKS), emergency braking systems (EBS), etc. Liu and Kaber (2025) observed no less than 46 different forms or functional or service automation across contemporary automated vehicles (AVs). These systems are implemented with various approaches, such as driver activation, driver and automation activation, or automated control. These basic types of control imply different levels or degrees of driving (task) automation (LODA). The SAE (2021) previously defined five LODA, including (1) "driver assistance", (2) "partial driving automation", (3) "conditional

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driving automation", (4) "high driving automation" and (5) "full driving automation", on top of manual vehicle control (LODA 0). Several available commercial products represent SAE LODA 2 AVs. Few current AVs support LODA 3 and higher driving automation (e.g., the Audi R8 with automated driving and takeover capability). Unfortunately, these existing LODA classifications are coarse and do not support detailed design guidance based on, for example, driver performance assessment in LODA 2 AV use.

Unfortunately, there are no established methods for continuously quantifying levels or degrees of vehicle automation. Some scales have been formulated based on types of human information processing (HIP) functions along with identification of discrete levels of human or automation function ownership (e.g., Parasuraman et al., 2000). Such approaches can be used to describe rough profiles of automation for human-in-the-loop systems but they do not provide a detailed understanding of how specific forms of system/vehicle automation vary nor do they provide the capability to predict effects of LODA on driver performance.

System Automation Rate Modeling

We observed a need to determine a rate or proportion of functional system automation to predict driver responses and support vehicle design. One way to formulate such a function is to start with an inventory of current automated vehicle driver assistance functions and to categorize the functions according to theoretical stages of HIP. We classified the 46 different forms of service/functional vehicle automation identified by Liu and Kaber (2025) for supporting driver performance. Classification of the functions captures the nature of the form of automation and counts allow for assessment of impact on the rate or proportion of vehicle automation (*AR*). Estimation of the *AR* value can occur for each stage of HIP, or across stages, to estimate an overall *AR*, for the vehicle system. The rate at each stage can be calculated as the ratio of purely automated (A) functions plus hybrid (H) functions, shared between automation and the human driver, to the total (T) functions required for HIP at a particular stage. The general and expanded forms of this ratio are shown in Eqn. 1 in which we assume any hybrid function is equally shared between automation and driver:

$$AR = \sum_{i=1}^{4} a_i r_i = \sum_{i=1}^{4} a_i \left(\frac{A_i + H_i/2}{T_i} \right) \qquad \text{Eqn. 1}$$

where, $i \equiv$ stage of information processing; $a_i \equiv$ weight of the i^{th} stage contribution to overall system automation for $\sum_{i=1}^{4} a_i = 1$; $r_i \equiv$ proportion of automated functions among all required functions at ith stage of processing; $A_i \equiv$ number of functions controlled by machines at i^{th} stage; $H_i \equiv$ number of functions jointly controlled by humans and machines at i^{th} stage; and $T_i \equiv$ total number of functions to be performed at each stage. Given the probability simplex of a_i, any elevated importance for one stage necessarily subtracts from the importance of any other(s). By enumerating available automated or hybrid driver assistance functions for each stage of HIP, one can

compute the overall *AR* value for different makes and models of vehicles in a continuous manner with those values ranging from [0,1]. In prior research (Liu & Kaber, 2021), we determined the *AR* for multiple vehicles (Ford Fusion and Tesla Model 3) that were previously classified as SAE LODA 2. We found substantial differences in the *AR* between these vehicles for several stages of HIP. The overall system-level *AR* value for the Tesla Model 3 was also almost double the *AR* for the Ford Fusion. In general, both the SAE LODA 2 vehicle *AR* values were less than 0.5 indicating substantial room for increased automation innovation and implementation in the specific models, relative to a fully autonomous vehicle ($AR = 1$).

Driver Situation Awareness Modeling

With reference to prior situation awareness (SA) theory (Endsley, 1995), driver SA can be defined as:

1. Perception of elements in driving environment (Level 1; e.g., roadway, traffic, guide signs, traffic control devices)
2. Comprehension of the meaning of elements relative to driver tactical objectives (Level 2; e.g., lane changes, vehicles passed, elapsed time or distance);
3. Projection of the status of elements in the near-future relative to driver strategic goals (Level 3; e.g., time to destination).

The most important implication of this concept is that SA, as a cognitive state, is considered to influence (driver) decision making and performance of actions in real-time (Endsley, 1995). Unfortunately, errors in driver SA have been identified as underlying causes in several automated vehicle accidents (NTSB, 2019). In May 7, 2016 a Tesla Model S crash into a tractor-trailer truck and a portable DVD player was found active in the vehicle. In March 1, 2019, a Tesla Model 3 also crashed into a tractor-trailer truck. The NTSB found that driver inattention due to over-reliance on vehicle automation was a factor in the crash. On March 18, 2018, a fatal collision occurred between an Uber automated test vehicle and a pedestrian (in Phoenix, AZ). The NTSB found that operator inattention to the state of the vehicle and distraction were critical factor in the crash. On the basis of SA theory and these incidents, a call to human factors researchers is how can we model vehicle automation and driver SA responses to assist designers in creating driver assistance systems that maintain engagement and awareness while effectively managing cognitive workload and supporting performance.

Some prior research (Onnasch et al., 2014; Kaber et al., 2009) has related the level or degree of system automation (DOA) to operator SA. The Onnasch et al. (2014) research was a meta-analysis of 18 experimental studies through which they observed a negative linear relationship between the DOA (increasing) and SA (decreasing). Kaber et al. (2009), in another integration of results across multiple studies, observed a curve-linear relationship of SA with the DOA applied in target monitoring and human robot teloperation tasks, as did Endsley and Kiris (1995) in the context of

automation applied to vehicle navigation. On the basis of this research, we inferred that any model of SA based on system DOA needs to include both linear and curve-linear parameters. Furthermore, current SA-related research by Endsley (2017) focused on a model of human autonomy system oversight indicates that operator task expertise as well as attitudes towards use of automation are key in the level of SA occurring during task performance. On this basis, we inferred that any model of driver SA would need to be a multi-parameter model with accounting for individual operator capabilities and tendencies.

In a model fitting exercise involving consideration of prior SA measurement data (Onnasch et al., 2014; Kaber et al., 2009), we evaluated linear, power and polynomial forms. Based on the trends in the literature and analytical methods, we observed that a scaled exponential function with shift was a best fit to prior characterizations of SA responses to system degree of automation. The specific form of the exponential function also allowed for accounting of operator characteristics/behaviors in predicting an SA response. Eqn. 2 presents the proposed multi-parameter model.

$$SA(R) = max\{\theta(e^{-\theta R} - 1) + b, 0\} \qquad \text{Eqn. 2}$$

where, $SA(R) \equiv$ SA response of the operator to the system AR (as modeled in Eqn. 1); $R \equiv AR$ of system with $R \in [0,1]$; $\theta \equiv$ parameter representing operator attitude towards automation $[-\infty, +\infty]$; and $b \equiv$ parameter representing operator domain expertise/functional proficiency with $b \in [0,1]$. In the model, θ is a decay parameter that imparts scale and curve characteristics to the SA response, based on whether a driver tends to be averse ($\theta < 0$), ambivalent ($\theta = 0$), or prone ($\theta > 0$) to the use of vehicle automation. The b parameter is the model intercept term and represents the offset of individual driver SA from the baseline level ($SA(R) = 0$) when either driving manually or with automation. Related to this, in manual vehicle operation, driver SA is not affected by automation and is strictly dependent on their expertise level (b) in the driving domain. The maximization operator applied to the function ensures that the max level of driver SA occurs during manual vehicle control (i.e., $AR = 0$). The function has the property of a monotonically decreasing SA response with increasing system AR, inline with Onnasch et al. (2014) observations. Furthermore, the function is convex when a driver's attitude towards vehicle functional automation is positive; i.e., a steeper descent of SA occurs with an increase in the AR (related to Endsley's (2017) contention that attitudes towards automation use influence SA). There are also some special cases of driver SA responses that are captured by the function. In specific, it is possible for a driver with high expertise, who is prone to automation use, to achieve lower SA than a comparatively low expertise driver, who is averse to automation use, in driving vehicles with common AR values. That is, the proposed model captures the impact of high automation overreliance and loss of SA even for expert drivers.

Summary

The new *AR* equation supports fine-grained analysis of vehicle LODAs. It provides a continuous measure of the proportion of automation of specific information processing functions as well as overall system automation. It also provides a basis for predicting the impact of vehicle automation on human cognition, such as driver SA, under various automated and hybrid function allocations. The proposed SA response function represents a novel mathematical model of SA with a fit to trends on prior SA measurement data. The function also accounts for the influence of operator characteristics (i.e., expertise and attitudes) on SA. It should be noted that the form of this model is not unique to the SA construct. It could possibly be useful for representing other human performance costs of automation (e.g., cognitive workload). The remainder of this papers focuses on the need validate the SA response function in terms of utility for predicting the effect of SAE LODA on driver cognition.

METHODOLOGY

To our knowledge, no prior empirical studies have assessed the impact of the various SAE LODAs (e.g., as modeled in driving simulation or represented by instrumented vehicle design) on objective measures of SA, such as the Situation Awareness Global Assessment Technique (SAGAT, Endsley, 1995b) or the Situation Present Assessment Method (SPAM; Durso et al., 1998). Some studies have assessed the driver behavior effects of adaptive cruise control (ACC; SAE LODA 1; Vollrath et al., 2011). Others have assessed driver cognitive workload and attention allocation to SAE LODA 2 versus manual driving (Biondi & Jajo, 2024). Still other work has examined driver performance and eye gaze and fixation effects of the range of SAE LODA crossed with various in-vehicle control designs, but there were no SA response measures collected.

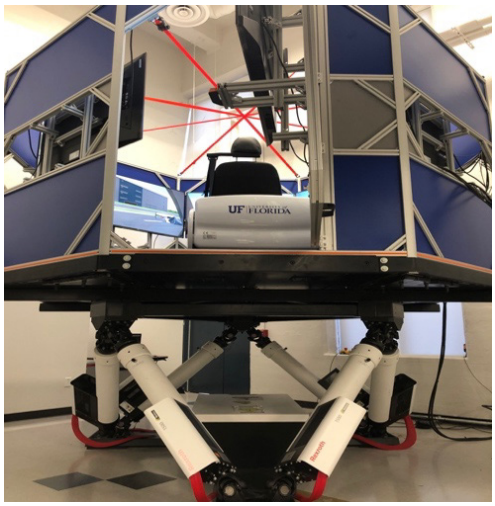


Figure 1: UF full motion driving simulator.

Apparatus and Settings

For the present research, we use the University of Florida (UF) advanced driving simulator with full-motion capability through a Bosch Rexroth eMotion 1500 platform (Boxtel, NL) integrated with an InnoSim quarter vehicle cab (Seoul, KR; modeled after a contemporary Hyundai sedan), and the latest version of the FORUM8 high fidelity driving simulation software (Tokyo, JP). The simulator was used to test the effect of SAE LODA on driver SA responses. For this study, we elected to simulate the following LODA:

- L0 - No driving automation ($AR = 0$) with driver full control of the simulated vehicle;
- L1 - Driver assistance ($AR = 0.26$), including ACC automatically adjusting vehicle speed to objects in the roadway along with required driver monitoring of the state of the vehicle as well as control interventions, whenever perceived as necessary; and
- L4 - High driving automation ($AR = 0.57$), specifically "near autonomous" vehicle capability, including lateral and longitudinal control plus navigation. There was no driver control input under this condition unless the automation failed in an emergency situation.

The AR value for L4 did not approach unity as there were numerous (46) forms of vehicle service or functional automation considered to support driver performance across the various stages of information processing.

Participants and Hypotheses

Thirty-six participants were recruited for the simulator study with half being "novice" drivers and the remainder being "expert", based on Shinar et al. (1998) observations on expert driving behavior. Novices had a maximum of 3 yrs. of driving experience and the experts had a minimum of 5 yrs. of experience. Driver demographics are summarized in Table 1.

Table 1: Experiment participant demographics.

Variable	Novice Drivers	Expert Drivers
Experience	1.6 ± 0.9 years	1.6 ± 0.9 years
Age	7.9 ± 2.1 years	7.9 ± 2.1 years
Sex	23.2 ± 4.5 years	23.2 ± 4.5 years

Based on our modeling work, we formulated four hypotheses for the empirical portion of this work, including:

- Hypothesis (H)1 – The LODA manipulation will have a significant effect on driver cognitive workload with lower workload occurring with higher levels of automation.
- H2 – An increase in the system-level AR will produce a decrease in driver SA.

- H3 – Driver expertise level will have a significant effect on SA with greater SA occurring for expert drivers (i.e., the *b* parameter in the proposed SA response model will be significant).
- H4 – The proposed SA response model will have a stronger fit to the experimental data than linear models of SA based on the SAE LODA or the new *AR* value alone.

The first hypothesis represented a manipulation check on the LODA independent variable to ensure that the specific vehicle control conditions influenced driver behavior.

Driving Scenario and Test Trials

A complex driving scenario was designed and modeled (in simulation) to test the SA effects of the SAE LODA. Two contemporary grade-separated intersection (GSI) designs were integrated with a long intervening highway segment. The designs included a quadrant (Q) and contraflow (CF; Liu et al., 2024), which were novel for all participants. Each participant completed two test trials at each LODA (for a total of six trials) with randomized order of GSI exposure (i.e., GSI-Q→GSI-CF or GSI-CF→GSI-Q).

Protocol and Data Analyses

The experiment protocol included driver training and testing. The training phase required all participants to meet simulator driving performance criteria, including limiting average absolute lane deviation to less than 1.37 ft. (Horrey & Wickens, 2004) and maintaining average absolute speed deviation below 1.6 mph (based on pilot testing). Drivers were permitted up to three training trials to achieve the performance criteria.

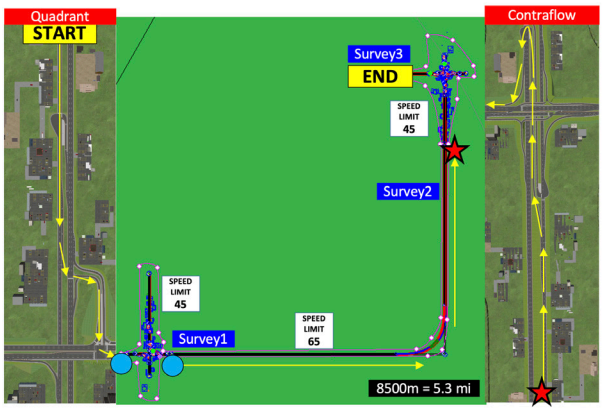


Figure 2: Driving scenario simulation model with two different GSI designs.

Test trials were structured to assess driver SA by using the SAGAT methodology (Endsley, 1995b). This involves querying driving dynamic knowledge on the roadway environment, their vehicle status, and the defined driving task. Three SA surveys were conducted during trials with one directly

following the first GSI exposure, another following the long intervening highway segment drive, and another directly following the second GSI exposure (see Figure 2). The surveys were comprised of scenario-specific SA queries based on driver goals, roadway features, and events occurring at the two GSIs and along the highway segment. For each survey, the simulator displays were blanked and a fixed number of multiple-choice queries were randomly selected from a large pool of queries organized according to Endsley's three-level SA framework. Level 1 queries addressed perception (e.g., How many green guide signs have you passed since the start of the simulation?); Level 2 addressed comprehension (e.g., How many miles have you driven after completing your last turn?); and Level 3 addressed projection (e.g., If there is a left turn ahead, what will the location of your destination be after that turn?). An "I don't know" option limited forced guessing. Driver responses to the SA queries were graded for accuracy based on the ground-truth of the driving simulation. We also assessed driver cognitive workload using the NASA Task Load Index (TLX). Demand ratings were conducted at the end of test trials (using a 20-pt. visual analog rating scale).

Regarding data analysis, the percent correct responses to SA queries and ratings of cognitive workload were analyzed using a mixed effects statistical model, including fixed effects representing the *LODA* and driver expertise (*DE*), the interaction of these terms along with a random effect representing the participant (*S*; nested within expertise levels of novice or expert). The model error term ($\boldsymbol{\varepsilon}$) captured response variance across replications of test trials within subjects. Eqn. 3 presents the full statistical model:

$$Y_{ijkl} = \mu + LODA_i + DE_j + (LODA*DE)_{ij} + S_{k(j)} + \boldsymbol{\varepsilon}_{l(ijk)} \qquad \text{Eqn. 3}$$

where, *Y* is the driver SA or workload response in each test trial, μ is the average sample response across experimental conditions, *i* is the setting of *LODA*, *j* is the level of *DE*, *k* is the participant number (within expertise level), and *l* is the trial identifier (within participant). Post-hoc analysis of any significant model terms was conducted using Tukey's Honestly Significant Difference tests with $\alpha = 0.05$ as a criterion significance level.

Regarding comparison of the proposed SA response function with statistical models, we computed two linear regressions on models with either the SAE LODA or the *AR* value as sole predictors. The regression model formulations included intercept values (β_0) to represent baseline sample responses.

RESULTS

Cognitive Workload

Starting with the experimental manipulation check, results revealed significant variations in TLX demand component ratings as well as overall TLX scores (the rank weighted sum of demand ratings) among the SAE LODA ($F_{(2,176)} = 106.34$, $p < .001$). Tukey's tests indicated SAE L4 demanded significantly less cognitive work than L1 and L0; however, the workload responses did not statistically differ among SAE L0 and L1. Furthermore, there was no expertise effect on the overall TLX scores (Expert TLX = 33.25;

Novice TLX = 35.57); i.e., the pattern of perceived driving demands was statistically the same across participant groups.

Situation Awareness

Mixed model results also revealed a significant effect of the SAE LODA on the accuracy of driver SA ($F_{(2,176)} = 15.03$, $p < .001$). Tukey's tests indicated SAE L0 lead to significantly greater driver SA (70%) than L1 (64%) and L4 (62%); however, driver SA accuracy did not statistically differ among SAE L1 and L4. There was a significant effect of driver expertise level on SA accuracy ($F_{(1,34)} = 11.47$, $p = .002$). Expert drivers demonstrated higher SA scores (70%) than novice drivers (60%) by about 16.7%. The pattern of SA accuracy across LODA was the same for both expert and novice groups; therefore, no significant interaction effect was detected.

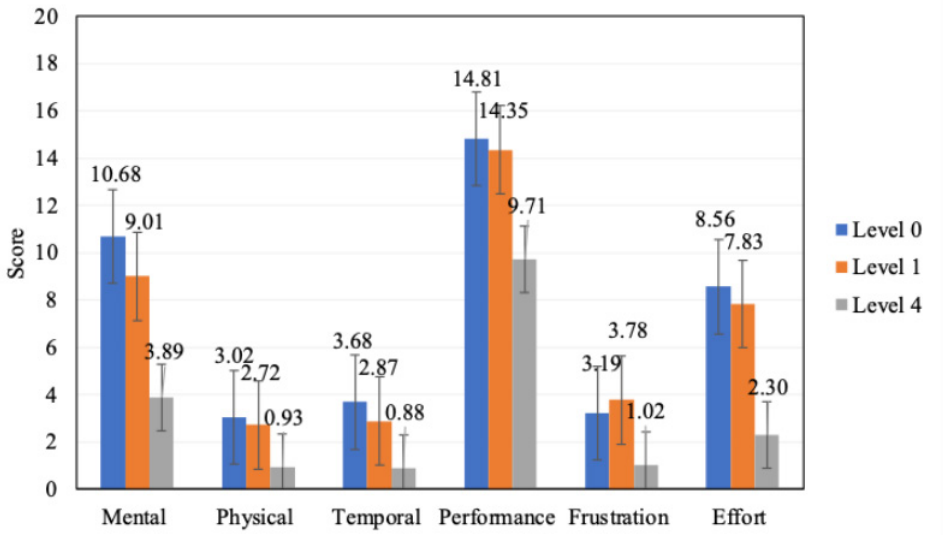


Figure 3: Driver cognitive workload demand ratings (L4 < L1 & L0; L0 = L1).

Model Fitting and Predictive Utility

For the proposed SA response function, we fit the exponential model with shift to the test trial data for each participant group; expert and novice drivers. The two fit models are presented as Eqns. 4 and 5. The models reveal that both groups of drivers were prone to automation use with novices being more enthusiastic about functional utility than experts.

$$SA = 0.31*(e^{(-0.31*R)}-1) + 0.72 \quad \text{Eqn. 4}$$

$$SA = 0.46*(e^{(-0.46*R)}-1) + 0.65 \quad \text{Eqn. 5}$$

Consequently, the expert drivers experienced slower decay in SA when using automation and for experiment conditions with higher LODA. This was likely due to elevated knowledge of driving situations and vehicle control

strategies. In fact, the model intercept values (b) indicated expert drivers to have greater SA accuracy (72%, on average) than novices (65%), when using manual control (LODA = 0; $AR = 0$).

As with the proposed SA model, the linear model in AR (i.e., $SA = -0.13R + 0.69$) also revealed a negative relation of SA with (increasing) vehicle functional automation. Baseline SA accuracy across drivers was fit at $b = 0.69$. The linear models in the LODA yielded identical results to the mixed effects statistical model with a significant effect of LODA on driver SA accuracy and the same patterns of means breakout based on Tukey's tests (L0>L1 & L4; L1 = L4).

DISCUSSION

For discussion of our results, we return to the four experiment hypotheses. The experimental manipulation-check revealed driver cognitive workload to be significantly lower at higher LODA, in line with the observations of Onnasch et al. (2014). However, the relation was not strictly linear as workload ratings for LODA 1 and 4 were not statistically differentiable. Consequently, we inferred that H1 was partially supported by the experiment results. Regarding H2, we found that higher simulated vehicle AR values were significantly associated with lower driver SA accuracy but this relationship was also not strictly linear. The SA accuracy levels for LODA 1 and 4 were not significantly different; thus, H2 was also partially supported. Regarding driver expertise, in line with Endsley's (2017) theory, we observed a significant difference in driver SA accuracy based on expertise level (indicating support for H3).

Finally, through quantitative model comparisons, we found the new SA response model, to be superior in fit to the experiment data and in predictive accuracy relative to the other linear regression models for both expert and novice drivers. Furthermore, the parameters included in the new *SA(R)* model intuitively represent common driver characteristics (i.e., θ – attitude; b – expertise) and promote explainability of model predictions.

CONCLUSION

The primary contribution of the present research was a driving simulation study for some quantification of the relation of SAE LODA to driver SA responses and to provide a basis for validation of a new mathematical SA response function. Experiment results supported our hypotheses of a negative relation of increasing vehicle automation rate (AR) with driver SA but that the relationship was not strictly linear. Furthermore, the new SA response model, capturing driver expertise and attitudes towards automation, also proved to have greater utility for predicting driver SA under various LODA, as compared to statistical models. The mathematical properties of the new model (convexity) also support its future application as a tool to determine how to optimize driver SA through training and vehicle functional automation.

Having said this, there are numerous limitations to this research, including current application of the *AR* equation being limited to automative systems. Any extension to other domains requires elaborate and laborious task/function analysis. The current application of the SA response model was also limited in its discrete representation of driver expertise (i.e., novice or expert), when expertise is commonly considered to present a continuous spectrum of domain knowledge and cognitive skill rather than fixed states. Finally, the driving simulator we used, advanced as it may have been, still suffers from the limitation of drivers (accurately) perceiving no real risk of vehicle crashes with some exhibiting atypically aggressive driving behaviors during test trials. In future research, we seek to expand the set of SAE LODA being tested and to make use of an instrumented vehicle and test track to further promote ecological validity of our experiments and validity of results for real-world applications.

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