CrIS | Crash Imminent Safety UTC

Final Report

Project Title: Cognitive Attention Models for Driver Engagement in Intelligent and Semi-autonomous Vehicles

September 30, 2018

Submitted to:	US Department of Transportation (USDOT) Research and Innovation Technology Administration (RITA)
Program Director/PI:	Umit Ozguner Crash Imminent Safety University Transportation Center Director Professor Emeritus TRC Inc. Chair on Intelligent Transportation Systems Department of Electrical and Computer Engineering The Ohio State University ozguner.1@osu.edu 614-292-5141
Project Lead:	John Lee, University of Wisconsin-Madison jdlee@engr.wisc.edu 608-890-3168
Participating:	D. Fisher (UMass); A. Homaifar (NCA&T); D. Woods (OSU)
DUNS Number:	832127323, EIN Number: 31-6025986
Recipient Organization:	The Ohio State University
Recipient Grant Number:	DTRT13-G-UTC47
Project/Grant Period:	10/01/2013-09/30/2018
Submission Date:	09/30/2018

Signature of Submitting Official:

CENTER FOR AUTOMOTIVE RESEARCH

OVERVIEW

This is the Final Report of the Project

Cognitive Attention Models for Driver Engagement in Intelligent and Semi-autonomous Vehicles

Project Lead: John Lee (UW)

Emerson Electric Quality & Productivity Professor
Department of Industrial and Systems Engineering
Email: jdlee@engr.wisc.edu
Office: 608-890-3168 Fax: 608-262-8454
513 University Avenue, Madison, WI 53706

Other Investigators: Donald Fisher (UMass), Abdollah Homaifar (NCA&T), David Woods (OSU)

Project Description

The focus of this project is to improve the state-of-the-art in human cognitive modeling in order to more accurately describe the human-machine interfaces that take place in the pre-crash scenarios. This project develops a cognitive attention model that provides a fundamental understanding and analysis capability for driver attention. In particular, the model will be used to understand how drivers respond to vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) information cues in pre-crash scenarios. It also addresses how to re-engage a driver who may be partially or completely disengaged from key attention elements while operating a semi-autonomous vehicle. We seek to understand driver engagement over a range of human physiological and behavioral factors, including age and drowsiness.

As vehicle systems become more autonomous, human drivers engage in other activities and tasks—in other words, drivers disengage from the driving situation. This is especially true of look-ahead functions that support early responses to defuse risky situations, such as taking back vehicle control when entering an area with a high density of pedestrians. It will be especially important to monitor for these situations as vehicle systems become more autonomous. Re-engagement can take many forms, such as alerting/warning, redirecting driver attention to look ahead to developing risk, directing the driver to take charge of some control functions while automation handles others, or reconfiguring automated subsystems.

The primary approach we will pursue is the development and use of a computational model of attention. Computational simulations of attention now exist that can be applied to the re-engagement challenge for driving and added to driving simulators as a new resource. We have been developing one that is specifically designed to handle situations where multiple sensors and algorithms assess anomalies and risk at multiple temporal and spatial scales. This simulation of attention can be used for design of warnings and automation to facilitate re-engagement. It can also be used as a critical measuring tool to assess the effectiveness of re-engagement under different conditions and with different types of response to pre-crash risk assessment. While the model is general, our focus in the CrIS UTC is to develop the model as it applies to the pre-crash University Transportation Centers Program time interval; this interval will be longer than the immediate pre-crash interval, because of the importance of modeling attention state before the immediate event, and because we hypothesize that early attention-engagement

strategies will significantly improve pre-crash safety.

The overall Project was undertaken with the collaboration of four Universities and involved three specific thrusts. In the following pages, the research accomplished will be presented in terms of these three thrusts in three subprojects.

Overview

Aims of project

Overall outcomes of the project

Synergistic activities (e.g., collaborations with others outside the UTC and using data from previous research to develop driver models)

Overview of chapters (i.e., papers produced)

Title: Simulation-Based Safety Benefit Estimates: Do Differences in Associations between Driver Model Parameters Matter?

Authors:

Vindhya Venkatraman[1*] (venkatraman@wisc.edu)

Ja Young Lee[1] (jayoung.lee@wisc.edu)

John D. Lee[1] (john.d.lee@wisc.edu)

Chris W. Schwarz[2] (chris-schwarz@uiowa.edu)

Timothy L. Brown[2] (timothy-l-brown@uiowa.edu)

Addresses:

1. Cognitive Systems Lab,
   University of Wisconsin-Madison,
   1513 University Avenue,
   Madison, WI 53706
2. National Advanced Driving Simulator,
   University of Iowa-Iowa City,
   2401 Oakdale Boulevard,
   Iowa City, IA 52242

Corresponding author: Vindhya Venkatraman (venkatraman@wisc.edu)

ABSTRACT

Purpose: Rear-end collisions are common, accounting for 32.4% of all crashes in the United States. Vehicle-based safety technologies, such as forward collision warning systems, may be useful in preventing these crashes, or mitigating their severity. Safety benefits of such warning systems can be estimated using computer simulations, and driver models are crucial to simulation-based benefits estimation. Most applications use driver models based on the information-processing framework within which the behavioral parameters, such as reaction times and deceleration rates, are often sampled from independent distributions. Accounting for dependence between model parameters using mathematical functions called copulas might improve the accuracy of driver models. The study investigates if models that account for associations should be used in the place of models that consider parametric independence.

Methods: Data from a driving simulator experiment, in which some drivers were warned of impending collision by a forward collision warning system and others were not, were used to develop the driver models. Eight driver models—four independent-stage models and four copula-based dependent-stage models—were developed for two rear-end collision-imminent situations. Measures of crash risk and crash severity were estimated by simulating the driver models in computational counterfactual simulations of the collision-imminent events.

Results: Associations between the driver model parameters indicate that assumptions of independence might be invalid. The results from the counterfactual simulations show that the copula-based dependent-stages models predict larger reductions in estimated crash risk and severity than the independent-stages models. Model predictions of crash risk and severity show that the predictions of the copula-based dependent-stages models vary differentially from the independent-stages models across different initial event kinematics.

Conclusions: Copulas provide a viable means for modeling dependencies between driver model parameters. The resulting models generate different safety benefits estimates of collision warning systems compared to independent-stage models. This suggests that the assumption of independence might be an oversimplification of collision-avoidance driver behaviors, and shows the need for models that account for the associations between model parameters. The results discussed in this paper have implications for evaluating vehicle safety systems, designing vehicle automation algorithms, and improving driver safety.

Keywords: Driver Model; Safety Benefits Estimation; Forward Collision Warning System; Copula; Counterfactual Analysis; Rear-End Collision

1. INTRODUCTION

Rear-end collisions occur when one vehicle collides with the rear of another vehicle (National Highway Traffic Safety Administration, 2014). These collisions are prevalent in the United States—in the year 2014, they contributed to 32.4% of all crashes and 6.6% of all fatal crashes (National Highway Traffic Safety Administration, 2014). Forward Collision Avoidance and Mitigation (FCAM) systems help drivers avoid rear-end collisions, and in the event of a crash, reduce crash severity (Jermakian, 2011). FCAM systems warn the driver of imminent collision, or warn and then perform a combination of braking and steering actions to substitute for, or amplify, the driver's collision avoidance actions. FCAM systems have the potential to prevent or mitigate 70% of all police reported rear-end crashes in the United States, 57% of all non-fatal rear-end injury crashes, and 48% of fatal rear-end crashes (Jermakian, 2011).

A persistent challenge to the design of these systems is the quantification of how their algorithms (e.g., design of timing, alert modality, alert duration, and urgency) affect safety. Estimation of safety benefits during the design process can identify potential improvements prior to large-scale fleet deployment of these technologies (Kusano, 2013). Safety benefits can be measured as the number of crashes prevented (crash risk); and if a crash is unpreventable, as the severity reduction in occupant injuries (crash severity). The comparative benefits of a specific algorithm over alternatives, or over the absence of the FCAM system, will predict which alternative maximizes safety outcomes. The traditional approach to benefits' estimations uses observations from human-in-the-loop experiments typically conducted in driving simulators, test-track environments, or as naturalistic studies. Increasingly, computer simulations—the use of computers to represent the process dynamics of a system (e.g., driver, vehicle, or situation) with a mathematical model of that system—are emerging as practical alternatives, particularly during the FCAM design process. In particular, a technique called counterfactual analysis is gaining increased attention for use in estimation of safety benefits (Bargman, Boda, & Dozza, 2017; Victor et al., 2015). Counterfactual analysis provides a means of simulating many different component behaviors, such as driver behaviors, event kinematics, or FCAM algorithms, for a given safety-critical event and predicting outcomes for each configuration of the components.

Driver models—mathematical representations of driver behavior—are an integral part of simulation-based benefits analysis. Accurate driver models are required for valid and

generalizable estimates of safety benefits (Bargman et al., 2017; Markkula, Benderius, Wolff, & Wahde, 2012; McLaughlin, Hankey, & Dingus, 2008). The most commonly used models have been developed based on the information-processing approach. These models assume that driver behavior can be treated as independent and sequential stages of sensation, perception, decision-making, and action. Models with these assumptions are called as the independent-stages models in this paper.

Contrary to the assumptions, the distinct stages of driver behavior are unlikely to be independent of each other. Empirical evidence suggests different features of the information may be processed in parallel across multiple stages (Cowan, 1988). These parallel stages can influence each other, leading to interdependence rather than independence across stages. Representing such dependencies between stages as associations between driver model parameters might improve the accuracy of benefits estimates. Copula functions (Frees & Valdez, 1997; Yan, 2007) can be used to model associated variables as multivariate joint distributions, without the assumption of multivariate normality or the need to cast variables in explanatory-response relationships as in a regression analysis. Samples drawn from the multivariate distribution can be used as parameter values in driver models. Models that account for associations between the driver's behavioral outcomes within the information-processing framework, such as correlation between reaction time and deceleration rate, are called as dependent-stages models in this paper. Differences in safety benefits estimated from independent- and dependent-stages models would indicate the utility of considering more complex models of driver behavior: should models that consider parametric associations be used in the place of simpler models that assume parametric independence?

This study explored the use of copula-based dependent-stages models as viable alternatives to independent-stages models in benefits' estimations of a forward collision warning system. Two rear-end collision scenarios were considered in which FCAM systems might offer important safety benefits. The first scenario was imminent collision with a stopped lead vehicle. Collisions with a stopped lead vehicle were identified as the third most-harmful pre-crash scenario, contributing to approximately USD $30 billion in comprehensive crash costs and about 200,000 functional years lost from the US population between 2004 and 2008 (Najm et al., 2013). The second scenario was imminent collision with a decelerating lead vehicle. Collisions with a decelerating lead vehicle were ranked as the eighth most harmful pre-crash scenario, with about

USD $12.5 billion in comprehensive crash costs and approximately 85,000 functional years lost in the same time period (Najm et al., 2013). These two scenarios contribute to 15% of all annual crash-related costs (Najm et al., 2013) and more than two-thirds of all annual rear-end collision-related costs.

Driver behavior data in these two scenarios were collected using a driving simulator. Some drivers in the experiment were warned of imminent collision using a forward collision warning (FCW) system, whereas others received no warning (baseline control group). The driver model parameters were brake reaction time, jerk, and a constant deceleration rate. Two driver models were developed to describe braking behaviors in four categories (two warning conditions in each of two collision scenarios). The driver model is stated as: "The following driver initiates a braking response with a constant jerk **j**, at a constant deceleration rate $\boldsymbol{\alpha}$, after a reaction time $\boldsymbol{\tau}$ upon the driver's sensation of the lead vehicle braking." The dependent-stages driver models accounted for the association between the three variables by sampling from trivariate joint distributions; the independent-stages driver models sampled the variables from independent distributions. Thus a total of eight driver models were developed; these models were then each applied in counterfactual simulations to simulate the models in the same collision-imminent kinematics as the experimental drivers. Crash risk and crash severity measures were used to quantify the safety benefits of the FCW system in comparison to outcomes from the no-warning baseline condition.

2. DRIVER MODELS AND SAFETY BENEFITS

The information-processing approach is perhaps the most influential psychological framework applied to driver behavior models. The central idea supporting the approach is that information flows through a person in a finite number of discrete stages—external stimuli is sent from the sensory organs as symbolic codes to the neuronal networks in the brain, these codes are transformed by cognitive processes (e.g., decision making and response selection) to muscle actions (Figure 1). Actions are then performed upon the environment (J. D. Lee, Wickens, Liu, & Boyle, 2017; Wickens & Carswell, 2012).

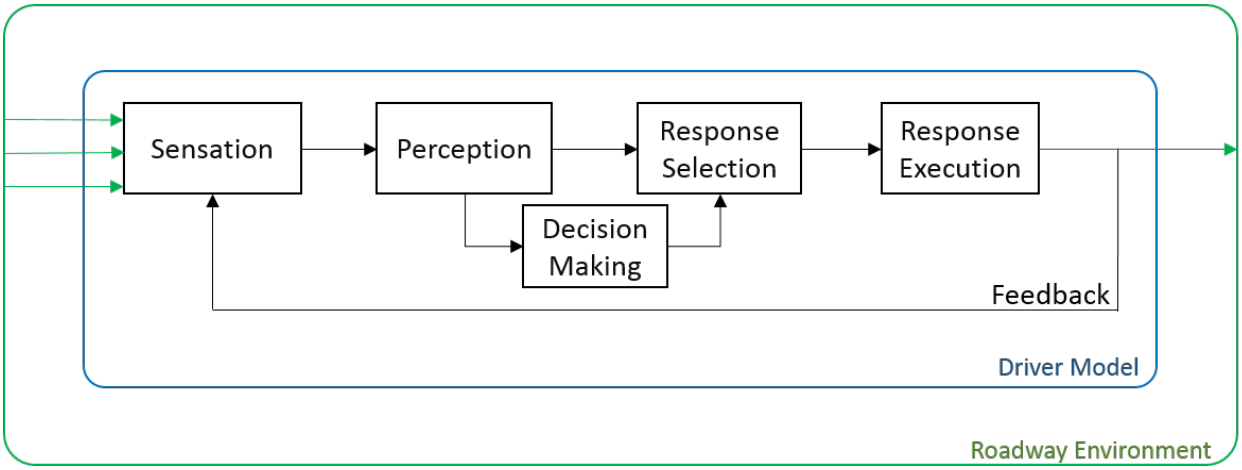

Figure 1. Model of driver response based on an information processing model. Adapted from (J. D. Lee et al., 2017).

2.1 Independent-Stages Models

The independent-stages models are based on two central assumptions of the information-processing approach. First, as represented in Figure 1, these models treat driver behavior as independent stages (e.g., sensation, perception, decision-making, and action). Second, behavior is usually assumed to be constant over the duration of each of these stages, for example, a constant deceleration is applied to simulate drivers' braking behaviors in the action stage, and feedback-based response correction is seldom considered. The current analysis tests if the independent stages approach is consistent with how drivers actually respond.

One common representation of the independent-stages model can be described thus: "the following driver initiates a braking response at a deceleration level $\boldsymbol{\alpha}$ after a reaction time $\boldsymbol{\tau}$ upon the onset of a stimuli (e.g., illumination of brake lights of lead vehicle or the onset of a forward collision warning)." Reaction times and deceleration profiles are not constant, nor consistently correlated, across drivers or across situational kinematics (M. Green, 2000; Summala, 2000). In one application, a log-normal distribution of reaction time (M = 1.21 s, SD = 0.63 s) derived from a naturalistic study (Sivak, Olson, & Farmer, 1982) has been used in FCAM benefits' estimation (Kusano & Gabler, 2010, 2012). The authors used discrete values for deceleration—0.2 g (1.96 m/s^2) for soft and 0.4 g (3.92 m/s^2) for hard braking responses. The values for reaction time and deceleration rates differ between models used for benefits estimations across automakers (Lee & Peng, 2005); often the models assume constant values of reaction times and deceleration rates for all drivers and situations (Bella & Russo, 2011; K. Lee & Peng, 2005). The

deceleration profiles typically resemble a step-response with infinite jerk **j**, which is impossible to achieve. Models that parameterize jerk are rare (Bargman et al., 2017; Markkula, Engström, Lodin, Bärgman, & Victor, 2016), however, jerk seems to reflect the perceived urgency of the situation well (Markkula et al., 2016), making the case for including jerk as a driver model parameter. With the inclusion of jerk as a model parameter, the model in this paper is specified as follows:

"The following driver initiates a braking response with a constant jerk **j** and a deceleration rate $\boldsymbol{\alpha}$ after a reaction time $\boldsymbol{\tau}$ upon the driver's sensation of the lead vehicle braking."

The focus of the analysis is on the parameterization of the model: should associations between the parameters ($\boldsymbol{\tau}$, **j**, $\boldsymbol{\alpha}$) be considered?

2.2 Dependent-Stages Models using Copula Functions

Information processing is rarely sequential; features of acquired sensory data are most likely simultaneously processed (Cowan, 1988). Behavior is a product of these dependent processes and the observed variables are better represented as co-occurring phenomena. Driver models may be better representative of the driver's behavior if the observed associations between parameters can be modeled.

Few driver models have accounted for such associations. One notable example is a study by Fitch and colleagues (2008) in which the safety benefits of a FCAM system for heavy vehicles were estimated. The reaction time parameter in their driver model was sampled from a distribution of perception-reaction time. Linear regression was then used to model the parametric association using deceleration level as the response variable and perception-reaction time as the explanatory variable. However, under the dependent-stages perspective, neither variable necessarily explains the other. Instead, both outcomes should be jointly observed and modeled as the products of the flexible behavioral process. When the focus is on understanding and replicating the co-occurrence of behavioral outcomes, regression models—with focus on explaining outcome variables using explanatory variables—may not be suitable to model the association (Frees & Valdez, 1997). Regression-based models and correlations (such as Pearson's correlation coefficient) typically assume normal distributions and linear dependence; however, it is likely that a behavioral process such as collision-avoidance is non-linear with

different associations between the tails and centers of the multivariate joint distributions of the outcome variables.

In mathematics the word 'copula' denotes a set of functions that models the association between variables in multivariate distributions (Sklar, 1959). Copulas have been widely used in economics and financial applications (Durante & Sempi, 2010; Melchiori, 2003), biological system behavior modeling (Kim et al., 2008), crash-related injury modeling (Eluru, Paleti, Pendyala, & Bhat, 2010; Yasmin, Eluru, Pinjari, & Tay, 2014), and recently in driver behavior modeling (Venkatraman, Lee, & Schwarz, 2015). Copula-based multivariate distributions can be described using two components: the marginal distribution functions of each variable and a copula function that describes the interdependence. Association between variables can be described using a flexible set of measures including distance measures, and correlation coefficients such as the non-parametric and monotonic Kendall's tau or Spearman's rho (Rüschendorf, 2013). In this sense, a copula isolates the marginal functions from the dependency structure (Aas, Czado, Frigessi, & Bakken, 2009; Yan, 2007), such that the marginal distributions do not influence the estimation of dependency.

A multivariate distribution is a copula C between [0, 1] with unit uniform marginal distributions. According to Sklar's theorem, every multivariate distribution F with marginal distribution functions $F_1(x_1), \dots, F_n(x_n)$ can be written as a copula C (Sklar, 1959):

$$F(x_1, \dots, x_n) = C\{F_1(x_1), \dots, F_n(x_n)\}$$

The copula, in turn, can be represented using the inverse distribution functions, $F^{-1}(x)$

$$C(u_1, \dots, u_n) = F\{F_1^{-1}(u_1), \dots, F_n^{-1}(u_n)\}$$

In the trivariate case, a continuous vector X is formed from the variables X_1, X_2, and X_3

$$X = (X_1, X_2, X_3)$$

Using probability integral transformation, the vector X can be transformed into the unit uniform distribution U in [0, 1] such that any desired marginal functions can be applied to the transformed random variables. Correlation coefficients, such as Kendall's tau and Spearman's Rho, if used as the measure of association, are invariant under this transformation (Fredricks & Nelsen, 2007; Frees & Valdez, 1997). Kendall's tau is more robust to the effects of outliers in small sample sizes, as typical in crash data, and was used in this paper.

Multivariate copulas of three or more dimensions, or variables, can be represented by vine structures. Vines split the dimensions into pair-copulas—bivariate copulas on the unit uniform square $[0, 1]^2$. These pair-copulas measure dependency between pairs of dimensions, and then build up the multi-dimensional distribution from the pairs. Association parameters are calculated based on conditional probabilities. Bivariate copulas from a wide range of parametric families (Durante & Sempi, 2010; Frees & Valdez, 1997; Melchiori, 2003) can be fit to the data using vine pair-copulas (Schepsmeier et al., 2016).

2.3 COUNTERFACTUAL ANALYSIS USING COMPUTER SIMULATIONS

Counterfactual analysis is a model-based simulation technique increasingly used in safety benefits applications. The underlying assumption is that the observed event outcome is one possible realization of a stochastic process, and that by modeling the process that generated it, we can produce a better estimate of the full distribution of likely event outcomes. Safety critical events from experimental or naturalistic data are identified, and the benefits of the safety system in each event is estimated by running simulations using different FCAM algorithms, or with the presence and absence of the FCAM system (Bargman et al., 2017). Each counterfactual simulation will replace the original driver's behavior from the experiment or naturalistic event, with an instance of driver behavior generated by the driver model. Safety-relevant outcomes are predicted using crash risk and severity (CR/S) measures. The combination of outcomes from all simulations of one experimental event provide model-based CR/S measures for that event. Combining outcomes from multiple events for one type of crash (e.g. collision with a stopped lead vehicle) provides model-based CR/S measure for that crash type. In transportation research, counterfactual simulations have been used in traffic modeling and accident reconstruction (Davis & Swenson, 2006; McLaughlin et al., 2008), and safety benefits estimations using data from naturalistic studies (Bargman et al., 2017; Victor et al., 2015).

The design of counterfactual simulations for benefits analysis typically proceeds as follows:

1. Kinematic information (positions, speeds, accelerations), environmental information (weather, road condition), as well as drivers' behaviors (reaction times, deceleration profiles) from relevant safety critical events are extracted either from naturalistic data or human-in-the-loop experiments. Driver behavior data may be used to create or tune driver model parameters.

2. The objectives of the analysis drive the identification of an anchor point in the event. The anchor point specifies the instant in time prior to which the facts of the actual event for the following driver hold true. Starting from the anchor point, the event is simulated counterfactually; for example, the human driver's evasive maneuvers are removed and replaced by behavior generated by a driver model. The location of the anchor point in the event timeline is therefore an important decision that influences the accuracy and relevance of the predictions to the analysis objectives. The event kinematics and environmental information at the anchor point is used to set the initial state conditions of the simulation variables, such as vehicle velocities and separation distances. Multiple simulations are performed for each experimental event.

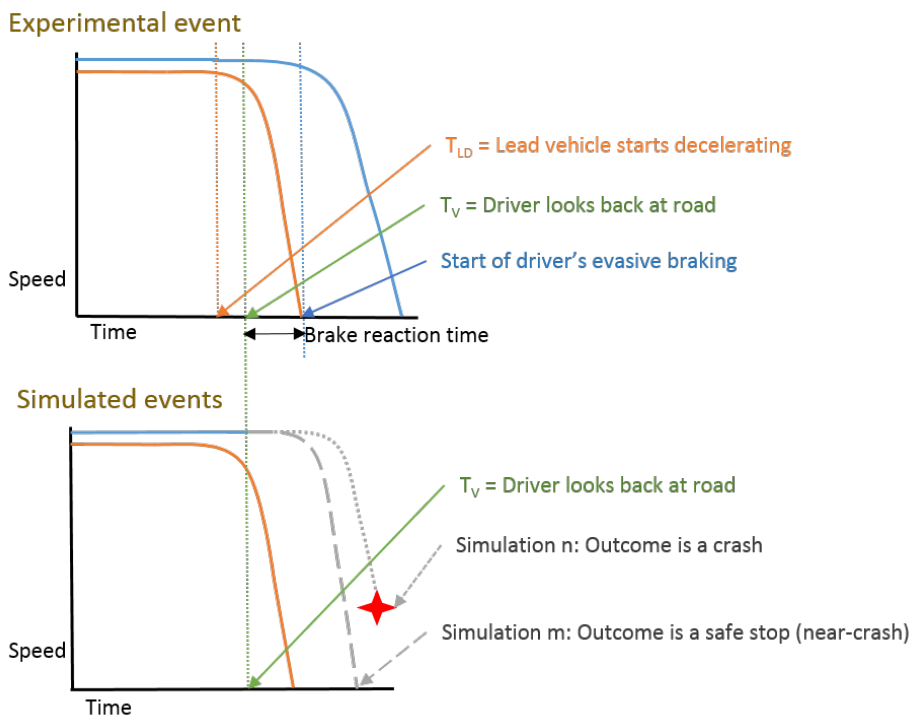

Figure 2. Counterfactual simulations. The top graph represents the experimental event speed time-series for the two vehicles. The bottom graph represents the counterfactual simulations for that event.

In Figure 2, the top graph represents the speed profiles of the lead vehicle (orange curve) and the subsequent collision avoidance response of the following driver's vehicle (blue curve) from the experimental event. The orange vertical line indicates the instant in time (x-axis) when the lead vehicle starts decelerating; the blue vertical line is the corresponding following driver's onset of braking. The bottom graph represents the counterfactual simulations for that event—the lead

vehicle behavior is retained, as is the following driver's response up until the anchor point (green vertical line). The anchor point in this study is defined as the instant of time in which each driver in an event looked back at the forward roadway, away from the secondary task, just before starting a braking avoidance maneuver. The different gray-colored curves indicate model-based braking profiles simulated after the anchor point. Note that the anchor point in the current analysis pertains only to the behavior of the following driver's vehicle; the lead vehicle movement is retained as in the original experimental event.

2.4 MEASURES OF CRASH RISK AND CRASH SEVERITY

The choice of measures in quantifying benefits is important (Green, 2015). To quantify safety benefits of the forward collision warning system in this study, crash risk and crash severity were measured. Crash risk is measured as the probability of crashes—ratio of the number of crashes to total crash and non-crash outcomes. Crash severity is defined only for crashes. Severity can be described using kinematics-based and injury–based measures.

Delta Velocity (Delta-V): This kinematics-based measure is the change in velocity of the involved vehicles at the point of impact. In Equation 1, we assumed that the masses of the two vehicles are identical (m), while the speeds at impact are V_1 and V_2. V_0 is the initial velocity of the following vehicle.

$$\text{Delta} - \text{V} = \text{V}_0 - \frac{\text{m}_1\text{V}_1 + \text{m}_2\text{V}_2}{2\text{m}} \quad (1)$$

Maximum Abbreviated Injury Scale (MAIS): The Abbreviated Injury Scale classifies injury severity of occupants on a 1 to 6 integer scale: 1 being minor injury and 6 being fatal injury. MAIS is the most severe injury suffered by a person involved in an accident (Kusano & Gabler, 2012). We used MAIS 1+, MAIS 2+, and MAIS 3+ injury probability calculated from Delta-V (kmph); the relationship was derived from 2001-2014 NASS Crashworthiness Data System (CDS) with logistic regression (Equations 2 – 3). We filtered the dataset to include MAISn+ only for a passenger vehicle rear-ending another vehicle. The logistic regression may include predictors other than Delta-V, such as seat belt use, but we estimated predictions for the simplest case (i.e., average belt use, average age, etc).

$$\text{MAIS } 1+ = \frac{\exp(-0.53+0.056\Delta\text{V})}{1+\exp(-0.53+0.056\Delta\text{V})} \quad (2)$$

$$\text{MAIS } 2+ = \frac{\exp(-3.3+0.064\Delta V)}{1+\exp(-3.3+0.064\Delta V)} \quad (3)$$

$$\text{MAIS } 3+ = \frac{\exp(-4.5+0.069\Delta V)}{1+\exp(-4.5+0.069\Delta V)} \quad (4)$$

3. SIMULATOR EXPERIMENT

The driving simulator experiment was conducted in 2010 at the National Advanced Driving Simulator (NADS) facility in Iowa City, Iowa. A specific goal of the experiment was to understand drivers' collision avoidance behaviors in rear-end situations as aided by warnings from forward collision warning systems (Lerner et al., 2011).

A 2 (collision scenario) x 2 (scenario order) x 3 (warning system) mixed-factorial design was used. Drivers in the experiment were exposed to two distinct rear-end collision scenarios—an imminent collision with a stopped lead vehicle and an imminent collision with a decelerating lead vehicle. Collision scenario was a within-subjects variable—all drivers experienced both scenarios—scenario order and warning system were between-subjects variables. The order in which the stopped lead vehicle and decelerating lead vehicle events were administered was a between-subjects variable. Half the participants, balanced by gender, experienced the collision-imminent event with a stopped lead vehicle first, followed by the decelerating lead vehicle event. The other participants experienced the events in reverse order.

The forward collision warning system was a between-subjects variable—16 participants were randomly assigned, balanced by gender, to each of three possible conditions. One group was not aided by any warning—baseline no-warning condition. A second group was aided by a combination visual and auditory warning. The visual alert was delivered as a heads-up display LED strip. The lights flashed for 4 seconds at a pulse train period of 200 ms, and a 50% duty cycle. The audio alert was delivered as a tone that beeped for a total length of 4 seconds at a period of 400 ms, and a 50% duty cycle. A third group was aided by a haptic brake pedal pulse warning—no visual or auditory alert was applied. A momentary deceleration (duration ~ 150 ms) of approximately 0.22 g was applied; this was not expected to substantially affect speed profiles when the driver initiated braking.

3.1 Participants

A total of 48 participants (gender-balanced) between 35 and 55 years of age were recruited for the study. Participants were included based on multiple criteria—health, driving experience, use of driving equipment and technology in their vehicle; as well as self-reported potential for distraction while driving. Specifically, participants reported being in good general health, held a valid drivers' license for at least two years prior to the study, and drove a minimum of 10,000 miles per year. Participants who reported owning a vehicle equipped with a forward collision warning system, and those that reported never engaging in distracting tasks while driving, were excluded.

After providing informed consent, participants received information on the vehicle technologies (e.g. forward collision warning system, infotainment system, seat design, etc.) and the secondary task by watching a self-paced slide-deck presentation. Next, participants practiced driving in the simulator to facilitate their adaptation to the vehicle controls, secondary task, and simulator visuals. After the practice session, participants engaged in a single 35-minute drive.

3.2 Apparatus

The NADS-1 is a high fidelity, immersive driving environment (Figure 3, left) with a 360-degree field of view and a large motion base that allows for sustained acceleration cues. All participants drove a 1996 Chevy Malibu sedan. A Face Lab™ 5.0 eye-tracking system was mounted above the steering wheel (Figure 3, right). Four camera views including a view of the driver's face were recorded.

Figure 3. NADS-1 driving simulator (left). Driver position in the cab with the forward roadway view, and eye tracker mounted above the steering wheel (right).

3.3 Scenario Specifications

Drivers were asked to follow a lead vehicle in the right lane of a two-lane bidirectional rural highway. The posted speed limits for both events were 55 mph. In the decelerating lead vehicle event, the vehicle directly ahead of the driver's vehicle decelerated for approximately 2.0 seconds to a speed of approximately 20 mph and then accelerated. In the stopped lead vehicle event, the vehicle ahead of the driver very abruptly decelerated to a stop.

3.4 Secondary Task

A tracking task involving a simulated insect on a touch-display was used to ensure that the participants' focal and peripheral visual attention would be diverted away from the roadway at the start of the imminent collision events (Lerner et al., 2011). The task required the participants to turn and reach into the rear passenger compartment to trace the path of a moving insect on a touch screen display. The insect buzzed to indicate the start of the task, and continued to buzz until the participant successfully caught it. The insect was controlled by an algorithm that moved it away from the participant's finger in random directions at varying speeds. The insect was designed in such a way that it could not be caught until the forward collision event had been triggered, i.e., the lead vehicle had started decelerating in either scenario.

4. RESULTS

Event time-series data (e.g., speeds, brake pedal forces, steering movements) were collected at 240 Hz from the NADS-1 driving simulator and down-sampled to 60 Hz for analysis. The R statistical software (R Core Team, 2017) was used for data preparation and analysis. Eye tracker data were extracted to mark the times at which the driver's gaze moved towards or away from the forward roadway (equivalently, front windshield).

Ninety-six rear-end collision events were expected to be extracted from the dataset (48 participants x 2 collision scenarios). However, a substantial number of events were removed either because of missing data in the eye-tracker or simulator time-series (29 events, ~ 30%), or because the participant primarily steered during the event with very little braking (3 events, ~ 3%). Hence, data from 64 events were extracted (~ 67% of dataset), of which there were 35 stopped lead vehicle events and 29 decelerating lead vehicle events. Eleven of the stopped lead vehicle events and 10 of the decelerating lead vehicle events were in the baseline no-warning

condition. Due to the small number of available events, events with the two FCAM warning modes (brake pedal pulse and visual auditory) were combined. A simple linear regression model was fit to predict each of the three variables—brake reaction time, jerk, and maximum deceleration—with the warning condition (warning present and baseline) and event order. No significant differences in brake reaction time, jerk, or maximum deceleration rate due to the warning mode were observed in either the decelerating or stopped lead vehicle events; except in the stopped lead vehicle events in which the main effect the presence of a warning system resulted in reduced jerk ($p < .05$). No significant main effects due to event order were found in either scenario ($p > .05$). The events were therefore separated into four groups based on the collision scenario and the warning condition: collision with either a decelerating lead vehicle or a stopped lead vehicle, in the presence or absence of a forward collision warning system.

The objective of the analysis was to quantify the benefits of a forward collision warning system on collision avoidance over its absence in each of the scenarios. Time-series data of driver responses (braking and steering profiles), warning onset (for those events with warnings), eye glance data (eye orientation), and event kinematics (vehicles' speeds, positions, accelerations) were combined. The time at which each driver's visual attention returned forward just before the driver's evasive response started, was marked (T_V). The time of FCAM warning onset, other than in the baseline condition, was recorded (T_W). The warnings were set to be triggered at approximately 3.5 s time to collision. In the baseline condition, T_W was marked as the time when this time to collision threshold was crossed. The visual perceptual conditions in this study were generally supra-threshold at the time that the participants looked back at the roadway—the rates of change of optical angle were greater than or equal to 0.01 rad/s (Markkula et al., 2016). Therefore, the brake reaction time (BRT) was calculated as the time to the start of evasive braking—application of brake force greater than 13.4 N (3.0 lbf)—from the time of eye glance return to the forward roadway (T_V). Note that this is not from the start of the warning trigger for the following reason: The insect task was not completely successful in visually distracting the driver long enough for the warnings to fire. Instead, many drivers looked back at the roadway before the warning onset, but after the lead vehicle started decelerating, in all but 3 of the 64 events. Hence, estimated brake reaction times were generally greater than 3.5 s. The brake reaction time (s), jerk (g/s), and the maximum deceleration (g) applied by the driver in each of the 64 events were extracted for use in the driver models. The NADS-1 affords high

deceleration, greater than 1.0 g (9.81 m/s^2), due to ideal conditions that may be rare in normal driving, but not uncommon in collision-imminent events where drivers brake to vehicle limits (S. E. Lee, Llaneras, Klauer, & Sudweeks, 2007; Markkula et al., 2012). It was therefore assumed that braking to the vehicle limits was intended by the drivers in the experiment and maximum deceleration from each event was extracted and used in the models.

4.1 Estimated values for the independent-stages model parameters

Four independent-stages models were created from the experimental dataset. In each of these models, the brake reaction time, jerk, and deceleration variables were sampled from independent univariate distributions based on the four combinations defined by collision scenario and warning condition (Table 1).

Collision Scenario	Warning System	Variable	Parameters	
			Mean Log	SD Log
Stopped lead vehicle	System present	Brake reaction time (s)	1.56	0.19
		Constant jerk (g/s)	-1.00	0.40
		Constant deceleration (g)	-0.19	0.22
	System absent	Brake reaction time (s)	1.67	0.23
		Constant jerk (g/s)	-0.60	0.36
		Constant deceleration (g)	-0.02	0.21
Decelerating lead vehicle	System present	Brake reaction time (s)	0.66	0.53
		Constant jerk (g/s)	0.88	0.49
		Constant deceleration (g)	-0.22	0.23
	System absent	Brake reaction time (s)	0.81	0.58
		Constant jerk (g/s)	-0.88	0.22
		Constant deceleration (g)	-0.39	0.58

Table 1. Parameter values for the independent-stages models. All variables are fit to the lognormal distribution.

4.2 Estimated values for the dependent stages model parameters

The VineCopula package in R (Brechmann & Schepsmeier, 2013; Schepsmeier et al., 2016) was modified to include small sample sizes (≥ 10 instead of strictly > 10), and used to develop the dependent stages driver models. Experimental driving data usually contains smaller numbers of data (8-12 participants in each condition) and care should be taken in interpreting the measures of associations and other parameters estimated from small samples.

BRT, jerk, and deceleration variables were transformed to the unit uniform distributions, and the dependency structure of the pair-copulas was specified using a regular vine form. Kendall's tau was used as the measure of association, and the best-fit copula family for each of the different models was selected (Table 2). Note that copula functions were fit to eight of the twelve pair-copulas; only four were estimated to be independent distributions. The inverse probability integral transformation was then applied to the copula-based trivariate unit distribution to obtain the lognormal trivariate distribution of BRT, jerk, and deceleration, which was sampled and applied to the driver model parameters. The pair-wise distributions for the stopped lead vehicle, system present condition are shown in Figure 4.

Collision Scenario	Warning System	Vine pair copula	Tau	Copula family	Copula Parameter, θ
Stopped lead vehicle	Warning system	BRT, Jerk	0.31	180 Rotated Clayton	0.91
		Jerk, Deceleration	0.48	180 Rotated Clayton	1.87
		(Deceleration, BRT) | Jerk	0.33	Independent	0.00
	Baseline	BRT, Jerk	0.24	Gaussian	0.53
		Jerk, Deceleration	0.75	180 Rotated Gumbel	2.73
		(Deceleration, BRT) | Jerk	0.05	Independent	0.00
Decelerating lead vehicle	Warning System	BRT, Jerk	0.30	Gaussian	0.50
		Jerk, Deceleration	0.58	Gumbel	2.19
		(Deceleration, BRT) | Jerk	0.20	Independent	0.00
	Baseline	BRT, Jerk	0.07	Independent	0.00
		Jerk, Deceleration	0.24	180 Rotated Gumbel	1.80
		(Deceleration, BRT) | Jerk	-0.16	270 Rotated Clayton	-1.36

Table 2. Copula Families and Parameter Values for the Dependent-Stages Models.

4.3 Counterfactual simulation set-up

In addition to the driver model parameters, state variables that denote the event kinematics at the return of drivers' attention (at T_V) were extracted to set up the initial event conditions in the counterfactual simulations.

The R statistical software (R Core Team, 2017) was used for the counterfactual simulations. A simple vehicle dynamics model based on the equations of motion was developed to simulate the movement of both the lead and following vehicles. The initial conditions depended on the particular event being simulated. Twenty thousand simulations were performed for each of the 64 experimental events—10,000 of these sampled the three variables from a trivariate copula distribution (dependent-stages model), and 10,000 simulations sampled variables from three independent univariate distributions (independent-stages model). Thus, a total of 1.28 million simulations were performed.

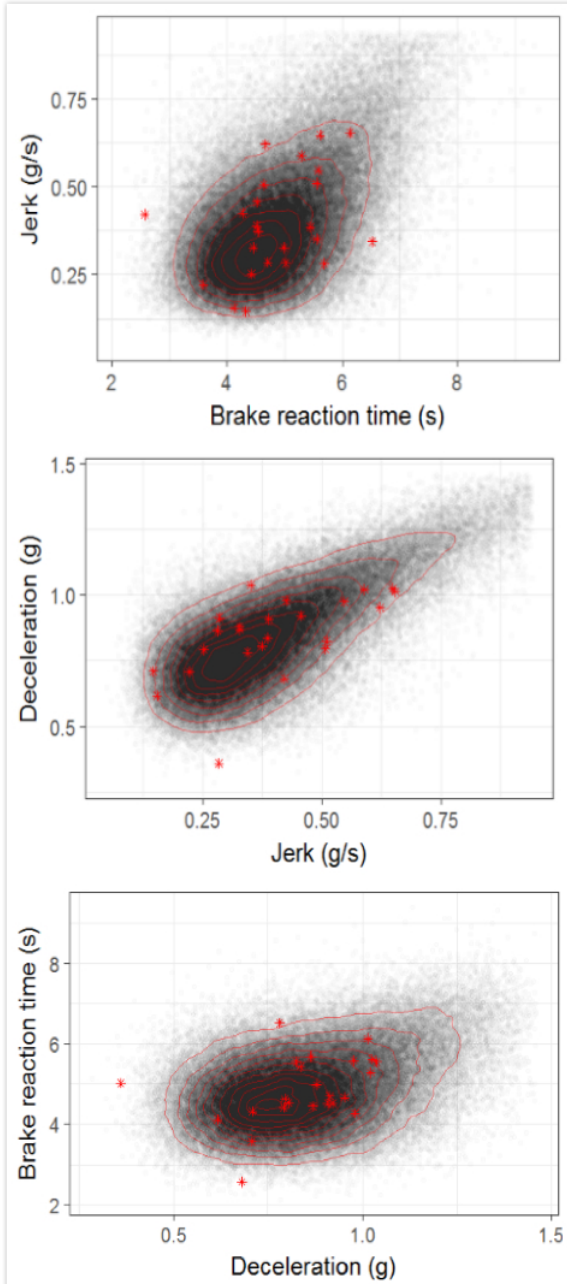

Figure 4. Pair-wise distributions for the trivariate copula (stopped lead vehicle, warning system condition). BRT and jerk, as well as, jerk and deceleration are modeled as 180° rotated Clayton copulas. The jerk and deceleration pair-copula as modeled as an independent distribution. The black dots represented the sampled observations from the simulated copula. The red stars represent the data from the human-driver experimental events.

4.4 Estimation of safety benefits

Crash risk was estimated as the proportion of crashes, and crash severity measures were calculated for those counterfactual simulations that resulted in a crash. The two sample, two-tailed Kolmogorov-Smirnov test

was used to perform pairwise comparisons between Delta-V distributions predicted by the dependent and independent stages models. Each of the four pairwise comparisons reported in Table 3 indicate that the values come from different distributions and the cumulative density functions of the dependent stages models are stochastically greater than the independent stages models. Therefore, the copula-based dependent stages models predict less severe crashes in every condition than the independent stages models.

Collision Scenario	Model 1	Model 2	Warning	K-S test	
				D	p-value
Stopped lead vehicle	Dependent Stages Model	Independent Stages Model	Baseline	0.03	$p < .001$
			Warning System	0.06	$p < .001$
Decelerating lead vehicle	Dependent Stages Model	Independent Stages Model	Baseline	0.02	$p < .001$
			Warning System	0.04	$p < .01$

Table 3. Comparison of Delta-V similarity between the two models across scenarios.

Figure 5 shows the cumulative density function of Delta-V from the simulated crashes. The difference between predictions of the independent- and dependent-stages models in both warning conditions of the decelerating lead vehicle scenario is small (though statistically significant as shown in Table 3)—both models similarly predict crash severity. A larger difference is observed between model predictions in the stopped lead vehicle scenario. To understand the effect of these differences on the predicted safety benefits, the percent reduction in CR/S measures were estimated.

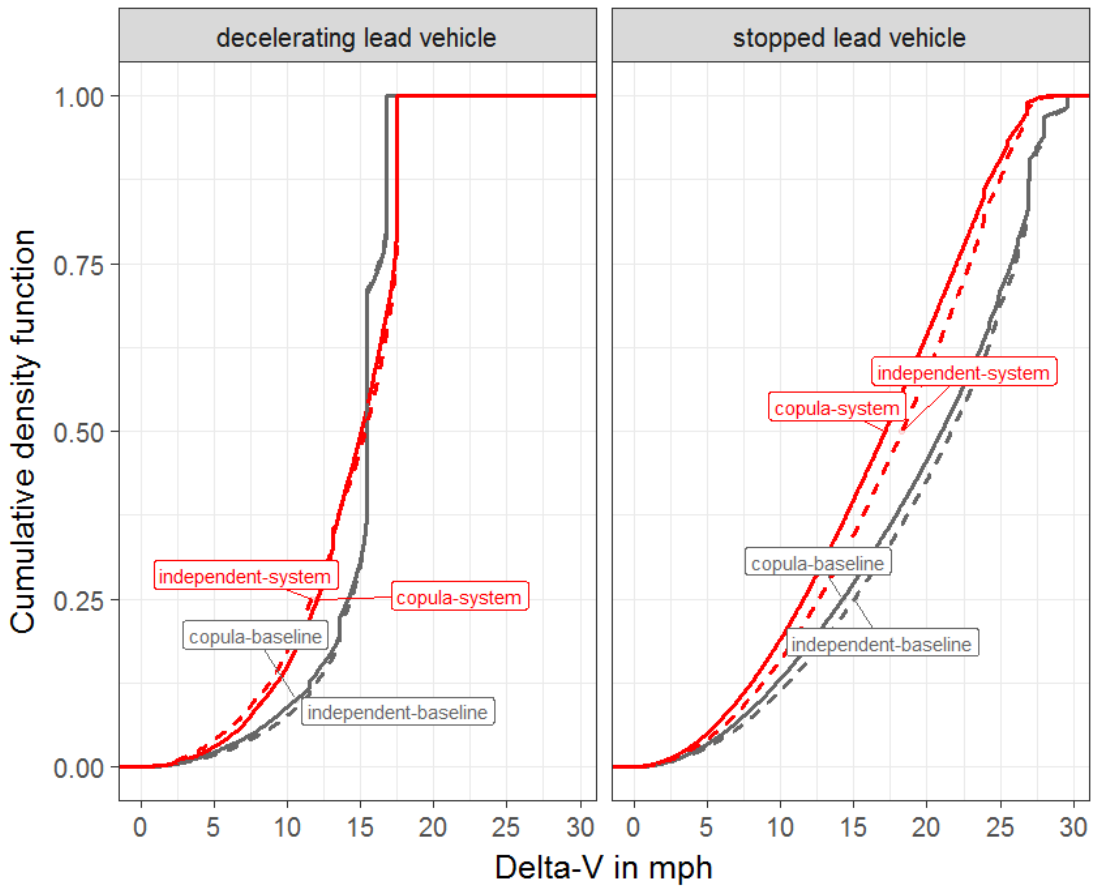

Figure 5. Comparison of the cumulative density function for Delta-V between the independent- (dashed lines) and copula-based dependent-stages (solid lines) models across warning and collision scenario conditions. The warning "system" conditions are in red color; "baseline" no-warning conditions are in gray.

The percent reduction in a CR/S measure (e.g. crash risk, MAIS) when a FCAM system is used, in comparison to the baseline, predicts the safety benefits of the system.

$$\text{Percent reduction in crash risk and severity} = \frac{100*(\mathrm{CR/S}_{\mathrm{Baseline}} - \mathrm{CR/S}_{\mathrm{Warning\ System}})}{\mathrm{CR/S}_{\mathrm{Baseline}}} \quad (5)$$

Crash risk, median values of Delta-V, and median values of MAIS 1+, 2+, and 3+ injury probability were estimated using Equations 1-4 for all the models; the safety benefits were estimated using Equation 5. Table 4 lists the percent reductions in CR/S measures when using a forward collision warning system in comparison with a baseline no-warning. The dependent-stages models predict higher safety benefits of the forward collision warning system—higher percent reductions in crash risk and severity—than the independent-stages models. The differences in predicted outcomes range from approximately 1% to 11%.

Collision Scenario	Driver Model	%reduction in crash risk	%reduction in median Delta-V	%reduction in median MAIS 1+	%reduction in median MAIS 2+	%reduction in median MAIS 3+
Stopped lead vehicle	Independent Stages	-8.02	15.53	6.44	22.46	26.95
	Dependent Stages	2.84	18.41	7.83	25.69	30.46
Decelerating lead vehicle	Independent Stages	54.82	0.64	0.27	0.80	0.95
	Dependent Stages	55.76	2.52	1.05	3.12	3.68

Table 4. Percent reduction in crash risk and median crash severity measures.

When the predictions of the independent- and dependent-stages model are compared in each event, however, the percent difference in median delta-V ranges widely (Figure 6). This suggests that the benefits predictions of the dependent-stages model predict outcomes for certain event kinematics better than others.

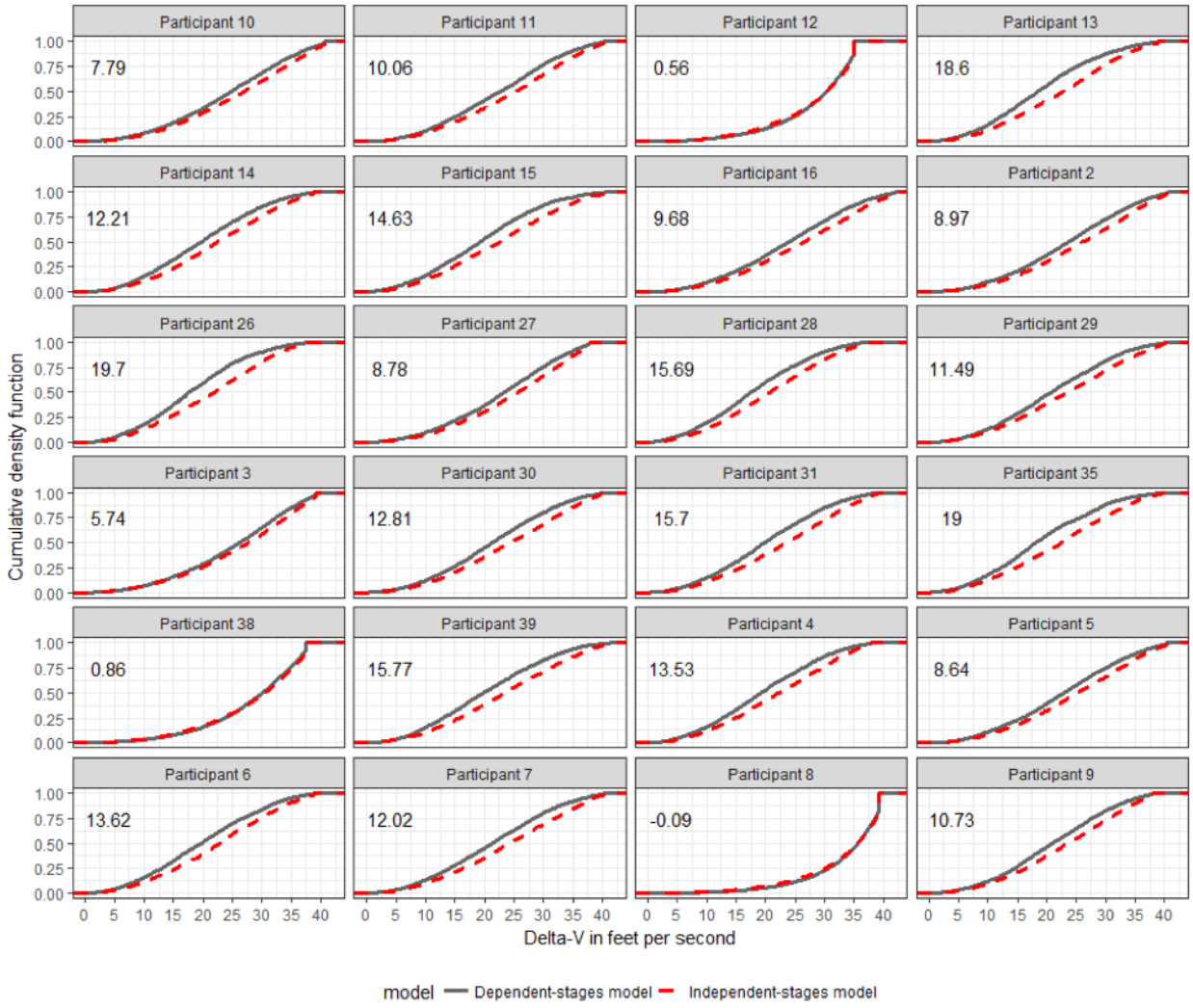

Figure 6. Comparisons between the independent and dependent stages models in the stopped lead vehicle-warning system condition. Percent reduction in median delta-V is labeled in each event. Cumulative density function for delta-V are plotted.

5. DISCUSSION

Models based on the information-processing approach are commonly used to estimate safety benefits of vehicle technologies; however, the validity of their assumptions in representing drivers' response processes has repeatedly been questioned. The empirical evidence for parallel processing of different features of the sensed information across different stages and memory stores—equivalently, in different cognitive processes—indicates that the observed behavior cannot sufficiently be approximated as a linear, unidirectional, independent process, but is a flexible product of interdependent co-occurring processes (Cowan, 1988). Dependencies

between the stages can be mathematically represented using measures of association between behavioral variables; considering the response process in terms of dependent stages can more accurately represent the information-processing mechanisms than the independent-stages models.

Copula functions were used in this paper to model these associations as the dependent-stages models. As shown in Table 2, the presence of bivariate pair-copulas for eight of the twelve pair-copula distributions indicates that the assumption of independence between these variables is invalid. Independence is predicted between brake reaction time and deceleration in three of the four cases (Table 2) only when conditioned on jerk, suggesting that assumptions of independence in bivariate models with brake reaction time and deceleration might also be incorrect. In comparison with the independent-stages models, the copula-based models predict lesser crash risk and severity (Table 3 and Figure 5) as well as larger reduction in estimated benefits when using a forward collision warning system across all experimental conditions (Table 4). The reductions range from 1% - 11%.

Improvements to the quality and quantity of the data might improve the results of this type of simulation-based safety benefits analysis. The secondary task manipulation used in the simulator experiment was not completely successful in distracting the drivers until the warnings fired; this would have improved the accuracy of safety benefits predicted specifically as a function of the warning system. In terms of quantity, as with most human-in-the-loop experiments in driving, the participant sample used in the analysis is small. Estimations of copula fits, of parametric associations as correlation measures, and of the parameters of the marginal distributions, may be less accurate than desired.

The predictions of the dependent-stages and independent-stages models are differentially different between the stopped and decelerating lead vehicle events, as shown in Figure 5. This might partly be due to potential differences in collision-avoidance behavioral strategies across crash types. Copulas might help capture the range of strategies across different crash events. A related application of copulas is in describing time-dependent covariates between measures. Models that account for time-dependent covariates capture mechanisms and strategies used by drivers better than those that ignore such interrelations between measures (Donmez, Boyle, & Lee, 2008). The two models differentially predict outcomes even within a particular crash type

across different initial event conditions. An example from one experimental condition is given in Figure 6. These differences indicate that 'one model type may not fit all'; the information processing framework may be failing to capture certain dynamics of drivers' braking behaviors. Models based on the direct perception framework (Flach, Smith, Stanard, & Dittman, 2003; Gibson, 1979)—perception is assumed to occur in the light rather than in the brain—might be more suitable to model collision-avoidance. These models have been applied in modeling driver braking and steering profiles (D. N. Lee, 1976; Markkula et al., 2016; Salvucci & Gray, 2004), and the choice to brake or steer in imminent rear-end collision situations (Venkatraman, Lee, & Schwarz, 2016). Thus far, most models have assumed a linear combination of perceptual variables as predictors of driver behaviors; copulas might expand these models by describing the associations between the perceptual dimensions.

Driver models have a long history, but are still immature. For the better part of the last century, attempts have been made to understand the complexities of drivers' routine and collision-imminent behaviors (Brown, Lee, & McGehee, 2000; Gibson & Crooks, 1938; Markkula et al., 2012; Michon, 1985; Plöchl & Edelmann, 2007; Ranney, 1999). Successful interventions of vehicle safety technology depend on the accuracy and robustness of the predictions of these driver models. Estimates of safety benefits are only as good as these models (e.g., vehicle dynamics, driver model, scenario models) used in the simulations, and driver models are less mature than models of vehicle dynamics and sensor systems (Markkula et al., 2012). Fundamentally, the assumptions of the information-processing approach are insufficient in modeling cognitive processes; representing the dependencies between these cognitive processes, as well as external situational variables, is critical assessing the benefit of increasingly sophisticated vehicle technologies. Copulas provide a viable means for modeling these dependencies.

6. ACKNOWLEDGMENTS

This work was supported by grants from the Toyota Collaborative Safety Research Center (CSRC) and the Ohio State University Transportation Center (UTC). The authors also thank the staff at the National Advanced Driving Simulator for help with the experiment, and the members of the Cognitive Systems Lab at the University of Wisconsin-Madison for their comments on previous drafts of the paper

REFERENCES

Aas, K., Czado, C., Frigessi, A., & Bakken, H. (2009). Pair-copula constructions of multiple dependence. Insurance: Mathematics and Economics, 44(2), 182–198. http://doi.org/10.1016/j.insmatheco.2007.02.001

Bargman, J., Boda, C. N., & Dozza, M. (2017). Counterfactual simulations applied to SHRP2 crashes: The effect of driver behavior models on safety benefit estimations of intelligent safety systems. Accident Analysis and Prevention, 102, 165–180. http://doi.org/10.1016/j.aap.2017.03.003

Bella, F., & Russo, R. (2011). A collision warning system for rear-end collision: A driving simulator study. In Procedia - Social and Behavioral Sciences (Vol. 20, pp. 676–686). http://doi.org/10.1016/j.sbspro.2011.08.075

Brechmann, E. C., & Schepsmeier, U. (2013). Modeling Dependence with C- and D-Vine Copulas: The R Packatge CDVine. Journal of Statistical Software, 52(3), 1–27. http://doi.org/10.18637/jss.v052.i03

Brown, T. L., Lee, J. D., & McGehee, D. V. (2000). Attention-Based Model of Driver Performance in Rear-End Collisions. Transportation Research Record, 1724, 14–20.

Cowan, N. (1988). Evolving conceptions of memory storage, selective attention, and their mutual constraints within the human information-processing system. Psychological Bulletin, 104(2), 163–191. http://doi.org/10.1037/0033-2909.104.2.163

Davis, G. a., & Swenson, T. (2006). Collective responsibility for freeway rear-ending accidents? Accident Analysis & Prevention, 38(4), 728–736. http://doi.org/10.1016/j.aap.2006.01.003

Donmez, B., Boyle, L. N., & Lee, J. D. (2008). Accounting for time-dependent covariates in driving simulator studies. Theoretical Issues in Ergonomics Science, 9(3), 189–199. http://doi.org/10.1080/14639220701281135

Durante, F., & Sempi, C. (2010). Copula Theory : an Introduction. Copula Theory and Its Applications, 198, 3–31. http://doi.org/10.1007/978-3-642-12465-5

Eluru, N., Paleti, R., Pendyala, R. M., & Bhat, C. R. (2010). Modeling multiple vehicle occupant injury severity:A copula-based multivariate approach. Transportation Research Board, 1–24.

Fitch, G. M., Rakha, H. A., Arafeh, M., Blanco, M., Gupta, S. K., Zimmermann, R. P., & Hanowski, R. J. (2008). Safety Benefit Evaluation of a Forward Collision Warning System (DOT HS 810 910). Washington, DC.

Flach, J. M., Smith, M. R. ., Stanard, T., & Dittman, S. . (2003). Collisions: Getting them under control. In H. Hecht & G. J. . Savelsbergh (Eds.), Time-to-contact (pp. 67–91). Advances in Psychology Series.

Fredricks, G. A., & Nelsen, R. B. (2007). On the relationship between Spearman's rho and Kendall's tau for pairs of continuous random variables. Journal of Statistical Planning and Inference, 137(7), 2143–2150. http://doi.org/10.1016/j.jspi.2006.06.045

Frees, E. W., & Valdez, E. A. (1997). Understanding Relationships Using Copulas. In 32nd Actuarial Research Conference (pp. 1–25).

Gibson, J. J. (1979). The Ecological Approach to Visual Perception. Book (Vol. 40). http://doi.org/10.2307/989638

Gibson, J. J., & Crooks, L. E. (1938). A Theoretical Field-Analysis of Automobile Driving. The American Journal of Psychology, 51(3).

Green, M. (2000). "How Long Does It Take to Stop?" Methodological Analysis of Driver Perception-Brake Times. Transportation Human Factors, 2(3), 195–216. http://doi.org/10.1207/STHF0203_1

Green, P. (2015). SAE Surface Vehicle Recommended Practice J2944 Operational Definitions of Driving Performance Measures and Statistics.

Jermakian, J. S. (2011). Crash avoidance potential of four passenger vehicle technologies. Accident Analysis and Prevention, 43(3), 732–740. http://doi.org/10.1016/j.aap.2010.10.020

Kim, J.-M., Jung, Y.-S., Sungur, E. A., Han, K.-H., Park, C., & Sohn, I. (2008). A copula method for modeling directional dependence of genes. BMC Bioinformatics, 9, 225. http://doi.org/10.1186/1471-2105-9-225

Kusano, K. D. (2013). Methodology for Determining Crash and Injury Reduction from Emerging Crash Prevention Systems in the U.S. Virginia Polytechnic Institute and State University.

Kusano, K. D., & Gabler, H. C. (2010). Potential occupant injury reduction in pre-crash system equipped vehicles in the striking vehicle of rear-end crashes. Annals of Advances in Automotive Medicine/Annual Scientific Conference, 54, 203.

Kusano, K. D., & Gabler, H. C. (2012). Safety benefits of forward collision warning, brake assist, and autonomous braking systems in rear-end collisions. IEEE Transactions on Intelligent Transportation Systems, 13(4), 1546–1555. http://doi.org/10.1109/TITS.2012.2191542

Lee, D. N. (1976). A theory of visual control of braking based on information about time-to-collision. Perception, 5(4), 437–459. http://doi.org/10.1068/p050437

Lee, J. D., Wickens, C. D., Liu, Y., & Boyle, L. N. (2017). An Introduction to Human Factors Engineering.

Lee, K., & Peng, H. (2005). Evaluation of automotive forward collision warning and collision avoidance algorithms. Vehicle System Dynamics, 43(10), 735–751. http://doi.org/10.1080/00423110412331282850

Lee, S. E., Llaneras, E., Klauer, S. G., & Sudweeks, J. (2007). Analyses of Rear-End Crashes and Near-Crashes in the 100-Car Naturalistic Driving Study to Support Rear-Signaling Countermeasure Development. Distribution, (October), 1–125.

Lerner, N., Jenness, J., Robinson, E., Brown, T. L., Baldwin, C., & Llaneras, R. (2011). Crash Warning Interface Metrics Final Report (No. HS-811 470a).

Markkula, G., Benderius, O., Wolff, K., & Wahde, M. (2012). A Review of Near-Collision Driver Behavior Models. Human Factors: The Journal of the Human Factors and Ergonomics Society, 54(6), 1117–1143. http://doi.org/10.1177/0018720812448474

Markkula, G., Engström, J., Lodin, J., Bärgman, J., & Victor, T. (2016). A farewell to brake reaction times? Kinematics-dependent brake response in naturalistic rear-end emergencies. Accident Analysis & Prevention, 95, 209–226. http://doi.org/10.1016/j.aap.2016.07.007

McLaughlin, S. B., Hankey, J. M., & Dingus, T. a. (2008). A method for evaluating collision avoidance systems using naturalistic driving data. Accident Analysis and Prevention, 40, 8–16. http://doi.org/10.1016/j.aap.2007.03.016

Melchiori, M. R. (2003). Which Archimedean Copula is the Right One? SSRN Electronic Journal. http://doi.org/10.2139/ssrn.1123135

Michon, J. A. (1985). A critical view of driver behavior models: What do we know, what should we do? In L. Evans & R. . Schwing (Eds.), Human Behavior and Traffic Safety (pp. 485–520). New York: Plenum Press.

Najm, W. ., Ranganathan, R., Srinivasan, G., Smith, J. ., Toma, S., Swanson, E., & Burgett, A. (2013). Description of Light-vehicle Pre-crash Scenarios for Safety Applications based on Vehicle-to-vehicle Communications. No. DOT HS 811 731.

National Highway Traffic Safety Administration. (2014). Traffic Safety Facts 2014. Retrieved from http://www-nrd.nhtsa.dot.gov/Pubs/811620.pdf\nhttp://www-nrd.nhtsa.dot.gov/Pubs/809778.pdf

Plöchl, M., & Edelmann, J. (2007). Driver models in automobile dynamics application. Vehicle System Dynamics (Vol. 45). http://doi.org/10.1080/00423110701432482

R Core Team. (2017). R: A language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing. Retrieved from https://www.r-project.org/

Ranney, T. A. (1999). Psychological factors that in influence car-following and car-following model development. Transportation Research Part F, 2, 213–219.

Rüschendorf, L. (2013). Mathematical risk analysis (Springer S). Springer-Verlag Berlin Heidelberg. http://doi.org/10.1007/978-3-642-33590-7_1

Salvucci, D. D., & Gray, R. (2004). A two-point visual control model of steering. Perception, 33(10), 1233–1248. http://doi.org/10.1068/p5343

Schepsmeier, U., Stoeber, J., Brechmann, E. C., Graeler, B., Nagler, T., & Erhardt, T. (2016). VineCopula: Statistical Inference of Vine Copulas. Retrieved from https://cran.r-project.org/package=VineCopula

Sivak, M., Olson, P. L., & Farmer, K. M. (1982). Radar-measured reaction times of unalerted drivers to brake signals. Perceptual and Motor Skills, 55(HS-036 264).

Sklar, A. (1959). Fonctions de répartition à n dimensions et leurs marges. Publ. Inst. Statist. Univ. Paris, 8, 229–231. http://doi.org/10.1007/978-3-642-33590-7

Summala, H. (2000). Brake Reaction Times and Driver Behavior Analysis. Transportation Human Factors, 2(3), 217–226. http://doi.org/10.1207/STHF0203_2

Venkatraman, V., Lee, J. D., & Schwarz, C. (2015). From few to many: Using copulas and Monte Carlo simulation to estimate safety consequences. In Proceedings of the Eighth International Driving Symposium on Human Factors in Driver Assessment, Training, and Vehicle Design. Salt Lake City, Utah.

Venkatraman, V., Lee, J. D., & Schwarz, C. (2016). Steer or Brake? Modeling Drivers' Collision Avoidance Behavior Using Perceptual Cues. Transportation Research Record: Journal of the Transportation Research Board2, 16-6657.

Victor, T., Dozz, M., Bärgman, J., Boda, C. ., Engstrom, J., Flannagan, C., … Markkula, G. (2015). Analysis of Naturalistic Driving Study Data: Safer Glances, Driver Inattention, and Crash Risk (Final Report No. S2-S08A-RW-1).

Wickens, C. D., & Carswell, C. M. (2012). Information processing. In G. Salvendy (Ed.), Handbook of human factors and ergonomics (4th ed., pp. 117–161). John Wiley & Songs, Inc.

Yan, J. (2007). Enjoy the Joy of Copulas : With a Package copula. Journal Of Statistical Software, 21, 1–21. Retrieved from http://www.jstatsoft.org/v21/i04

Yasmin, S., Eluru, N., Pinjari, A. R., & Tay, R. (2014). Examining driver injury severity in two vehicle crashes - A copula based approach. Accident Analysis and Prevention, 66, 120–135. http://doi.org/10.1016/j.aap.2014.01.018

Overview of Project 3 work:
3.2 - The Smooth Transfer of Control between the Responsible Human Driver and the Artificial Driving Suite (ADS)
3.3 - Assessing the Risks of Autonomy through Regulation of Maximum Safe Operating Envelopes

Authors:
David Woods (woods.2@osu.edu)
Asher Balkin (balkin.4@osu.edu)

The Ohio State Univeristy
Integrated Systems Engineering

3.2 The Smooth Transfer of Control Between the Responsible Human Driver and the Artificial Driving Suite (ADS)

This sub-project asked several questions about bumpless transfer of control in shared control between human driver and *Artificial Driving Suite* (ADS). How does the responsible human transfer authority to the ADS for it to handle the vehicle within a defined limit of authority or a *safe operational envelope* (SOE)? Then when the situation and context change — the ADS is reaching the end of the delegated operational envelope — how does the human take back authority resuming direct control or re-task the ADS within a new limit of authority?

Note how this work introduces new concepts about human-autonomy systems. The automation is not a thing but rather a suite or network of automated computations which are based on multiple sensor inputs/processing and represent a software intensive system. To call a vehicle autonomous commits the *reification fallacy* mistaking a network of interacting processes as if it were a single thing (see Feltovich, P. J., Hoffman, R.R., Woods. D.D. and Roesler, A. (2004). Looking at Cognitive Engineers Doing Cognitive Engineering: Implications of the Reductive Tendency for the Design of Complex Sociotechnical Systems. *IEEE Intelligent Systems*, 19(3), 90-94.). Thus an accurate label for autonomous capabilities in cars is Artificial Driving Suite or ADS. An ADS and all ADS's have limits, some of which derive from the *creeping complexity costs* associated with software intensive networks. This basic constraint means that an ADS has an *operational envelope*, and its '*safe*' operational envelope changes with as environment, purpose, consequences and capabilities change. As an artificial system all ADS are fundamentally at risk of failure due to *brittleness*. Brittle systems experience rapid performance collapses, or failures, when events challenge boundaries. One difficulty is that the location of the boundary is normally uncertain and moves as capabilities, context, and interdependencies change. Overcoming the fundamental brittleness risk for automated systems with autonomous capabilities requires utilizing techniques to build and sustain resilient performance based on concepts from Resilience Engineering.

Paper 1 "*The Risks of Autonomy: Doyle's Catch*"[1] provides an overview of the risks that emerge as autonomous capabilities are deployed increasing the scale and complexity of the resulting integrated system. Paper 2 "*Four Concepts of Resilience and the Implications for Resilience*

---

[1] Woods, D. D. (2016). The Risks of Autonomy: Doyle's Catch. *Journal of Cognitive Engineering and Decision Making*, 10(2), 131-133.

Engineering"[2] explains basics and addresses misconceptions about the factors that produce resilient performance.

Based on this foundation, the project developed a new architecture for shared control of vehicles with autonomous capability based on Resilience Engineering concepts. The architecture directly addresses the brittleness problem and designs the means for bumpless re-engagement in shared control systems where human roles and ADS interact through delegating, monitoring and changing a shared SOE.

The new architecture for shared control in human-autonomy systems was developed with additional funding from National Science Foundation jointly with adaptive control engineers from MIT. The key to the approach for resilient shared control is regulating the parameter of Capacity for Maneuver (*CfM*) – the remaining range or capacity to continue to respond to ongoing and upcoming demands. Control then should seek to minimize the risk of exhausting a unit's capacity for maneuver as that agent responds to changing and increasing demands (risk of saturation). In the scenarios studied Capacity for Maneuver is lost when the ADS is reaching the end of the delegated operational envelope. The increasing risk of saturating *CfM* triggers re-engagement and re-authorization of a new SOE. The results indicate resilient shared control based on reducing the risk of saturating *CfM* allows for timely and effective human re-engagement following an anomaly. Paper 3 "A Shared Pilot-Autopilot Control Architecture for Resilient Flight. *IEEE Transactions on Control Systems Technology*"[3] provides the details of the new architecture and demonstrates the benefits for simulations of vehicles and human operators.

3.3 Assessing the Risks of Autonomy through Regulation of Maximum Safe Operating Envelopes

Current methods to develop and deploy autonomous capabilities focus on potential benefits and downplay new risks.The risks are associated with the increasing complexity of the computational and sensing resources needed to deliver autonomous capabilities. As this complexity increases, new risks appear and grow — related to the brittleness of complex systems, risks that cannot be addressed with conventional approaches using levels of automation or improved human-machine interfaces. This subproject looked at new directions to consider benefits and risks when deploying new autonomous capabilities. First, based on additional funding on Human-Autonomy Teaming from NASA via joint work with Georgia Institute of Technology, considered a new model for risk-informed calculation of maximum safe operating envelopes for delegating

---

[2] Woods, D. D. (2015). Four Concepts of Resilience and the Implications for Resilience Engineering. *Reliability Engineering and Systems Safety*, 141, 5-9. doi:10.1016/j.ress.2015.03.018.

[3] Farjadian, A. B., Annaswamy, A. M., Thomson, B. and Woods, D. D. (2018). A Shared Pilot-Autopilot Control Architecture for Resilient Flight. *IEEE Transactions on Control Systems Technology*. Revised.

authority to ADSs. The work explored feasibility of near real-time computation and utilization of maximum safe operating envelopes (SOE) to regulate transfers of authority between an ADS and responsible human roles. This initial work identified the need to develop a new method for *Resiliency Trade Space Studies* to assess and mitigate potential risks from deployments of autonomous capabilities. The new method was demonstrated, with follow on funding from NASA, on a real current case of deploying new autonomous capabilities — "A Resiliency Trade Space Study of Detect and Avoid Autonomy on Drones When Communications are Degraded." Paper 4 presents the method for Resiliency Trade Space Studies of new deployments of autonomous capabilities.[4]

Foundational Results

The above work also led to a major advance in Resilience Engineering applicable to autonomous systems. The advance is a the first comprehensive theory about networks of people and machine agents as an adaptive system. The theory was crucial to the development of the above project results and can guide other innovative designs of human-autonomy systems. Paper 5 "The Theory of Graceful Extensibility: Basic Rules that Govern Adaptive Systems."[5] presents the formal general theory. The theory is already being applied to other systems with high autonomy (Grayson, 2018).

Other Publications, Invited Addresses, Workshops

Farjadian, A. B., Annaswamy, A. M. and Woods, D. D. (2017). Bumpless Reengagement Using Shared Control between Human Pilot and Adaptive Autopilot. In Proceedings of the 20th World Congress The International Federation of Automatic Control (IFAC), Toulouse, France, July 9-14, 2017.

Grayson, M. R. (2018). Approaching Saturation: Diagnosis and Response to Anomalies in Complex and Automated Production Software Systems. MS Thesis: The Ohio State University.

Woods, D. D. Invited Talk, "Risks of Autonomy: The Future is Already Here and It Doesn't Work as Advertised." International Symposium Human Factors in Automation, TNO, Soesterberg, The Netherlands, October 12-13, 2016. http://csel.org.ohio-state.edu/videos/Woods_TNO_Talk.mp4

---

[4] Woods, D. D. and Balkin, E. A. (2018). A Resiliency Trade Space Study of Detect and Avoid Autonomy on Drones When Communications are Degraded. Report for NASA Ames Research Center June 30, 2018.

[5] Woods, D. D. (2018). The Theory of Graceful Extensibility. *Environment Systems and Decisions,* 38:433–457. https://doi.org/10.1007/s10669-018-9708-3

Woods, D. D. Invited speaker, “Transformative concepts in human-autonomy teaming: New roles, new risks, new opportunities.” NextGen Flight Deck Symposium, NASA Langley Research Center, Hampton, VA, February 15-16, 2017.

Woods, D. D. Invited speaker, Expert Workshop on Control and Responsible Innovation in the Development of Autonomous Machines, Hastings Center, Garrison, NY, April 25-27, 2016.

Woods, D. D. Plenary Address, Autonomous capabilities: The future is already here & it’s not as advertised. 19th International Symposium on Aviation Psychology (ISAP), May 10, 2017.

Woods, D. D. Workshop on Autonomy, Complexity and Resilience. Human Factors and Systems Safety Thinking. EuroControl, Brussels Belgium, September 28, 2017.

Woods, D. D. “Stories of technology change reveal the congestion, cascades & conflicts that arise when apparent benefits get hijacked,” Workshop on New Perspectives on Sustainability and Resilience. Launch of Purdue’s interdisciplinary initiative on “Building Sustainable Communities,” Purdue University, West Lafayette, IN, March 23-24, 2017.

Woods, D. D. “Deploying Autonomous Capabilities: Resilience, Detect & Avoid, & Degraded Comms,” RTCA Special Committee Meeting, Washington DC, July 10-11, 2017