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Abstract

Automated vehicles (AVs) promise to revolutionize driving safety. Driver models can aid in achieving this promise by providing a tool for designers to ensure safe interactions between human drivers and AVs. In this project, we performed a literature review to identify important factors for AV takeover safety and promising models to capture these factors. We also conducted a driving simulation experiment to address a research gap in silent automation failures. Finally, we developed a series of models to predict driver decision-making, braking, and steering responses using crash/near-crash data from the SHRP 2 naturalistic driving study and a driving simulation experiment. The analyses highlight the importance of visual parameters (in particular, visual looming) in driver responses and interactions with AVs. The modeling analysis suggested that models based on visual looming captured driver responses better than traditional baseline reaction time and closed-loop models. Further, the analysis of SHRP 2 data showed that gaze eccentricity of the last glance plays a critical role in driver decision-making. With further development, including the integration of important factors in takeover performance identified in the literature review and refinement of the role of gaze eccentricity, these models could be a valuable tool for AV software designers.

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Introduction

Automated vehicles (AVs) promise significant reductions in driving crashes, injuries, and deaths. To achieve this promise, technology developers must resolve technological and social challenges [1–3]. Of particular concern are transitions of control from AVs to human drivers [1, 2]. In these situations, human drivers may be tasked with regaining vehicle control and performing a crash avoidance maneuver. Researchers have worked to understand transition issues through experimentation and on-road testing e.g., [4–6]. However, on-road testing might present a safety risk and may not be sufficient to establish that technologies are safe without millions of miles of data [7]. Experimentation, on the other hand, is productive but costly, particularly for tasks such as calibrating design variables. Driver process models are a complementary approach to on-road testing and experimentation that can be used to explore the safety impacts of automation design through simulation [8]. Driver process models simulate human behavior using characteristics of the driving environment and relevant vehicle parameters to predict likely safety outcomes (Figure 1). Using these models, the impact of possible AV algorithm configurations can be quickly assessed by simulating thousands of trials across various kinematic scenarios and aggregating the outcomes of those trials.

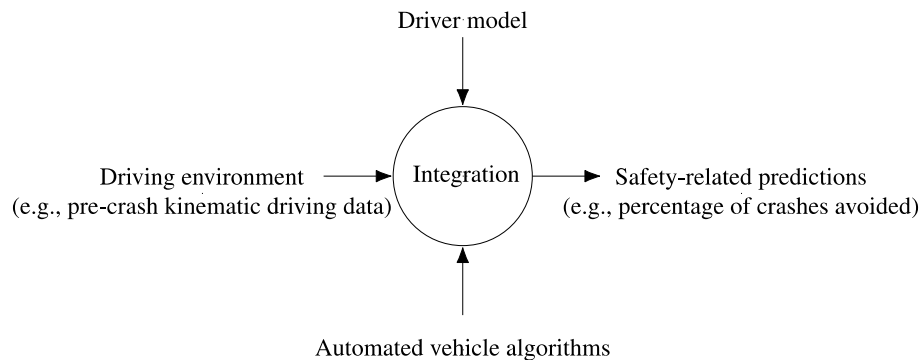


Figure 1. Illustration. Role of driver process models in predicting safety-related outcomes. Reproduced with permission from [9].

The most significant drawback in using driver models to predict safety outcomes is that the accuracy of safety-related predictions is highly dependent on the ability of the driver model to accurately replicate the scope of human behavior [8]. Although there is a long history of driver models for manual driving [9, 10], there are few models of driver behavior during interactions with AV technology. Developing new models can be challenging due to the variety of existing approaches and the fact that empirical data is often needed to refine model parameters and validate models [9]. One method for identifying promising models is through review of empirical studies of driving context, which can be used to identify influential factors on driver behavior and the models that best capture that influence. Such a review can also highlight gaps in the modeling literature that can be filled with additional empirical studies and model development.

The overall goal of this project was to develop a driver process model to predict driver behavior during control transitions. This goal was accomplished in four phases: (1) a literature review was performed to identify factors that influence driver behavior during takeovers and applicable existing driver models; (2) a model was developed to predict driver evasive maneuver decision-making during manual rear-end emergencies; (3) a driving simulation study was performed to analyze driver behavior in silent and alerted failures in a platooning scenario; and (4) a series of models was fit to predict post-takeover braking and steering control in the simulated scenarios.

Literature Review

The goals of this project's literature review were to identify factors that influence takeover time and post-takeover control and use those factors to identify promising driver process models for takeover performance. The review process consisted of two distinct searches, one focused on empirical studies of AV takeovers and one focused on models of driver behavior. The complete findings of the review are published in [11], but key elements are reproduced here for context.

Methods

The reviewed articles were gathered by iterative searches of the Transportation Research International Documentation database, Compendex, Scopus, Web of Science, and Google Scholar. Two groups of search terms were used to identify promising articles. The inclusion criteria were peer-reviewed publications (conference and journals), written in English, and published after 2012. The review of the AV experimental literature included only articles that described an experiment including at least one scenario where a control transition from automated to manual driving was required. The articles were required to include a description of the study design, apparatus, method, and takeover performance results. Naturalistic driving studies, closed test-track studies, and driving simulation studies were included. Studies that described automated-to-manual control transitions in non-driving domains were excluded. The review of the driver modeling literature contained all articles that reported on a newly developed model of driving behavior or decision-making or a significant enhancement of a prior model. Due to the scarcity of models of automated driving behavior, the review included models of manual driving behavior.

The search terms included all variants of the words driver, behavior, automated, takeover, and mode; see [12] for a full list of search terms. The initial searches returned 3,263 results. These results were reduced to 468 candidate articles. Those articles were augmented with an additional 168 articles identified from the reference lists of candidate articles. Following a review of abstracts and full reading of the articles, 83 unique articles were included in the review of empirical takeovers and 60 articles were included in the review of driver models (see Appendix B). Some additional articles were included in each section to provide important contextual information (e.g., an article from D.N. Lee [12] that defines the role of visual angles in responses).

Review of Automated Vehicle Takeover Studies

The review of the AV takeover literature found that most studies assessed takeover performance using takeover time and takeover quality. Takeover time was generally defined as the time between the onset of the event that precipitated the takeover and the driver’s first demonstrable vehicle control input (i.e., more than 10% brake pedal actuation or 2 degrees of steering input). Takeover quality did not have a consistent definition but was based on safety analog measures, such as time to collision (TTC), maximum acceleration, or maximum control input. The review highlighted takeover time budget (i.e., TTC or time to lane crossing [TLC] at the time of the takeover request, or critical event onset for absence of a takeover request); the presence (or absence) of a takeover request (the absence of a takeover request is called a silent failure where the automation fails or encounters an operational limit without a preceding warning); the driving environment; handheld secondary tasks; takeover request modality (i.e., visual, auditory, or tactile); the level of automation, driver impairment (alcohol or fatigue); and repeated exposure to takeovers as significant factors in determining takeover time. The review similarly found that all these factors, along with non-handheld secondary tasks, contributed to takeover quality. The complete set of significant factors and their impacts is summarized in Table 1.

Takeover time budget, repeated exposure effect, presence of a takeover request, and handheld secondary tasks have the strongest impact on takeover time. With decreasing time budgets, less exposure to takeovers, silent failures, and handheld secondary tasks, the increase in takeover time leads drivers to begin their action at a point with more kinematic urgency, thereby resulting in more severe and potentially unsafe maneuvers. The takeover time can be further increased by complex traffic scenarios and secondary tasks that create more difficult response decisions. These impacts may be mitigated by multimodal, informative takeover requests; however, the benefits are subject to the utility of the handover design.

Table 1. The Impact of Factors on Takeover Time and Post-takeover Longitudinal and Lateral Control

Factor affecting takeover	Impact on takeover time	Impact on lateral control	Impact on longitudinal control
Increased time budget	Increasing	<ul style="list-style-type: none"> • Decrease in maximum lateral acceleration • Decrease in standard deviation of lane position • Decrease in standard deviation of steering wheel angle 	<ul style="list-style-type: none"> • Decrease in maximum longitudinal acceleration • Increase in minimum TTC • Decrease in crash rates
Increased repeated exposure to takeover	Decreasing	<ul style="list-style-type: none"> • Decrease in maximum lateral acceleration 	<ul style="list-style-type: none"> • Increase in minimum TTC • Decrease in crash rates
Presence of takeover request	Decreasing	<ul style="list-style-type: none"> • Increase in high frequency steering corrections 	Insufficient evidence
Handheld secondary task vs. mounted	Increasing	<ul style="list-style-type: none"> • Increase in maximum deviation of lane position • Decrease in minimum TLC 	<ul style="list-style-type: none"> • Decrease in minimum TTC • Decrease in time headway

Factor affecting takeover	Impact on takeover time	Impact on lateral control	Impact on longitudinal control
Increased alcohol consumption	Increasing	<ul style="list-style-type: none"> • Increase in standard deviation of lane position 	<ul style="list-style-type: none"> • Increase in longitudinal acceleration
Increased traffic density	Increasing	<ul style="list-style-type: none"> • Increase in maximum lateral acceleration 	<ul style="list-style-type: none"> • Increase in maximum longitudinal acceleration • Decrease in minimum TTC
Decreased escape path	Increasing	<ul style="list-style-type: none"> • Increase in maximum lateral acceleration 	<ul style="list-style-type: none"> • Increase in maximum longitudinal acceleration • Decrease in minimum TTC • Increase in crash rates
Adverse weather conditions	Increasing	<ul style="list-style-type: none"> • Increase in maximum lateral acceleration • Increase in standard deviation of steering wheel angle 	<ul style="list-style-type: none"> • Decrease in minimum distance headway • Increase in maximum longitudinal acceleration • Increase in crash rates • Increase in brake application frequency
Non-handheld secondary task vs. no secondary task	No effect to a minor increase	<ul style="list-style-type: none"> • Increase in maximum and average lateral acceleration • Increase in average deviation of lane position • Increase in maximum steering wheel angle • Increase in time to change lane • Increase in lane change error rates 	<ul style="list-style-type: none"> • Decrease in minimum TTC • Increase in crash rates
Multimodal takeover request vs. unimodal	Decreasing	<ul style="list-style-type: none"> • Decrease in standard deviation of lane position • Decrease in maximum lateral position 	Insufficient evidence

Reproduced with permission from [11]. Note: There is insufficient evidence of the impact of level of automation, age, trust, and fatigue.

Given these findings, the following criteria for takeover performance models were identified:

1. Models of AV takeover should produce similar decisions to manual driving in emergencies.
2. Models should include a mechanism to induce a delay between manual and automated driving.
3. Models should link the takeover time (i.e., time to initial driver action) to the takeover time budget such that takeover times increase with time budgets. Model predictions should also show a relationship between mean and standard deviation of takeover times.
4. Models should include the ability to model silent failure situations, where drivers are more likely to fall into a low time budget scenario and respond based on TTC.
5. Models should reflect the delays in responses caused by uncertainty in the driving environment.

6. Models should capture the impact of handheld secondary tasks on takeover time and the negative influence of secondary tasks on post-takeover control. [11]
7. Models are needed to address takeovers across different levels of automation, in particular SAE level 2 and level 3 automation.

Beyond these factors, the review identified *age*, *trust*, *levels of automation*, and *silent failures* as critical gaps in the current literature. Silent failures were identified as a priority since they occurred in several on-road fatal crashes.

Models of Driver Behavior

The review of driver models showed that models of driver behavior in emergencies generally focused on a single avoidance action (e.g., braking or steering behavior). Thus, the review categorized the models into four groups: braking models, steering models, decision-making models, and combined models. Combined models represented the group of models that included some combination of decision-making, steering, and braking.

Driver Braking Models

Driver braking models were classified into three types: cellular automata, relative velocity, and visual angle. Of these, visual angle models are preferred for modeling AV takeovers because there is a significant amount of evidence that suggests that TTC at the transition of control is the primary determining factor in takeover time and quality [4, 13]. Studies show that drivers estimate TTC through visual looming, the ratio of the angular size of the forward vehicle and its rate of change [12, 14]. More recent studies have shown that when interacting with automation, drivers react to differences between predicted and observed TTC, rather than observed TTC alone [15]. Given these findings, the review of braking models focused specifically on visual angle models of braking.

Contemporary research on visual angle models of driver behavior has focused primarily on visual evidence accumulation models. The intuition behind these models is that drivers receive visual information (e.g., brake lights, visual looming) regarding the need to brake or accelerate and that they react to this evidence only when the accumulated evidence exceeds a threshold [16, 17]. Evidence accumulation models have been validated on several large naturalistic datasets [18, 19] and have also been fit to brake response times from driving simulation studies [15, 20, 21]. Recent work has extended the framework to include the effects of driving distraction [22]. The use of evidence accumulation models is also supported by the findings from a meta-analysis of the empirical studies of takeovers that there is a general linear relationship between the *takeover time* and *takeover time budget* (TTC at the start of the event) [11]. Of the reviewed models, evidence accumulation models are the only framework that can capture this relationship.

Driver Steering Behavior Models

The review identified three primary types of driving steering models: closed-loop control theoretic models, open-loop models, and hybrid open-closed-loop models [11]. These are distinguished by

their depiction of the driver. Closed-loop models include the driver as an optimal controller of a vehicle system (e.g., [23, 24]), open-loop models (e.g., [25]) depict the driver as a passive monitor that responds to system perturbations by drawing on preprogrammed input patterns (called motor primitives), and hybrid models (e.g., [17]) combine the open-loop monitoring with closed-loop corrective behavior. Under closed-loop models, there is a special class of cybernetic models that includes a more complex model of the human visual or muscular system (e.g., [26, 27]). The review identified hybrid models and cybernetic models as the most promising for AV takeovers. This selection was based on the finding that motor-intensive secondary tasks significantly impact takeover performance, as well as the comparative analysis in [25] that showed a role for open-loop models in steering avoidance and closed-loop models in post-avoidance stabilization steering. Modeling both of these phases is critical as the empirical studies of post-takeover control suggest that drivers may take up to 40 s to return to normal vehicle control [28]. However, given the lack of application of steering models to takeover data, the review suggested that additional comparative analysis such as the one in [27] was needed.

Driver Decision-making Models

The review found few process models of driving decision-making. However, several studies investigated factors that contribute to decisions to steer or brake. These models used logistic regression or machine learning to identify the factors that influenced drivers' evasive maneuver decisions. A persistent finding across these models is that visual information plays a significant role in driver decisions. For example, Venkatraman et al. [29] found that the optical angle of the forward vehicle and visual looming were the strongest predictors of driver decision-making. The findings were consistent with Hu et al. [30] and Wu, Boyle, and Marshall [31], who also identified visual information as an important parameter. One limitation across these models was the lack of consideration of gaze location, more specifically gaze eccentricity, the horizontal and vertical angles between the current gaze location and the straight ahead line of sight [32].

Combined Models

The review identified two promising combined process models of takeovers. Markkula et al. [33] used a multiple evidence accumulator framework to predict driver responses to takeovers from a partial AV. The model includes evidence for the need to brake or change lanes, which is driven by visual looming and integrates a gaze mechanism to modulate evidence accumulation if the driver is looking at the forward vehicle or away. The model captures the decision-making process well; however, it does not project post-takeover control and it does not include factors that influence takeover performance beyond the visual information. The other promising model was proposed in Seppelt and Lee [34]. It includes a component (based on the work of Degani and Heyman [35, 36]) which models the driver's understanding of the system state. When the driver's mental model and the system's actual model are consistent, the model predicts that drivers will respond immediately to takeover requests. In contrast, when there is a disconnect between driver expectations and system states, the model predicts that drivers will default to perceptual parameters such as TTC.

This model is promising because it directly includes the interface of the driver and the automation, which is beneficial for modeling driver trust, silent failures, and impairment factors.

Discussion

The review identified key factors that influenced driver behavior following automated takeover requests and a set of promising models for further exploration. The review also indicated gaps in the literature for both topics. A critical gap in the empirical studies was investigations of silent failures, particularly given that silent failures played a role in several recent fatal crashes. The investigation revealed a significant gap in the modeling literature on the role of gaze eccentricity and visual information on driver decision-making in emergency scenarios. In addition, there was a general lack of models depicting driver post-takeover steering and braking behavior. Studies suggest that there may be some overlap between manual and automated driving behavior [37]; however, the nature of this overlap is not well understood and warrants further investigation. Finally, the review highlighted a common thread of visual information and evidence accumulation modeling frameworks across the various types of models (i.e., braking, steering, and decision-making). This thread suggests that visual information models are worthwhile to pursue as a general model of driver post-takeover control.

Modeling Driver Decision-making in SHRP 2

One of the primary gaps identified in the modeling literature was the availability of driver decision-making models that considered the effects of gaze eccentricity. More generally, there was an identified gap in driver decision-making models based on naturalistic driving data. The goal of this phase of the project was to partly address that gap with a machine-learning analysis of driver decisions in rear-end emergencies using naturalistic driving data from the Second Strategic Highway Research Program (SHRP 2).

Method

SHRP 2 Data Reduction and Analysis

Radar data from 286 rear-end crashes and near-crashes (CNCs) were extracted from the SHRP 2 data repository. The CNC data contained both braking and steering and braking responses. The data included 31 s of radar data (1 s after the trigger value and 30 s before), subject driver eye-glance behavior, and existing annotations, including (i) time stamp for the trigger in the event, (ii) subject driver variables (gender, age), (iii) time stamp of the initiation of evasive braking and/or steering response by the subject vehicle, (iv) time stamp for start of subject driver's physical reaction to awareness of impending crash or near-crash, (v) driver eye-glance data, (vi) driver perceived impairment, and (vii) driver secondary tasks. The video data were sampled at 15 Hz and the radar data were sampled at 10 Hz. The rear-end events were manually reviewed to generate data, including new annotations for gaze eccentricity for last glance (defined below), to add attention allocation, escape path feasibility, escape glances, and last glance locations. These new

annotations were assessed relative to the visual cue onset point (VCOP), which is the time when it was believed that the driver received the first visual input of a potential crash. This time was defined according to a threshold, TTC_{th}^{-1} , of 0.1 or 0.2 s^{-1} . We considered two thresholds for TTC_{th}^{-1} : 0.1 and 0.2 s^{-1} . We analyzed VCOP condition for both thresholds and developed a machine learning model to compare their performance. A pictorial depiction of VCOP and last glance are shown in Figure 2 along with the value of TTC^{-1} and the driver glance location with respect to time. In the top graph in Figure 2, the driver was looking forward when TTC^{-1} reached TTC_{th}^{-1} (i.e., eyes-on-threat situation). We denoted this time instance as the VCOP. However, if TTC^{-1} reached TTC_{th}^{-1} when the driver was looking away, as shown in the bottom of Figure 2, VCOP was defined for the time instance (T_{LG}) when the driver's gaze returned to the forward roadway (i.e., eyes-off-threat situation). Thus, the driver's last glance was defined in relation to VCOP with eyes-off-threat, indicating that the last glance overlapped the VCOP (bottom of Figure 2) or eyes-on-threat when the driver's last glance occurred before the VCOP (top of Figure 2).

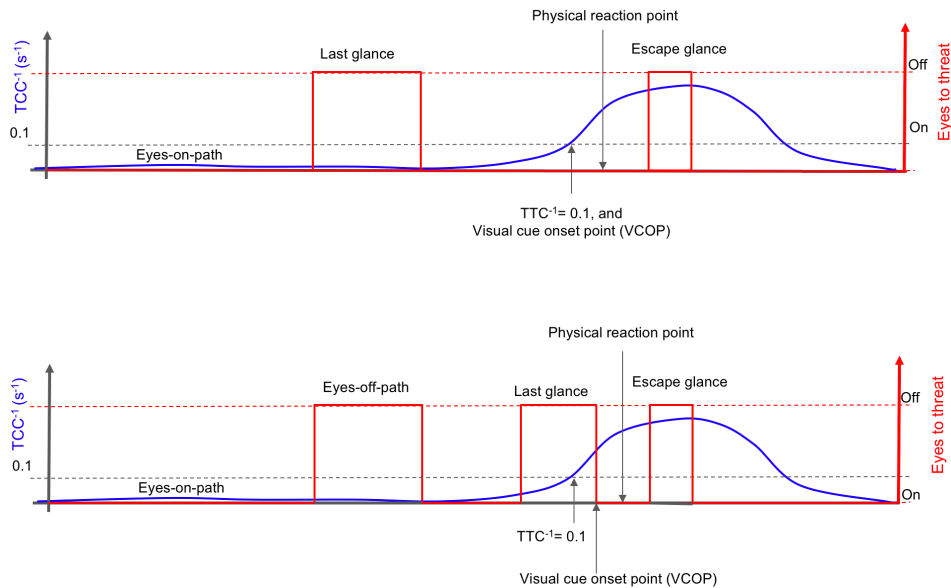


Figure 2. Graphs. Two VCOP cases: eyes-on-threat (top); eyes-off-threat (bottom). $TTC_{th}^{-1} = 0.1$.

Machine Learning Analysis

A machine learning analysis was used to develop a predictive model of driver evasive maneuvers and to perform inference on factors that influence driver evasive maneuvers. The analysis used a random forest (RF) approach, which is an ensemble of decision trees [38]. After initial processing, we found a total of 286 events, most of which were “braking only” (249 events). This led to a class imbalance for training the RF. In order to address the class imbalance problem, the *steering and braking* events were up-sampled using a random sampling method. This method randomly chooses *steering and braking* events and duplicates them to add as an extra evidence. Seventy percent of the data was used for training and 30% was used for testing. We used entropy-based information gain criteria for splitting the nodes in the decision tree structure. Hyperparameters (total number

of trees in the forest, maximum depth of the tree, maximum features for node splitting, minimum number of data points required for a split, etc.) were optimized using a three-fold cross-validation process. The final hyperparameters selected were 500 trees, at a depth of six. The inferential analysis was performed by studying the relative importance of variables and a partial dependence plot. We also applied typical decision logic by using the decision tree with the highest F1 score (which is the harmonic mean of the precision and recall).

Results

Prediction Results

Table 2 shows the results of the RF prediction for the test set. The model with $TTC_{th}^{-1} = 0.1$ performed better than the model with a threshold of 0.2. However, both models accurately predicted driver decisions for most of the dataset. These results suggest that the RF classifier was capable of accurately predicting the driver’s maneuver.

Table 2. Comparison of Classification Accuracy of Two RF Models

Model	Accuracy	Precision	Recall
RF model with $TTC_{th}^{-1} = 0.1$	95.86%	100%	91.42%
RF model with $TTC_{th}^{-1} = 0.2$	85.45%	78.95%	90.81%

Inferential Results

Figure 3 displays the results for the analysis of variable importance, including all the variables provided as input features to the RF. The six most important variables for classification were *TTC at the physical reaction* (19.3% accuracy loss when removed), *TTC at the VCOP* (18.1%), *escape path feasibility* (12.2%), *eyes-on-threat before (EOTB) VCOP* (9.8%), *last glance duration* (8.4%), and *combined last glance eccentricity* (7.9%). The horizontal and vertical glance eccentricity also show significant contributions. As we have already included them in the *combined last glance eccentricity*, we will not explicitly include them in subsequent analysis.

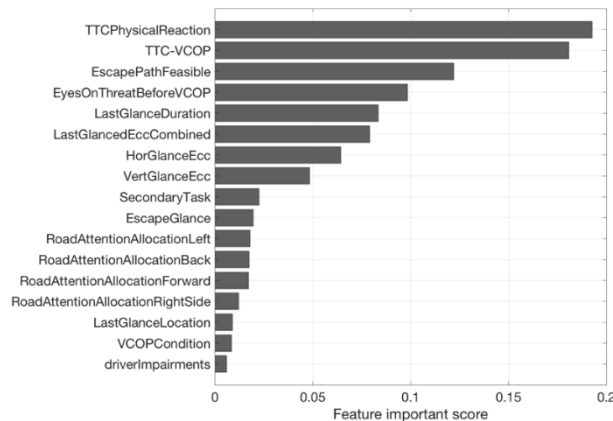


Figure 3. Chart. Variable importance in the RF model. Features are fully described in Appendix C.

The decision tree with the highest F1 score is shown in Figure 4, where Class 1 = *Braking only* (BR) and Class 0 = *Braking and steering* (SB) (all had braking as the first response). Although not a complete overview, the example tree illustrates the decision logic. For example, when the driver’s eyes are on threat for more than about a second before the looming reaches its threshold ($EOTBVCOP > 0.97$ s), and TTC values at VCOP and physical reaction are substantially high (TTC at VCOP = 10 in these scenarios), the driver tends to make a steering maneuver if there is an escape path making a lane change feasible. Conversely, the driver brakes if the steering maneuver is not feasible. When the TTC at the physical reaction is smaller (≤ 4.1 s), drivers tend to brake only, even if the steering maneuver is feasible. The drivers always tend to brake only if no escape path is feasible. In cases when the eyes-on-threat time before VCOP is substantially small ($EOTBVCOP < 1.0$ s), the driver can still choose the steering maneuver option, especially when the last glance gaze eccentricity is very high and the lane change is feasible. Typically, these glances may include checking the blind spot.

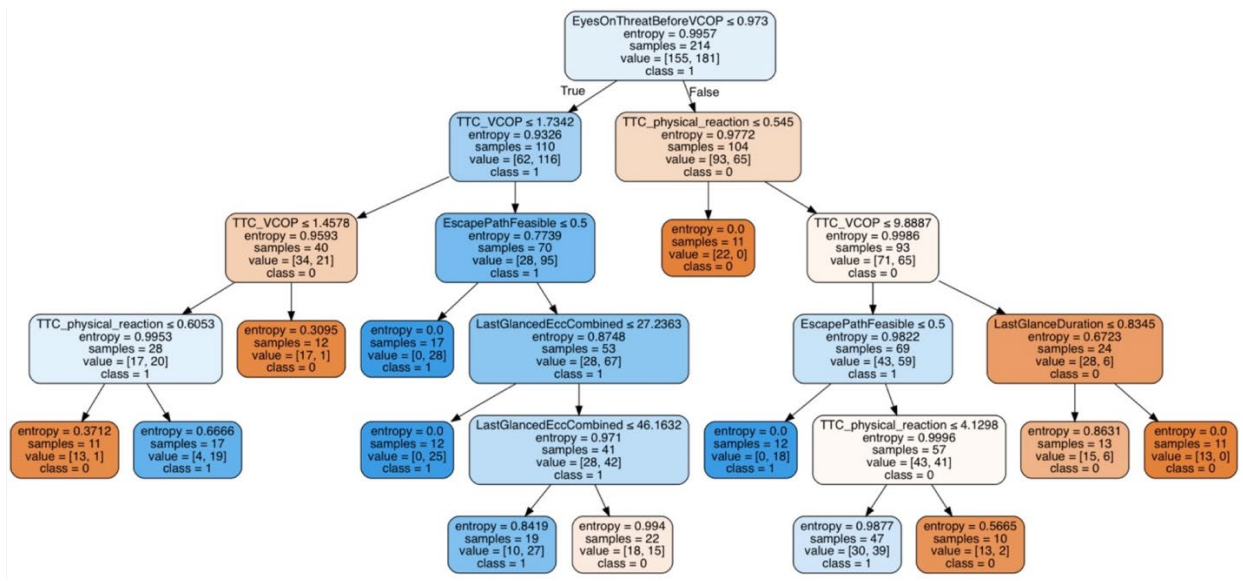


Figure 4. Chart. Structure of a single decision tree. Class = 1 represents BR and Class = 0 represents SB. Colors and hues are for visual contrast only. A larger version can be found in Appendix D.

Discussion

The results of this analysis suggest that visual information, the traffic scenario, the last glance duration, and gaze eccentricity sufficiently describe driver evasive maneuver decision-making. This finding adds to the prior work on evasive maneuvers, which suggests a critical role for visually estimated parameters such as TTC [15, 16, 19, 20, 29] and traffic scenarios [39–41]. However, the analysis presented in this work also describes a key role for gaze eccentricity. The findings suggest a complex relationship between evasive maneuver decision-making and eccentricity that warrants additional investigation. However, additional analysis must be completed given the relatively small sample used to train the models.

Simulator Study of Driver Takeover Behavior

The review of AV takeover studies identified silent failures and platooning scenarios as two significant gaps in the literature. A tertiary review also showed that the studies had a limited focus on traffic contexts where crashes occurred. Collecting data during silent failure and platooning scenarios is a critical step in developing models of post-takeover behavior. Another consideration is the real-world relevance of the scenarios investigated. Thus, we complemented the review with a topic modeling analysis of crash narratives in the California Department of Motor Vehicle’s (DMV’s) AV crash database [42] to identify crash themes, including 114 crash reports. The analysis found that rear-end crashes (Plots 2 and 3 in Figure 5), collisions during overtaking scenarios (Plot 4), and crashes during automated-to-manual transitions (Plot 1) were common themes [43]. Given these findings, we developed a driving simulation study to investigate the effects of silent failures, rear-end emergency scenarios, and overtaking scenarios during automated platooning. The study consisted of a $2 \times 2 \times 2$ design with alert type (silent failure, alerted) as a between-subject factor, and scenario (obstacle reveal, unexpected braking) and scenario criticality (critical, non-critical) as within-subject factors.

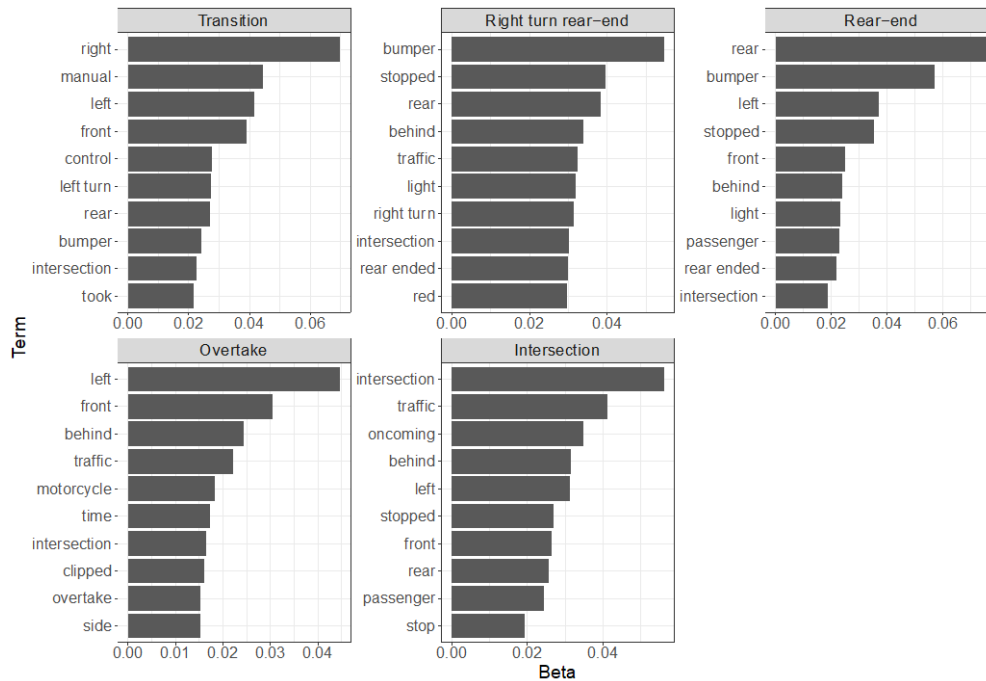


Figure 5. Charts. Topics in California DMV crash database. Reproduced with permission from [43].

Method

Participants

Sixty-four participants (32 males, 32 females) between 19 and 65 years old with a mean age of 41.44 (SD = 15.14) years were recruited to participate in this study. All participants were English speakers, reported normal or corrected-to-normal visual acuity and normal color vision, held a

valid driver's license, reported driving experience of at least 1.5 years ($M = 25.36$, $SD = 16.26$), were not taking any medications that may have affected the operation of a moving vehicle, had not previously participated in an experiment involving AVs, and had no prior experience driving automation-enabled vehicles (e.g., Tesla, Volvo). Informed consent was obtained from every participant, and they were compensated \$50 for their time. The study was approved by the Texas A&M University Institutional Review Board.

Apparatus

The study was conducted at the Texas A&M Transportation Institute's (TTI's) driving simulation lab, which consists of a Realtime Technologies Inc. (RTI) quarter-cab driving simulator and a physiological data collection suite (Figure 6). The simulator collected continuous steering wheel position, accelerator and brake pedal positions, velocity, TLC, time headway to an upstream object, and lane position at a 60-Hz sampling rate. The physiological data collection suite consists of a FOVIO eye-tracking system [44], a Zephyr BioHarness [45], and a Shimmer wireless Galvanic Skin Response (GSR) sensor [46].

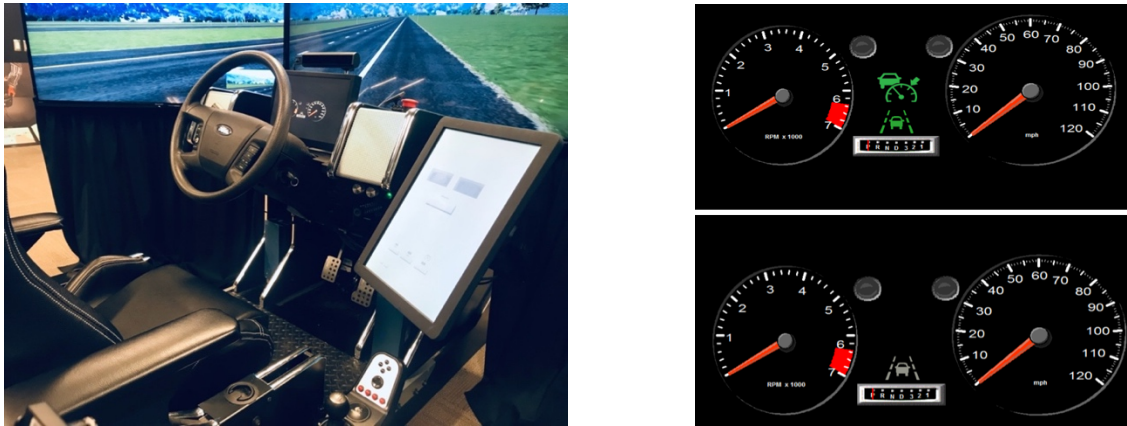


Figure 6. Photos. Left: Driving simulation lab setup including the quarter-cab, automation control screen (on the right side of the figure), and the eye-tracking apparatus (mounted above the instrument console near the steering wheel). Right: Instrument cluster when the automation is on (top figure) and is off (bottom figure).

The automated driving system in this simulator controlled the longitudinal and lateral vehicle guidance (SAE level 2 automation [47]) and could be activated with a button on a touch screen display (right of the steering wheel in Figure 6). After activation, the automation could be enabled with a button on the steering wheel and could be deactivated by pressing the same button or the brake. The automation status was indicated by a green icon on the instrument cluster (Figure 6).

Procedure

After consent, participants completed demographic and technology acceptance questionnaires and were trained on the automation and its operation via a paper-based manual. Participants were also informed that the automation was not capable of handling all situations and would request them to intervene if it encountered an operational limit. After the training, participants completed a manual and an automated practice drive where they were familiarized with the operation of the simulator. During the automated practice drive, participants entered a platoon and then enabled the

automation. After driving with the system for approximately 5 minutes, they were asked to resume control via a takeover request when the forward vehicle departed the highway via an exit ramp.

When the practice drives were completed, the participants drove four counterbalanced experimental drives representing each combination of the scenario criticality (critical, non-critical) and scenario (obstacle reveal, unexpected braking) conditions. The drives took place on a four-lane straight highway (two lanes in each direction) with a posted speed limit of 65 mph. The drives had natural surroundings (woods, farms) and ambient traffic of approximately 10 cars per mile on the oncoming traffic lanes. During all drives, the participants drove in a three-vehicle platoon with a 1-s time headway and a constant speed of 65 mph. After 5 miles of driving, a precipitating event occurred that required the participants to take over control of the vehicle. In the obstacle reveal scenario, the precipitating event was a stalled car in the vehicle's lane that appeared after the lead vehicle changed lanes. In the unexpected braking scenario, it was the lead vehicle in the platoon braking. In the alerted condition, the precipitating event triggered an auditory and visual takeover request. In the silent failure condition, participants received no indication of a failure. The criticality of the scenarios was determined by the TTC (obstacle reveal) or the deceleration rate (unexpected braking). The TTC to the lead vehicle was 5 s in the critical and 10 s in the non-critical obstacle reveal scenario. The deceleration rate was 5 m/s² in the critical and 2 m/s² in the non-critical unexpected braking scenario.

Results

From the 256 drives, 11 drives (8 in obstacle reveal and 3 in unexpected braking scenarios) resulted in crashes and were excluded from the analysis. A linear mixed-model analysis was used to investigate the takeover performance under the kinematic urgencies of the scenario and takeover request types. Thresholds of a 2-degree steering wheel angle and a 10% braking pedal position were used to define takeover time (following [48]) and takeover quality as measured by minimum TTC. This design was applied to both takeover scenarios (obstacle avoidance and unexpected braking). For all analyses, statistical significance was evaluated at $\alpha = 0.05$. The models' assumptions (e.g., homogeneity of variance) were also tested.

Takeover Time

Figure 7 shows the takeover time for obstacle reveal and unexpected braking events for critical and non-critical scenarios and under alerted and silent failure. The data were fit to two linear mixed models (one for each scenario) with the takeover time regressed on criticality, alert type, and their interaction. The overall model R^2 values were 0.21 and 0.35 for overtaking and braking, respectively. The statistical analysis showed a significant impact of scenario criticality on takeover time for obstacle reveal, $F(1,120) = 28.60, p < 0.001$, and unexpected braking events, $F(1, 64) = 41.32, p < 0.001$. However, no significant impact of silent failures or interaction between silent failures and scenario criticality was found. That said, the results in Figure 7 do show that median takeover time was longer in all of the silent failure conditions and was largest in the non-critical scenarios (right-side charts in Figure 7).

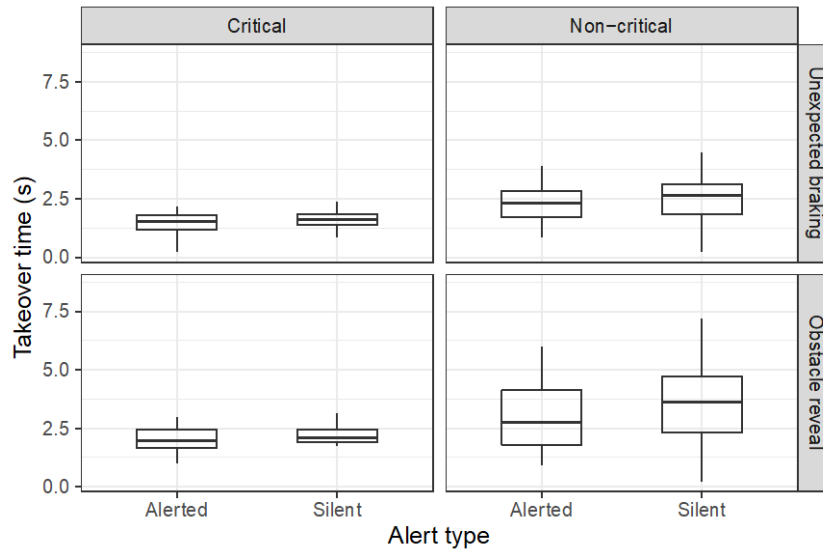


Figure 7. Charts. Takeover time under scenario criticality and alert type for tested scenarios.

Time to Collision

Figure 8 shows the minimum TTC following the obstacle reveal and unexpected braking events for critical and non-critical scenarios and under alerted and silent failure. The conditional model R^2 values were 0.60 and 0.51 for overtaking and braking, respectively. The statistical analysis showed a significant impact of scenario criticality on takeover time for obstacle reveal, $F(1, 58) = 146.07, p < 0.001$, and braking events, $F(1, 64) = 69.80, p < 0.001$. However, no significant impact of alert type or interaction between alert type and scenario criticality was found.

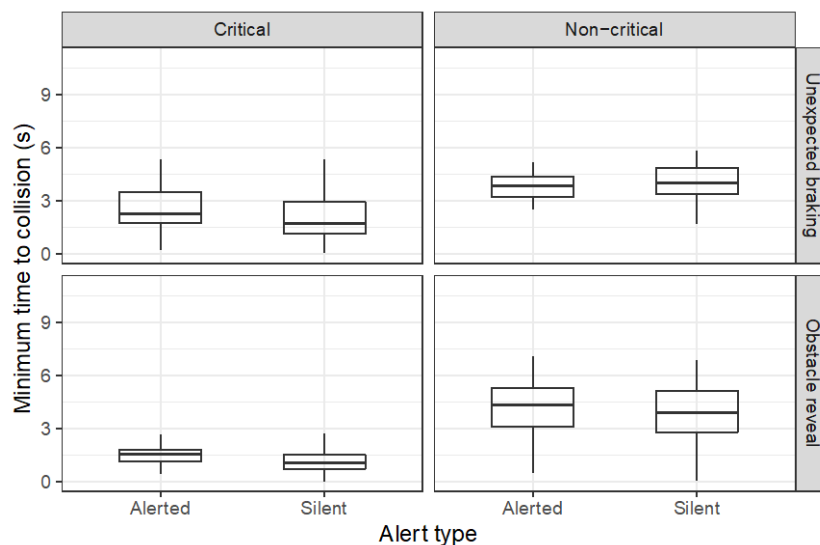


Figure 8. Charts. Minimum TTC under scenario criticality and alert type for tested scenarios.

Discussion

The study results confirm prior findings that scenario criticality plays a significant role in takeover time and post-takeover control [4, 13, 49] and this effect persists across scenarios and in platoons. Although silent failures were not found to be a significant factor in takeover time or post-takeover

TTC, there was a difference in the median values for silent failure cases: in all cases silent failures led to worse post-takeover control. This finding contrasts with other similar studies of silent failures [5, 15]. The finding could be attributable to random variance of the dependent measures. It is notable that in the takeover time regression analysis for obstacle avoidance, the fitted model explained only 21% of the variance in takeover time. This suggests that factors not explored in this experiment (e.g., trust) may have had a significant impact. This effect may have been compounded by the instruction to participants to keep their hands on the steering wheel and to stay focused on the drive. In this way these findings should be considered as a “best case scenario” for silent failures. Future work should investigate these complex relationships in more detail.

Modeling Post-takeover Control

The final phase of the project consisted of bringing together the knowledge from the review, the SHRP 2 analysis, and feedback from the project advisor, Dr. Gustav Markkula of Leeds University in the United Kingdom, to develop and validate models of driver post-takeover control. Following the observation in the review that models of braking and steering control are typically distinct, we fit braking and steering models separately. In each case, we developed a baseline comparison model and then compared the fit results with a promising model identified in the literature review.

Models of Driver Braking Behavior

The driver braking reactions were modeled by an evidence accumulation model based on the work of Markkula and colleagues [17, 18]. In this model, drivers receive various pieces of evidence such as the changes in the visual looming of the lead vehicle and respond with braking when the mismatch between their expected looming and actual looming exceeds a threshold. The model used in this study is defined by Equation 1:

$$\frac{dA}{dt} = kl(t) - M + v(t) \quad (1)$$

in which $l(t)$ is the looming prediction error, $v(t)$ is a zero-mean Gaussian white noise at time t with a standard deviation of σ , and k and M are free model parameters. The threshold for braking, A , was set to 1. The evidence accumulation braking model was compared with a simple reaction time model based on [8]. The braking control was modeled with a piecewise linear function assuming a constant acceleration (a_0), then a constant jerk (j), and finally a constant stable acceleration (a_1). The transition between the initial constant acceleration and the linear decrease in acceleration was governed by t_b , which we defined based on the braking onset model prediction.

Model Parameter Fitting

The evidence accumulation model parameters were optimized through a grid search across a set of fixed values for free parameters; the range of the search is given in Table 3. The model was run for each combination of the parameters and for the criticality of the scenarios, resulting in a distribution of brake deceleration onset times per scenario. The best combination of parameters was selected based on the smallest difference, measured by a two-sample Kolmogorov–Smirnov

(KS) test between the observed braking reaction times and predicted reaction times from the model. The reaction time distribution model consisted of a lognormal distribution fit to a sample of the data using the fitdistrplus package in R [50]. The two models were compared with both the KS statistics and Kullback–Leibler (KL) divergence. The braking control model was fit using a similar process, optimized across a_0 , j , and a_1 for critical and non-critical scenarios.

Table 3. Parameter Search Range for Braking Models

Model	Parameter	Searched range
Braking onset	k	[0, 8]
Braking onset	M	[-0.7, 0.7]
Braking onset	σ	[0.1, 0.6]
Braking control	a_0	[-2, 0]
Braking control	j	[-10, 0]
Braking control	a_1	[-8, 0]

Note. The unit of M and sigma is hertz, a_0 and a_1 are m/s^2 , and j is m/s^3 . k is unitless.

Model Fitting Results

For the braking onset model, the results of the KS test across the search values of k , M , and σ suggested that $k = 7.7$, $M = -0.3$, and $\sigma = 0.5$ led to the best model fit. For the braking control model, $a_0 = -0.4$, $j = -4.25$, $a_1 = -7.4$ resulted in the best model fit for critical and $a_0 = -0.4$, $j = -2.5$, $a_1 = -2.8$ resulted in the best model fit for the non-critical scenario. The KL divergence measure showed that the evidence accumulation model (0.06) had a smaller divergence from the experimental data compared to the lognormal distribution model (0.15). Figure 9 represents the cumulative density function with a histogram of the models compared to the experimental data. The figure highlights that while both models qualitatively replicate the data, the evidence accumulation model is a closer approximation.

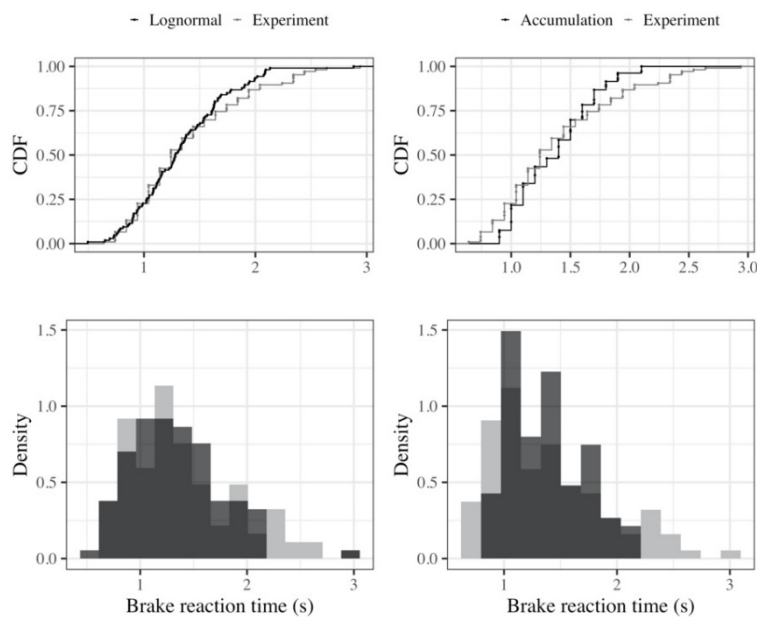


Figure 9. Graphs. Cumulative density function (top) and histograms (bottom) of the accumulation model, lognormal, and experimental data distributions.

The braking control models showed similar results to the brake onset models (see examples in Figure 10) although the fit differed substantially between the critical (left two plots in Figure 10) and non-critical (right two plots in Figure 10) scenarios. In the critical scenario, the mean root mean square error (RMSE) was 1.23 (SD = 0.66) and the mean R^2 was 0.90 (0.11), whereas in the non-critical scenario the mean RMSE was 1.25 (0.65) and the mean R^2 was 0.50 (0.30). One explanation for these results is that drivers in the non-critical scenario typically braked multiple times and therefore the piecewise linear braking pattern was a poor approximation of their behavior (note the right half of the rightmost plot in Figure 10).

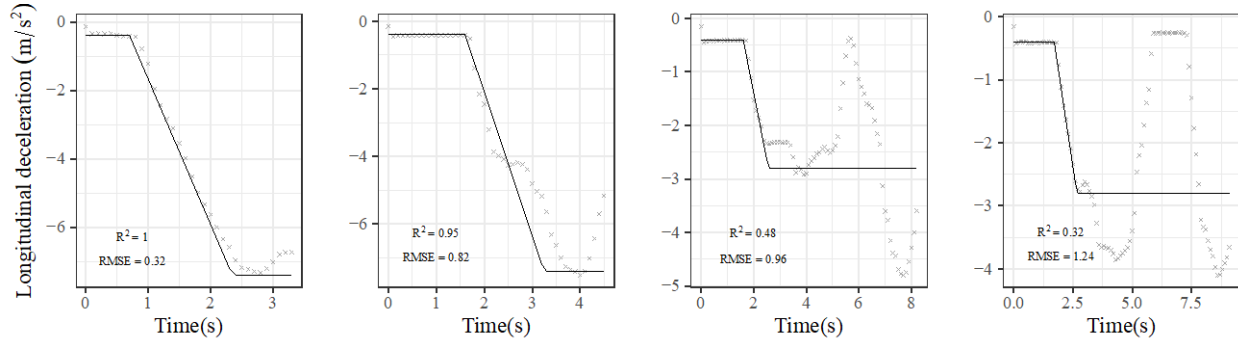


Figure 10. Graphs. Example braking control model results. Black lines indicate the predicted braking profiles and gray indicate the observed data.

Models of Driver Steering Behavior

The post-takeover steering maneuvers were modeled using a baseline closed-loop steering model [24] and a two-part avoidance and stabilization model based on the findings in [30]. The two-part model contained an open-loop avoidance steering component and a closed-loop stabilization component (also based on [24]). The open-loop avoidance component is comprised of at least one discrete open-loop correction in which the steering wheel angle rates have been shown to follow a Gaussian distribution function [25] as defined by Equation 3:

$$\dot{\delta}(t) = Ae^{-\left(\frac{(t-\mu)^2}{2\sigma^2}\right)} \quad (3)$$

In (3), $\dot{\delta}$ is the change in the steering wheel angle, A is the amplitude of the pulse based on a constant variable k and maximum visual looming after the event onset and prior to the avoidance maneuver initiation, μ is the mean of the steering input and was set to the time $T_S + T_A$ where T_S is the time when the steering input reaches half of its maximum value, and σ is the standard deviation of the model and was a function of time duration (T_H). k , T_A , and T_H were considered free parameters. The closed-loop stabilization steering component and baseline model were defined by:

$$\dot{\varphi} = k_n \dot{\theta}_n + k_f \dot{\theta}_f + k_i \theta_n \quad (4)$$

where, φ is the steering wheel angle, θ_n is the near point sight angle, and $\dot{\theta}_n$ and $\dot{\theta}_f$ are the changes in the near and far point angles, respectively. k_n , k_f , and k_i are gain parameters. The

difference between the baseline and closed-loop stabilization models is that the baseline model was fit to the entire post-takeover steering whereas the closed-loop stabilization model was fit to only the stabilization phase of steering, starting after the avoidance steering and ending after the vehicle had stabilized in the original lane.

Model Parameter Fitting

The parameters in each model were optimized by partitioning the experiment data into training and testing datasets conducting a grid search over a range of parameters (see Table 4). The participants were randomly divided into two groups. For the first half, the model was trained on the critical drive and was tested on the non-critical drive. For the second group, the model was trained on the non-critical drive and tested on the critical drive. Each combination of parameters was evaluated based on the minimum RMSE between the model predictions and the observed training data and the best set of parameters was chosen for each participant. Following the model fitting, the results were validated against the test dataset. R^2 values were also calculated against the test data to allow for comparison with [30].

Table 4. Parameter Search Range for Steering Models

Steering Model	Parameter	Searched range
Avoidance	T_H	[0.1, 1]
Avoidance	T_A	[-0.5, 0.5]
Avoidance	k	[0, 100]
Stabilization	k_f	[0, 100]
Stabilization	k_n	[0, 50]
Stabilization	k_i	[0, 10]
Baseline	k_f	[0, 100]
Baseline	k_n	[0, 50]
Baseline	k_i	[0, 10]

Model Fitting Results

The optimization results suggest that values of $k = [20, 70]$, $T_H = [0.2, 0.6]$, $T_A = [-0.5, 0.5]$, and lower values of k_f , k_n , and k_i , in particular, $k_f = [0, 25]$, $k_n = [0, 15]$, and $k_i = [0, 2]$, correspond to more accurate models. Within the best regions, the model is not sensitive to the gain parameter settings. The validation results against the test data (Table 5) show that the open-loop avoidance model generally replicates the trend in avoidance steering better than the closed-loop baseline model. The stabilization modeling results show similar R^2 values across the models, but a slightly better RMSE in the closed-loop model fit specifically to stabilization steering.

Table 5. Model Fitting Results for the Post-takeover Steering Models

	Avoidance: Open-loop	Avoidance: Baseline	Stabilization: Closed-loop	Stabilization: Baseline
RMSE	0.07 (0.065)	0.13 (0.33)	0.12 (0.13)	0.12 (0.14)
R^2	0.77 (0.29)	0.69 (0.27)	0.32 (0.10)	0.31 (0.10)

Figure 11 and Figure 12 provide examples of avoidance and stabilization steering profiles for the fitted model to the experimental data. The two-part model effectively replicates the trends, although it has substantially less entropy than the observed data. Future work should explore

expansions to capture the additional variability. Additionally, the open-loop avoidance model based on visual looming adequately represents the experimental data. Thus, these findings support the importance of visual looming across driver response models. Future work should also explore the validation of these models on real-world driving data, given the potential for differences in behavior between simulator and real-world scenarios.

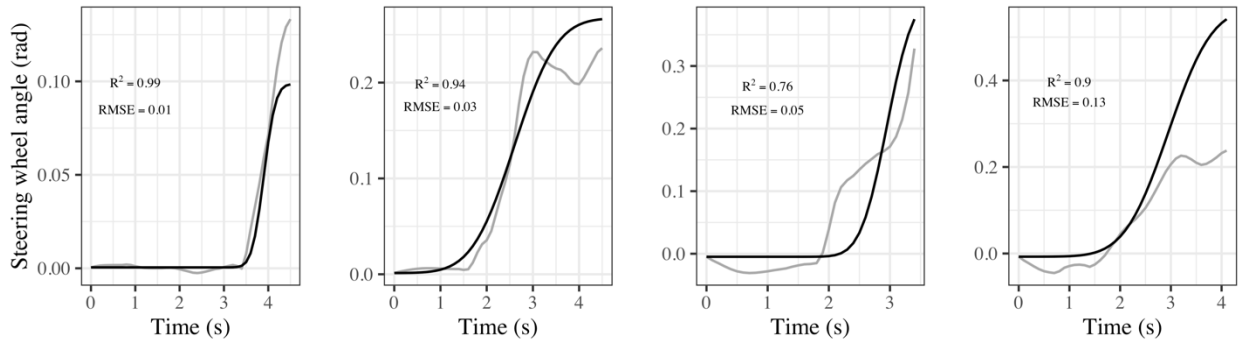


Figure 11. Graphs. Examples of avoidance steering maneuver for the experiment and fitted model. The black and grey lines represent the model and experiment, respectively. The first two examples represent good fits and the second two examples represent relatively poor fits.

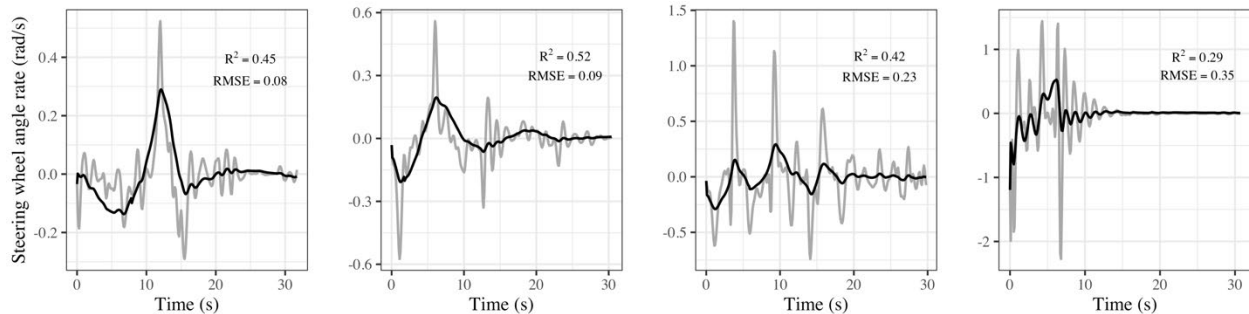


Figure 12. Graphs. Examples of stabilization steering maneuver for the experiment and fitted closed-loop stabilization model. The black and grey lines represent the model and experiment, respectively. The first two examples represent good fits and the second two examples represent relatively poor fits.

Conclusions

The collective findings of this project illustrate the importance of visual looming across driver responses. The literature review identified that looming, estimated by TTC, was one of the most significant factors in takeover time and post-takeover control. The analysis of SHRP 2 data identified TTC as a significant contributor to driver evasive maneuver decision-making, and the driving simulator experiment showed that TTC at the time of an automation failure significantly impacts driver response, more so than the failure type. The modeling analysis found that models based on visual looming effectively captured braking and avoidance steering responses. Moreover, the project highlighted the need for additional investigation of the impact of trust, silent automation failures, and gaze eccentricity on drivers' performance. Gaze eccentricity is particularly important given the finding from the SHRP 2 analysis that it significantly impacts driver decision-making.

Finally, the modeling results suggest that evidence accumulation braking models, and the two-part model of visual looming based on open-loop avoidance and closed-loop stabilization are effective for predicting driver post-takeover performance. Future work should continue to expand these models to capture the remaining critical factors identified in the review and investigate the influence of other environmental factors (e.g., time to brake, required acceleration).

Additional Products

Education and Workforce Development Products

Dr. McDonald led the development of a graduate-level course module (2 weeks; 4 lecture hours) of driver modeling, which was presented in ISEN 627 Decision Analysis: Behavioral, Cognitive, and Strategic Foundations. The lectures were also condensed into a guest lecture presented at VTTI to Dr. Zac Doerzaph's graduate class on advanced vehicle technologies. Hananeh Alambeigi presented on behalf of the project to a group of prospective students at Texas A&M about driving safety research and advanced vehicle technologies. The project financially supported two Ph.D. students, Hananeh Alambeigi and Wenyan Huang, and one undergraduate student, Jarett Dunne. One student, Cara Stolz, worked on the project as part of the SAFE-D summer intern program and assisted with data collection on the simulator study. Four additional undergraduates, Norbert Yuma, Srinivas Tankasala, Roberto Pacheco, Hayden Altman, and Will Heye, worked on the project as part of a for-credit research course in the Texas A&M Department of Industrial and Systems Engineering. Finally, VTTI supported Tobias Vogelpohl, a visiting Ph.D. student from TU Braunschweig. The project will be a core component of Ms. Alambeigi's dissertation and contributed to Dr. Vogelpohl's dissertation.

Technology Transfer Products

This project has produced two conference papers and two journal articles to date. The journal articles include the literature review, published in *Human Factors* [11], and the analysis of the SHRP 2 decision-making analysis, which has been submitted to *Accident Analysis and Prevention* [51]. The conference papers were an analysis of the California DMV's AV crash database used to identify relevant crash scenarios for the simulator study [43], which was presented at the Annual Meeting of the Transportation Research Board, and a paper describing the modeling work presented at the 2020 International Annual Meeting of the Human Factors and Ergonomics Society (HFES). Two journal articles describing the simulator experiment results and expanding on the modeling paper submitted to HFES are planned. We also plan to hold a webinar to present the findings of the modeling work and to make code for the model available via the project website.

Data Products

The project generated two datasets: one reduced SHRP 2 dataset and the dataset from the simulator study. Complete descriptions of the datasets can be found in this report and the associated journal articles [51]. Data are available at: [https://www.vtti.vt.edu/utc/safe-d/index.php/projects/\[tbd\]](https://www.vtti.vt.edu/utc/safe-d/index.php/projects/[tbd]).

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Appendix A. Abbreviations

Table A- 1. Abbreviations Used in this Document

Abbreviation	Full form
OST	Office of the Secretary of Transportation
US DOT	U.S. Department of Transportation
SAFE-D	Safety through Disruption
TTI	Texas A&M Transportation Institute
VTTI	Virginia Tech Transportation Institute
HFES	Human Factors and Ergonomics Society
SHRP2	Strategic Highway Research Program
TTC	Time to collision
TLC	Time to lane crossing
CNC	Crashes and near-crashes
VCOP	Visual cue onset point
EOTB	Eyes-on-threat before
RF	Random forest
BR	Braking
SB	Steering and braking
KL	Kullback–Leibler
KS	Kolmogorov-Smirnov
RTI	Realtime Technology Inc.
GSR	Galvanic Skin Response (GSR)

Appendix B. Literature Review Reference List

A bibliographic list of articles included in the literature review (2012–2018) in addition to the new articles found in the literature (2018–2020).

Automated Vehicle Takeovers

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Appendix C. Feature Names and Descriptions

Variable Name		Description	Values
Gaze Eccentricity (for last glance)	Horizontal Eccentricity	Zero vertical and horizontal glance eccentricity would be a driver looking straight ahead. Eccentricity was categorized into bins of 20 degrees (e.g., ‘down between 70-90 degrees’). Then, horizontal and vertical glance events were combined and differentiated between the directions of the glances by means of the instrumented vehicle driver left/right and up/down, respectively. The middle value in the range was used in the analysis (e.g., ‘down 40%’ was used instead of ‘down between 30-50 degrees’).	‘left 100 degrees’ ($n = 8$), ‘left 70 degrees’ ($n = 4$), ‘left 60 degrees’ ($n = 5$), ‘left 40 degrees’ ($n = 18$), ‘left 20 degrees’ ($n = 18$), ‘straight ahead’ ($n = 133$), ‘right 90 degrees’ ($n = 5$), ‘right 80 degrees’ ($n = 5$), ‘right 60 degrees’ ($n = 13$), ‘right 40 degrees’ ($n = 21$), ‘right 20 degrees’ ($n = 55$).
	Vertical Eccentricity		‘down 80 degrees’ ($n = 2$), ‘down 60 degrees’ ($n = 23$), ‘down 40 degrees’ ($n = 46$), ‘down 20 degrees’ ($n = 16$), ‘straight ahead’ ($n = 168$), ‘up more than 90 degrees’ ($n = 0$), ‘up 80 degrees’ ($n = 1$), ‘up 60 degrees’ ($n = 1$), ‘up 40 degrees’ ($n = 4$), ‘up 20 degrees’ ($n = 25$)
Road Attention Allocation	Forward	The attention allocated to the roadway in respect to the subject’s own lane, adjacent lanes, the rear of the vehicle, and the awareness of potential hazards in the present traffic environment	‘full’ ($n = 169$) or ‘intermittent’ ($n = 117$)
	Right		‘yes’ ($n = 44$) or ‘no’ ($n = 242$)
	Left		‘yes’ ($n = 73$) or ‘no’ ($n = 213$)
	Back		‘yes’ ($n = 56$) or ‘no’ ($n = 230$)
Escape Path Feasible		The feasible escape directions for an emergency maneuver. Reduced into a binary variable on the feasibility of an escape path.	‘yes’ ($n = 180$) or ‘none’ ($n = 106$)
Escape Glance		The direction of the escape glance made by the subject driver after becoming aware of an impending near crash or crash. Reduced to a binary variable of ‘yes’ or ‘no’	‘yes’ ($n = 132$) or ‘none’ ($n = 154$)
Last Glance Location		The last glance is operationally defined in Figure 2. The last glance location uses the driver glance data to define the driver’s glance location during the last glance. This was reduced into a binary value of ‘interior’ and ‘exterior’	‘exterior’ ($n = 199$) or ‘interior’ ($n = 87$)

Variable Name	Description	Values
Driver Impairments	The driver intoxicated, drugged, and/or sleepy/asleep	'yes' (n = 10) or "no" (n = 276)
Secondary Task	The driver performing a secondary task	'yes' (n = 190) or 'no' (n = 96)
Maneuver	What maneuver decision the driver used	Braking (n = 255) or Steering (n = 31)

Variables	Definition
VCOP Condition	The VCOP denotes the time instance when it is believed the driver received the first visual input of a potential crash. The VCOP condition has two values: 'eyes on threat', 'eyes off threat'
Last Glance Duration	Based on the glance location coded in the reduction data last glance duration is computed as the time duration in second.
TTC at VCOP	Once VCOP point is defined, the TTC value is computed from the radar data at the VCOP timestamp.
TTC at Physical Reaction	Denotes the TTC value at the time instance of physical reaction
Last Glance Eccentricity Combined	The combined horizontal and vertical gaze eccentricity. (see Figure C-1 and Eq. C-1)
Eyes on Threat before VCOP' (EOTB-VCOP)	The time duration when the driver looked forward before the VCOP point. This variable aims to capture how the driver accessed the roadway condition immediately before the threat.

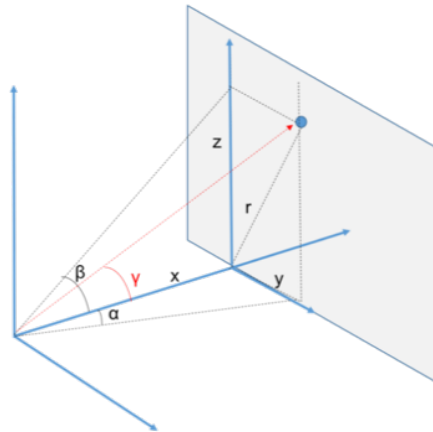


Figure C- 1. Schematic for the combined gaze eccentricity or computed from the horizontal gaze eccentricity and vertical gaze eccentricity

$$\gamma = \tan^{-1} \left(\sqrt{\tan^2 \alpha + \tan^2 \beta} \right) \quad \text{Eq. C-1}$$

Appendix D. Enlarged Decision Tree Figure

