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Int. J. Human-Computer Studies 70 (2012) 967–979

International Journal of Human-Computer Studies

www.elsevier.com/locate/ijhcs

Warn me now or inform me later: Drivers' acceptance of real-time and post-drive distraction mitigation systems

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Received 13 September 2011; received in revised form 5 June 2012; accepted 10 August 2012
Communicated by S. Wiedenbeck
Available online 29 August 2012

Abstract

Vehicle crashes caused by driver distraction are of increasing concern. One approach to reduce the number of these crashes mitigates distraction by giving drivers feedback regarding their performance. For these mitigation systems to be effective, drivers must trust and accept them. The objective of this study was to evaluate real-time and post-drive mitigation systems designed to reduce driver distraction. The real-time mitigation system used visual and auditory warnings to alert the driver to distracting behavior. The post-drive mitigation system coached drivers on their performance and encouraged social conformism by comparing their performance to peers. A driving study with 36 participants between the ages of 25 and 50 years old ($M=34$) was conducted using a high-fidelity driving simulator. An extended Technology Acceptance Model captured drivers' acceptance of mitigation systems using four constructs: perceived ease of use, perceived usefulness, unobtrusiveness, and behavioral intention to use. Perceived ease of use was found to be the primary determinant and perceived usefulness the secondary determinant of behavioral intention to use, while the effect of unobtrusiveness on intention to use was fully mediated by perceived ease of use and perceived usefulness. The real-time system was more obtrusive and less easy to use than the post-drive system. Although this study included a relatively narrow age range (25 to 50 years old), older drivers found both systems more useful. These results suggest that informing drivers with detailed information of their driving performance after driving is more acceptable than warning drivers with auditory and visual alerts while driving.

Keywords: Driver distraction; Distraction mitigation; Feedback; Technology Acceptance Model

1. Introduction

According to the Centers for Disease Control and Prevention, traffic-related crashes are the leading cause of death for those from 8 to 24 years old (Subramanian, 2012). Risky behaviors such as speeding, seat belt disuse, and alcohol consumption are predominant contributors to traffic-related fatalities (Sivak et al., 2007). Adding to these contributors is driver distraction—"the diversion of attention from activities critical for safe driving toward a competing activity" (Regan et al., 2009, p. 7). This is particularly true as ubiquitous computing introduces many new devices into the car, ranging from navigation aids to social networking applications. Even such common tasks as selecting a song from a playlist can lead drivers to look away from the road for a dangerously long time (Lee et al., 2012). Interface modality is also an important consideration because compared to visual interfaces, auditory interfaces can be less distracting and easier to use, but can increase task completion times (Sodnik et al., 2008).

As the number of devices carried into the vehicle increases, so does the potential for distraction to contribute to crashes. For example, 40% of drivers report using add-on media devices, 50% use hand-held cell phones, and 60% read text messages while driving (Lansdown, 2012). Even though many drivers believe engaging in these activities is not dangerous (Wogalter and Mayhorn, 2005), using a cell phone results in a fourfold increase in crash likelihood (McEvoy et al., 2005) and texting while

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http://dx.doi.org/10.1016/j.ijhcs.2012.08.002

driving is associated with a 23-fold increase in crash likelihood (Olson et al., 2009). In 2009 alone, distraction associated with these and other activities contributed to 5,474 deaths and nearly 448,000 injuries in the United States (NHTSA, 2010). To the extent that drivers fail to recognize the risk of distraction, providing drivers with feedback might help mitigate the adverse consequences of distraction.

1.1. Feedback to reduce driver distraction

The large number of distraction-related deaths and injuries has prompted many potential solutions, ranging from legislation that outlaws activities to design guidelines that minimize distraction (Regan et al., 2009). One approach to alleviate this issue uses in-vehicle technology to give drivers feedback on their performance. Feedback has substantial promise as a way of shaping safer behavior. According to Schmidt and Bjork (1992), "it [is] understood that any variation of feedback…that makes the information more immediate, more accurate, more frequent, or more useful for modifying behavior will contribute to learning" (p. 212). Hence, more accurate knowledge of skills and capabilities should enable drivers to make accurate assessments of their ability to use a device while driving and adjust behavior accordingly. This suggests that feedback might be a powerful way to reduce distraction-related crashes (Lee, 2009).

Evidence from several other driving studies confirms the promise of using feedback to reduce risky driving behaviors. For example, giving feedback about compliance of traffic laws led both young and older drivers to commit 3.5 fewer speed violations per 15–20 min drive and to stop 25% more often at stop signs and signalized intersections (de Waard et al., 1999). For traffic officers, feedback and supervisory inspections reduced the physical injury accident rate from 0.75 accidents to zero accidents per 100,000 miles (Larson et al., 1980). A feedback system warning drivers that they were following too closely reduced the amount of time drivers spent in short headways (<0.8 s) from 20% to 15% and increased the time spent in long headways (>1.2 s) from 57% to 65% (Shinar and Schechtman, 2002).

The effect of feedback has also been examined with driver distraction. A series of studies by Donmez et al. (2007, 2008) assessed how different types of feedback affected driving performance. Real-time feedback influences immediate performance, but does not provide detailed information that might be needed to affect long-term behavior (Donmez et al., 2008). Post-drive feedback is provided after the driver completes the trip and contains more detailed information that might change long-term behavior by helping drivers to be more aware of dangerous situations (Donmez et al., 2008). Real-time feedback led drivers to glance less toward the distracting device, thereby modulating their engagement in distracting activities (Donmez et al., 2007). When real-time feedback was combined with post-drive feedback, drivers responded to a braking lead vehicle more quickly and made longer glances to the roadway (Donmez et al., 2008).

Although real-time and post-drive feedbacks have proven to be beneficial in some instances, giving feedback does not always improve driving performance. For example, some characteristics of a driving coaching system (e.g., negatively framed feedback) led to no change or even undermined driving performance (Arroyo et al., 2006). Hence, only certain types of feedback actually increase safety.

One feedback approach that has yet to be tested relies on using social norm conformance to promote safe driving behavior. A powerful way to change behavior is to change attitudes towards the behavior and the subjective norm regarding the behavior (Ajzen, 1991; Fishbein and Ajzen, 1975). As stated by Bernheim (1994), "individual behavior is motivated by social factors such as the desire for prestige, esteem, popularity, and acceptance. As these factors are so widespread, they also produce conformism and those who do deviate from the norm are often penalized" (p. 842).

The notion of modifying one's behavior according to those within the same social network has been seen within the Framingham Heart Study with obesity (Christakis and Fowler, 2007), smoking (Christakis and Fowler, 2008), and happiness (Fowler and Christakis, 2008). Feedback enforcing social norms can also reduce binge drinking among college students (Agostinelli et al., 1995; Neighbors et al., 2004) and can encourage safe driving behaviors among pizza deliverers (Ludwig et al., 2002). Using social norm conformance to promote a behavior change can prove to be a particularly powerful form of feedback to deter driver distraction. Therefore, one of the goals of this study was to assess how different forms of feedback influence driver's acceptance of the feedback technology. In particular, following the methodology of Donmez et al. (2007, 2008), both real-time auditory and visual alerts were to be compared to post-drive reports that use social norm conformance to change behavior. While potentially powerful, such feedback must be accepted by drivers if it is to realize its potential.

1.2. Technology acceptance

Feedback effectiveness depends on drivers' acceptance and trust. Several frameworks and methodologies exist that describe how people adopt and accept new technology. Of particular prominence within the driving domain is a simple method that assesses system usefulness and satisfaction (Van Der Laan et al., 1997). Among the more advanced models, the Technology Acceptance Model (TAM) has proven to successfully predict technology use and is broadly used after more than three decades since its introduction. The TAM (Davis et al., 1989), built upon the Theory of Reasoned Action (TRA) of Fishbein and Ajzen (1975), posits that perceived usefulness (PU) and perceived ease of use (PEOU) are the main determinants of attitude toward a technology, which in turn predicts behavioral intention to use (BI) and actual use. Further research has shown that attitude only partially mediates the effect of PU on BI, thus suggesting that attitude could be excluded from the model (Davis and Venkatesh, 1996; Venkatesh

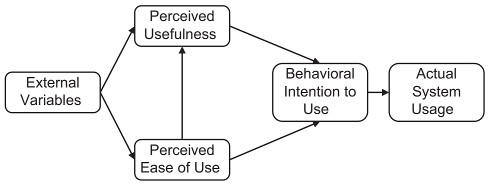

Fig. 1. Parsimonious Technology Acceptance Model.

and Davis, 2000). The resulting parsimonious TAM is shown in Fig. 1. The high reliability and validity of the TAM constructs are robust to measurement instrument design (Davis and Venkatesh, 1996). The TAM has been used to assess user acceptance in a variety of domains and has consistently explained a major proportion of variability in use intentions and behavior. These properties make the TAM an apt framework for understanding how people respond to technology innovations such as distraction mitigations systems.

The TAM provides a conceptual framework for quantitatively assessing the relationships between external variables (e.g., user characteristics and system features) and user's perceptions, as well as the relationships between these perceptions and user's attitudes and intentions. The TAM's flexibility has enabled researchers to assess the importance of many constructs and relationships not originally part of the model. Examples of such constructs are task-technology fit (Dishaw and Strong, 1999), trust (Gefen et al., 2003), experience and voluntariness (Venkatesh and Davis, 2000), and privacy invasion and fairness (Zweig and Webster, 2002). In another example, Yi and Hwang (2003) added three motivation variables, i.e., self-efficacy, enjoyment, and learning goal orientation, to the TAM framework to predict web-based information systems' use. Another implementation of TAM involved decomposing the TAM and extending it with constructs based on the expectancy disconfirmation theory to assess the continued intention to use e-learning services (Roca et al., 2006).

Despite extensive use of the TAM to assess information systems in other fields, only recently has it been applied to driving assistance systems. Xu et al. (2010) used the TAM to assess acceptance of advanced traveler information systems by incorporating four domain-specific constructs (information attributes, trust in travel information, socio-demographics, and cognition of alternate routes). Chen and Chen (2011) also used the TAM for evaluating acceptance of GPS devices, customizing the framework by adding perceived enjoyment and personal innovativeness constructs. Other studies have also used the TAM constructs in their analysis of driving assistance systems (Adell, 2010; Meschtscherjakov et al., 2009), finding that perceived system disturbance and perceived risk, as well as social factors, strongly influence behavioral intention to use a system. These studies demonstrate the applicability of the TAM framework to in-vehicle systems assessment and provide deeper background and structure of drivers' acceptance than simpler frameworks (Ghazizadeh et al., 2012).

1.3. Purpose of study

Distraction mitigation systems are a promising means of addressing driver distraction, but only if drivers accept them. In other domains, the TAM has predicted acceptance and offers a promising framework for assessing acceptance of distraction mitigation systems. Consequently, the goal of this study was to examine how a real-time mitigation system, using auditory and visual alerts, or a post-drive mitigation system, using the concept of social norms, affect driver acceptance.

2. Methods

2.1. Participants

Thirty-six drivers (18 females and 18 males) between the ages of 25 and 50 ($M=34$, $SD=8$) participated in the study. Given the nature of the mitigation systems, all drivers were required to have normal hearing or fully corrected hearing and were able to drive without the use of corrective eye glasses. Participants were required to have experience engaging in distracting activities while driving, including talking on a cell phone, sending or receiving text messages, or changing compact discs. They were also required to possess a valid driver's license for at least one year and to have driven more than 3000 miles per year.

2.2. Apparatus

Data were collected using the NADS-1, a high-fidelity, motion-based driving simulator located at the University of Iowa. The simulator had a Chevrolet Malibu cab that is equipped with eye and head-tracking hardware, active feel on steering, brake, and accelerator pedal, and a fully operational dashboard. A research grade Seeing Machines faceLAB^{tm} version 5.0.2 system with dash-mounted dual stereo head channels was used for eye tracking.

2.3. Driving scenario and distracting tasks

The study included driving through urban, interstate and rural roadways. Participants completed one self-paced radio task and three types of prompted secondary tasks: a reaching task, a visual/manual task, and a cognitive task that did not require them to take their eyes of the road. The reaching task required drivers to reach to the back passenger side seat and follow a moving display with their finger (see Fig. 4 for an example). The visual/manual task presented drivers with a series of matrices of arrows on a three-inch diameter touch screen mounted at the top of the center console, 4.5 in. horizontally and 8.5 in. vertically from the center of the steering wheel. The participant had to view this screen and discern whether one target arrow (approximately 0.5 in. tall) was present in a field of sixteen arrows (Fig. 2). In the cognitive task, drivers traversed an interactive voice response menu that required them to

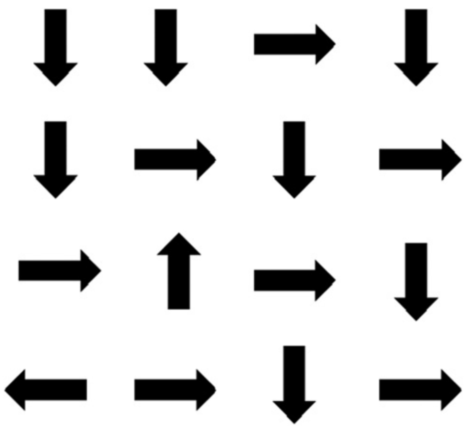

Fig. 2. Example of visual/manual task; the target arrow is pointing upward.

verbally respond to prompts from the system based upon information they were given concerning a fictional flight to determine if the flight was on time. When drivers were not engaged in the prompted distracting tasks, they were presented with the self-paced radio task that required them to adjust a setting to reduce the noise level.

2.4. Distraction detection and feedback

2.4.1. Distraction detection

In this experiment, both visual and cognitive distraction were detected. Visual distraction occurs when a driver looks away from the road, neglecting safety critical information—eyes off the road distraction. Cognitive distraction occurs when a driver thinks about something other than driving, neglecting safety critical information—mind off the road distraction (Victor, 2005). Using drivers' eye movements, an algorithm based on the amount of time drivers gaze at the percent road center (PRC) was used to gauge both visual and cognitive distraction (Victor, 2010; Victor et al., 2009). PRC was defined as a circle of ten degrees centered on the most frequent gaze angle during normal driving. For visual distraction, the PRC level was determined using a running 17.3-s window. For cognitive distraction, the PRC level was determined using a 60-s running window. After distraction was detected, the PRC level was reset to a nominal value based on the assumption that the associated real-time feedback would divert drivers' attention back to the roadway. The PRC level was determined using a combination of eye-tracking, head-tracking, and seat sensor data. When eye-tracking data was poor (e.g. if drivers were not looking straight ahead while completing the visual/manual or reaching task), a head tracker was used to determine drivers' eye movements. When the head tracker was unavailable, pressure sensors in the driver's seat were used to detect distraction. The difference between the left and right seat sensors was used to determine lateral shifts in weight. If the shift was above a certain threshold, it was interpreted as a glance away from the road center. When eye tracking, head tracking, and seat sensor data were unavailable (approximately 10% of the time), the algorithm calculation was paused until eye or head tracking was resumed or there was a shift in weight.

2.4.2. Real-time feedback

The real-time mitigation system was designed to direct driver's attention to the road with visual and auditory alerts when visual or cognitive distraction was detected. Visual alerts were displayed on the windshield to the left, right, and in the center of the driver's field of view using three white LED lights.

The LEDs in the left and right positions were intended to mitigate distraction when the driver's gaze was concentrated on the center of the road during periods of cognitive distraction, i.e., the PRC level was above 82%. The LEDs flashed in the same rate, but with an offset, creating a left–right alternating pattern (blink pattern: 50% duty cycle, 1000 ms period, 100 ms on/off). There was no auditory alert associated with cognitive distraction.

The LED in the center was used to redirect attention to the road during periods of visual distraction. There were two visual distraction alerts: (1) a long glance alert, activated when drivers had a single three-second glance away from the road center; and (2) a glance history alert, activated when drivers were currently glancing outside of the road center and had not spent enough time looking at the road center, i.e., the PRC level was below 60%. The flash rate was the same for both visual alerts and was synchronized with auditory tones. To differentiate the two visual distraction alerts, the long glance alert was indicated by a lower frequency tone than the glance history alert.

2.4.3. Post-drive feedback

The post-drive mitigation system was designed to encourage drivers to focus on the primary driving task by comparing their driving performance to their peers. It was comprised of a report card with: multi-level feedback about the driver's distraction level, a video of distracted driving from the completed trip, and related performance and behavior measures.

The first screen provided feedback about the driver's distraction level over the course of the drive (Fig. 3). It displayed a line graph of the maximum, normalized value of the distraction detection algorithm (referred to as "distraction level") across three levels of distraction (low, medium, and high). The feedback also compared participants' distraction level to their peer driver group. Peer data were generated from a previous experiment, weighting non-distracted drive data and distracted drive data 10–1 to present peer distraction-level data that was comparable to or better than the participant's data.

Participants also received a distracted driving score based on the comparison of the participant's distraction level to the peer distraction level, where

A Participant's average score was equal to or less than the peer score.

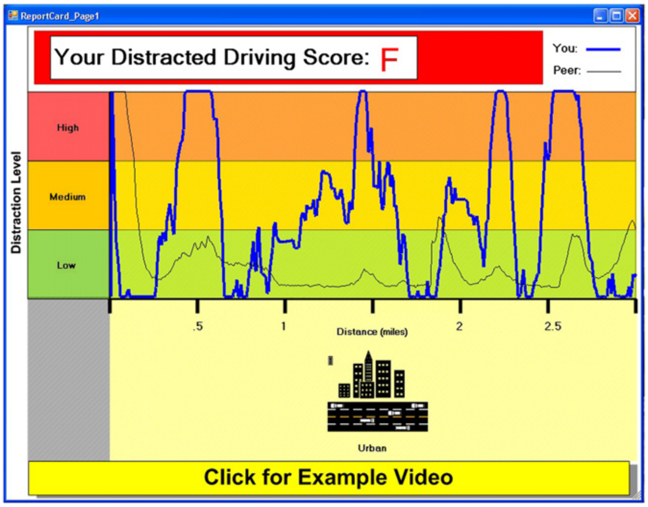

Fig. 3. Post-drive report card distraction level screen.

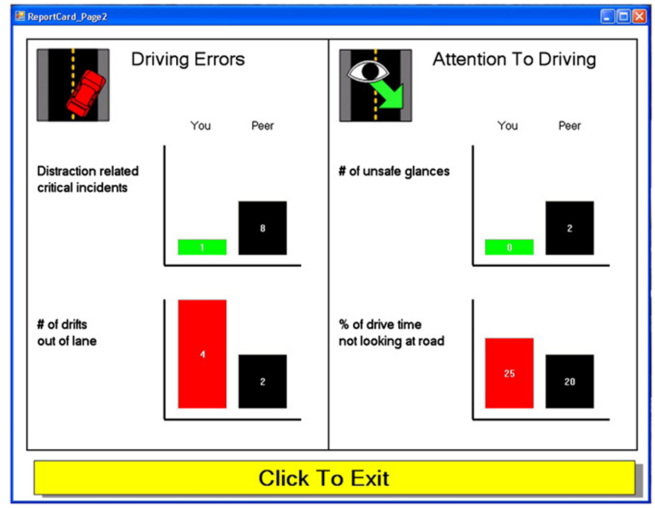

Fig. 5. Post-drive report card showing detailed distracted driving data.

Fig. 4. Post-drive report card showing video of distracted driving; in the video, the participant is completing the reaching task.

B Participant's average score was between 0% and 25% greater than peer score.

C Participant's average score was between 25% and 50% greater than peer score.

F Participant's average score was more than 50% greater than peer score.

From the distraction level screen, participants clicked a button to view a video of their distracted driving during the previous trip (Fig. 4). A second screen provided an explanation of the video, including the type of distraction (''too frequent glances off road'', ''tunnel vision—staring at the same area'', or ''eyes off road'') and the safety critical performance measure (''weaving'', ''lane departure'', or ''collision''). Next, a 15-s video showed the participant's face and forward view for 5 s preceding a distraction output by the distraction detection algorithm and spanning a 10-s event window. The instance of distracted driving displayed was determined by a distraction event scoring algorithm based on collisions, lane departures, and maximum lateral acceleration. If no criteria were met for the video selection, the participant did not view a video.

The last screen presented detailed performance and behavior measures using bar graphs (Fig. 5). ''Driving errors'' graphs represented distraction-related critical incidents and number of drifts out of lane, while ''attention to driving'' graphs represented number of unsafe glances (>3 s) and percentage of time not looking at the roadway.

2.5. Procedure

First, participants provided informed consent and completed a series of pre-experiment questionnaires. Then, they watched a presentation that described the simulator cab and the distracting tasks they would complete during their drives. Participants were instructed to complete as many tasks as quickly as possible, while driving safely.

After a brief overview of the simulator cab, participants practiced the distracting tasks in the vehicle cab without driving. Next, participants completed a practice drive that familiarized them with the driving simulator and provided practice on the distracting tasks while driving. Afterwards, participants completed a set of questionnaires and a second practice of the distracting tasks without driving.

Participants then completed a series of drives: (1) the distraction drive, a drive performing distracting tasks without feedback; (2) three short feedback training drives, to familiarize participants with their respective mitigation system while performing the distracting tasks; and (3) the feedback drive, a drive performing distracting tasks with feedback. Participants were divided into three equal groups. One third of the participants experienced post-drive feedback (hereafter referred to as the post-drive group) at the end of the distraction drive, after each road segment in the training drive, and following each road segment of the feedback drive. Another third of the participants experienced real-time feedback (hereafter referred to as the real-time group) during the entire training drive and the entire feedback drive. The remaining third of the participants (hereafter known as the no-feedback group) served as a control condition and received no feedback.

During the distraction and feedback drives, after each road segment, participants stopped driving during natural break points. While stopped, participants completed any deferred distracting tasks and a set of questionnaires. After the final drive, drivers completed a variety of post-experiment questionnaires and the technology acceptance survey. The real-time and post-drive groups gave technology acceptance ratings for the respective mitigation system they used (e.g., the real-time group rated the real-time mitigation system). The no-feedback group completed the technology acceptance survey by rating imagined products similar to the real-time and post-drive systems used in the study. In particular, the real-time mitigation system was described as a system that redirects attention to the roadway when one is distracted while the post-drive mitigation system was described as a system that provides feedback about distracted driving after the drive. The no-feedback group rated the real-time mitigation system first followed by the post-drive system. Participants were then debriefed and compensated. Fig. 6 displays the timeline of events that occurred in the driving simulator. While the real-time feedback is not shown in Fig. 6, it was presented to the real-time group throughout the entire training and feedback drives.

2.6. Assessment of technology acceptance

Driver acceptance was assessed using the TAM framework (Davis, 1989, 1993), which measures acceptance in terms of perceived usefulness (PU), perceived ease of use (PEOU), and behavioral intention to use (BI). A factor analysis was conducted to ensure that the questions loaded on the TAM constructs as expected. While the PU and BI factors emerged consistent with expectations, two questions that were initially grouped under PEOU, one pertaining to annoyance and one pertaining to distraction, separated from the other PEOU questions to form a new factor ('unobtrusiveness', henceforth). As such, four factors were evaluated in relation with acceptance: PU, PEOU, unobtrusiveness, and BI. Although unobtrusiveness is not included in the original TAM, previous research indicates that unobtrusiveness, or its opposite—annoyance—may affect system use and trust (Horowitz and Dingus, 1992; Lees and Lee, 2007; Meschtscherjakov et al., 2009; Tan and Lerner, 1995). Therefore, it was suspected that unobtrusiveness influences PU, PEOU, and BI.

Table 1 shows the survey questions and their associated acceptance measures. To form each measure of acceptance, survey questions were combined in an equally weighted average. Some items were re-coded so that higher values were associated with positive responses; these are indicated with an asterisk in Table 1. The real-time and post-drive groups each completed one set of questions related to the specific system they experienced. The no-feedback group completed one set of PU, PEOU, and unobtrusiveness questions about real-time feedback and one set about post-drive feedback. However, they were only asked a single set of BI questions about distraction warning systems in

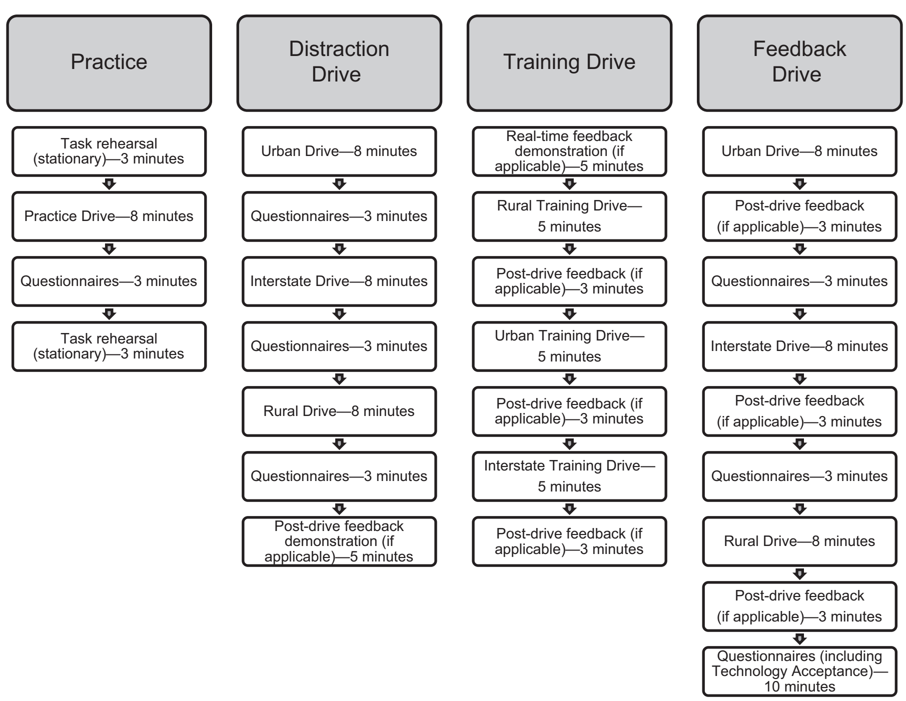

Fig. 6. Timeline for procedures in the driving simulator.

Table 1
Survey questions and their relation to the acceptance measures.

Acceptance measure	Survey question	Scale
Perceived Usefulness (PU)	"Using the distraction warning system would make me a safer driver"*	Strongly agree (1)→strong disagree (7)
	"Using the distraction warning system would make it easier to drive"*	Strongly agree (1)→strong disagree (7)
	"Using the distraction warning system would make me more aware of the driving situation"*	Strongly agree (1)→strong disagree (7)
	"Using the distraction warning system would reduce speeding events"*	Strongly agree (1)→strong disagree (7)
	"Using the distraction warning system would reduce distractions"*	Strongly agree (1)→strong disagree (7)
	"Using the distraction warning system would reduce lane departures"*	Strongly agree (1)→strong disagree (7)
	"Using the distraction warning system would improve my driving"*	Strongly agree (1)→strong disagree (7)
Perceived Ease of Use (PEOU)	"Using the distraction warning system would be easy to use"*	Strongly agree (1)→strong disagree (7)
	"Using the distraction warning system would be easy to learn"*	Strongly agree (1)→strong disagree (7)
	"Using the distraction warning system would be easy to understand"*	Strongly agree (1)→strong disagree (7)
Unobtrusiveness	"Using the distraction warning system would be annoying"	Strongly agree (1)→strong disagree (7)
	"Using the distraction warning system would be distracting"	Strongly agree (1)→strong disagree (7)
Behavioral Intention (BI) to Use	"At the actual price of $300, how likely would you be to consider purchasing a distraction warning system like the one you used during this study?"	Definitely would not consider (1)→ definitely would consider (5)
	"Would you consider purchasing a distraction warning system if you received an insurance discount?"	Definitely would not consider (1)→ definitely would consider (5)
	"Would you use a distraction warning system if it came standard in your vehicle?"	Definitely would not consider (1)→ definitely would consider (5)

*Items with an asterisk indicate those which were re-coded so higher values were associated with positive responses.

general, because that they had no actual experience using either feedback system and as such, their ratings of each specific system could be unreliable. The BI ratings of the no-feedback group were not used in the analysis, because they were not related to any one system.

The external variables used to predict technology acceptance include: age, gender, feedback condition, number of alerts, usefulness of alerts, and distraction engagement. Number of alerts (both visual and cognitive) was measured via z-scores for each participant to allow for equivalent comparison across feedback conditions. Z-scores were calculated within each feedback condition. Because previous studies indicate that lateral vehicle control is degraded by visual distraction (Goodman et al., 1999; Horrey et al., 2006; McCartt et al., 2006), for the real-time group, alerts were considered useful when a lane departure occurred within a six second window surrounding the alert. Alert usefulness was only calculated for the visual alerts. Following the concept of social norms, for the post-drive group, the report card was considered useful when the participants' performance was worse than a peer across the four performance measures (distraction-related critical incidents, lane departures, unsafe glances, and percent of time not looking at the road; see Fig. 5). Distraction engagement was computed by averaging the participant's reported frequency of engagement in activities such as making phone calls while driving, changing CDS while driving, etc. These external variables were expected to influence PU, PEOU, and unobtrusiveness—the three aspects of perceptions toward the system that in turn determine BI. As such, paths are drawn from the six external variables to PU, PEOU, and unobtrusiveness, and then from these three measures to BI. Fig. 7 integrates these variables and presents them in a revised TAM known as the Driver Acceptance Model.

3. Results

Data were reduced using MatLab 7.12.0 (MathWorks, 2011). All statistical analyses were done using R 2.14.2 (R Development Core Team, 2011). Descriptive statistics of the four acceptance measures are shown in Table 2. All Cronbach's alphas were near 0.90, indicating acceptable internal reliability. Note that the descriptive statistics in Table 2 (and also the hierarchical linear model that follows) are based on the responses from the real-time and post-drive groups only, because the focus was on those who experienced feedback. What is more, the no-feedback group did not respond to the BI questions for each specific system, which made their set of responses incomparable to the other two groups.

Given the high correlations between acceptance measures, it follows that individually, PU, PEOU, and unobtrusiveness all predicted BI (PU: $b=0.44$, $t(22)=3.27$, $p<0.01$; PEOU: $b=0.50$, $t(22)=3.69$, $p<0.01$; unobtrusiveness: $b=0.35$, $t(22)=2.78$, $p=0.01$). However, since PU, PEOU, and unobtrusiveness were also highly correlated with each other, a hierarchical linear model was used to determine how each measure predicted BI after accounting for relationships between the measures. Following the strength of the correlations shown in Table 2, PEOU was entered first, followed by PU, and then unobtrusiveness. Table 3 shows the regression coefficients and significance tests. The model including PEOU and PU (but not unobtrusiveness) best described the variation in BI (Step 2, Table 3). The addition of unobtrusiveness was not justified given the negligible effect of unobtrusiveness and the insignificant improvement in model fit (see Step 3, Table 3).

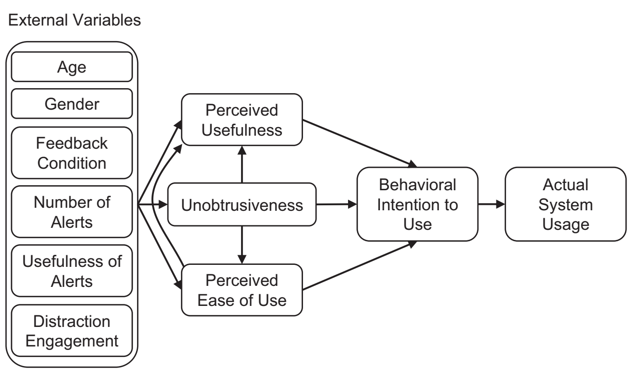

Fig. 7. Driver Acceptance Model applied to the features of this study.

The relationships between PU, PEOU, and unobtrusiveness were also analyzed. Following the TAM, PEOU predicted PU, $b=0.43$, $t(22)=2.13$, $p=0.04$, and accounted for 17.1% of the variance. Unobtrusiveness predicted both PU ($b=0.67$, $t(22)=5.60$, $p<0.01$), accounting for 59% of the variance, and PEOU ($b=0.37$, $t(22)=2.26$, $p=0.03$), accounting for 19% of the variance. Fig. 8 graphically displays these relationships using standardized regression coefficients.

3.1. Effect of feedback type and age on acceptance

It was expected that feedback condition, number of alerts, usefulness of alerts, and distraction engagement, along with age and gender, would be significant predictors of technology acceptance. After initial analysis, number of alerts, distraction engagement, and gender were excluded as they did not account for a significant amount of variance in any of the acceptance measures. In addition, alert usefulness was excluded as it was correlated with feedback condition (Pearson's $r=0.62$, $p<0.01$; the real-time group received fewer useful alerts). Linear regressions were fit for each of the three acceptance measures.

The model predicting PU accounted for 38% of the overall variance, $F(2, 21)=6.35$, $p<0.01$. Age was a significant predictor, $b=0.07$, $t(21)=2.29$, $p=0.03$,

Table 2
Means, standard deviations, Cronbach's alphas and correlations between acceptance measures; Cronbach's alphas are on the diagonal.

Variable	Mean	SD	PU	PEOU	Unobtrusiveness	BI
PU	4.37	1.35	0.93			
PEOU	5.26	1.30	0.41*	0.95		
Unobtrusiveness	3.46	1.52	0.77**	0.43*	0.88	
BI	3.03	1.04	0.57**	0.62**	0.51*	0.88

*$p<0.05$.
**$p<0.01$.

Table 3
Results of hierarchical linear model predicting BI.

Variable	Step 1	Step 2	Step 3
PEOU	0.50**	0.37*	0.37*
PU		0.30*	0.27
Unobtrusiveness			0.03
R^2	0.38	0.50	0.50
ΔR^2		0.12	0.0008
R^2 F statistic	$F(1, 22)=13.64$**	$F(2, 21)=10.63$**	$F(3, 20)=6.77$**
ΔR^2 F statistic		$F(1, 21)=5.09$*	$F(1, 20)=0.03$

*$p<0.05$.
**$p<0.01$.

indicating that as age increased by one year, usefulness ratings increased by 0.07. Age accounted for 15.6% of the variance. Feedback condition had a nearly significant effect, $b=0.84$, $t(21)=1.74$, $p=0.10$, indicating that the real-time group rated ease of use 0.84 lower than the post-drive group, i.e., the real-time group thought the system was less useful. While feedback condition was not significant, it accounted for 9.0% of the overall 38% model variance.

The model predicting perceived ease of use accounted for 44.6% of the variance, $F(2, 21)=8.44$, $p<0.01$. Feedback condition was a significant predictor, $b=1.70$, $t(21)=3.85$, $p<0.01$, indicating that the real-time group rated ease of use 1.7 lower than the post-drive group, i.e., the real-time group thought the system was less easy to use.

The model predicting unobtrusiveness accounted for 39.8% of the variance, $F(2, 21)=6.93$, $p<0.01$. Feedback condition was a significant predictor, $b=1.67$, $t(21)=3.09$, $p<0.01$, indicating that the real-time group rated unobtrusiveness of the system as 1.67 lower than the post-drive group, i.e., the real-time group found the system to be more obtrusive. Fig. 8 shows the relationship between the external variables and the acceptance measures as indicated by standardized regression coefficients.

3.2. Acceptance across feedback and no-feedback conditions

The responses from the no-feedback group were compared to the responses of those who received feedback to

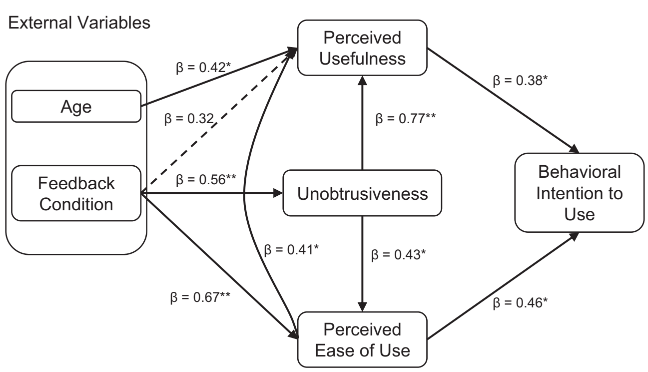

Fig. 8. Driver Acceptance Model with associated relationships (standardized regression coefficients) between variables where solid lines indicate significant relations and dashed lines indicate non-significant relations ($^{*}p<0.05$, $^{**}p<0.01$); Note that the regression coefficients are standardized, whereas the coefficients presented in the text are unstandardized.

determine whether experience with the feedback system affected acceptance. It should be noted that for the no-feedback group, the acceptance ratings were based on beliefs about the distraction mitigation systems in the absence of any prior exposure to either system. Previous research has measured pre-usage perceptions of a system and linked them to post-usage perceptions, finding that the pre-usage perceptions are updated sequentially with actual system use (Bhattacherjee and Premkumar, 2004; Böhm et al., 2009; Hsu et al., 2006; Kim and Malhotra, 2005). As such, the no-feedback group's acceptance ratings can be used as a baseline for gauging the pre-usage expectations and perceptions of the system—to be compared to perceptions of those who have used the system for some time (i.e., received feedback in either real-time or post-drive form).

When comparing the real-time versus the no-feedback group, for two of the three acceptance measures (PU and PEOU), feedback condition was a significant predictor (PU: $F(1, 22)=10.16$, $p=0.004$; PEOU: $F(1, 22)=8.57$, $p=0.008$; unobtrusiveness: $F(1, 22)=2.35$, $p=0.14$). These results indicate that the no-feedback group rated these two measures significantly higher than the real-time group when they were asked to imagine their response to real-time feedback (Table 4).

When comparing the post-drive with the no-feedback group, although the no-feedback group's ratings were higher for all the three measures of acceptance, feedback condition was not a significant predictor of any of the measures, (PU: $F(1, 22)=1.62$, $p=0.22$; PEOU: $F(1, 22)=3.18$, $p=0.09$; unobtrusiveness: $F(1, 22)=0.23$, $p=0.64$). Table 4 shows the mean values across the different groups.

The responses were also compared within the no-feedback group to see if drivers rated the two systems differently. The no-feedback group found both the real-time and post-drive systems to be similar on both ease of use and unobtrusiveness, PEOU: $F(1, 11)=0.76$, $p=0.40$, unobtrusiveness: $F(1, 11)=1.47$, $p=0.25$. However, they thought the post-drive system would be less useful, as indicated by a lower PU rating, PU: $F(1, 11)=6.27$, $p=0.03$. Fig. 9 shows the mean acceptance rating with standard error bars for all three acceptance measures for both the real-time and post-drive systems. The no-feedback group is shown in the "not used" category of system usage while both the real-time and post-drive groups are represented in the "used" category of system

Table 4
Means and standard deviations of acceptance measures for the no-feedback, real-time, and post-drive groups.

	PU	PEOU	Unobtrusiveness
Real-time system			
No-feedback	5.23 (0.81)	5.75 (0.95)	3.21 (1.12)
Real-time	3.75 (1.39)	4.42 (1.26)	2.54 (1.01)
Post-drive system			
No-feedback	4.39 (1.27)	5.56 (0.89)	4.08 (1.55)
Post-drive	4.99 (1.01)	6.11 (0.61)	4.38 (1.42)

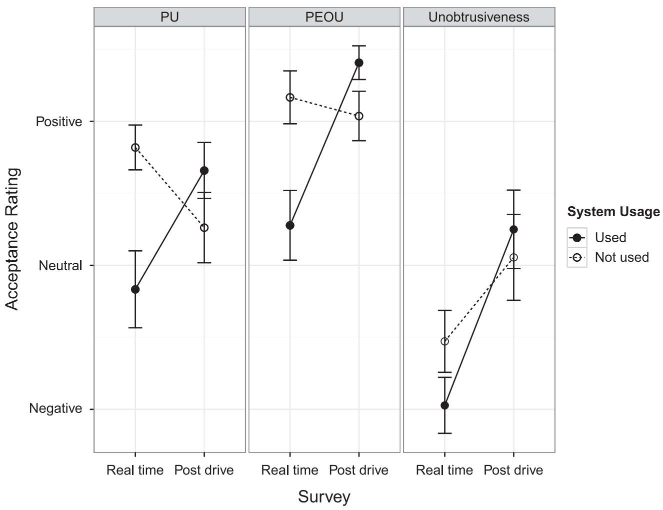

Fig. 9. Acceptance ratings of the different mitigation systems and experience.

usage. Overall, use of the system led drivers to see the post-drive feedback more positively and the real-time feedback less positively.

4. Discussion

Achieving the promise of distraction mitigation systems depends on driver acceptance. Applying the TAM framework to understand driver acceptance of two distraction mitigation systems provides insights that can guide feedback system design and enhance understanding of how TAM applies to the driving domain.

4.1. Acceptance of different types of feedback to mitigate distraction

This study used the TAM to examine driver response to two distraction mitigation systems. More specifically, a real-time system that alerted drivers through visual and auditory warnings was compared to a post-drive system that gave drivers a summary of their performance compared to peers. Drivers who experienced the real-time system found it more obtrusive and less easy to use than drivers who experienced the post-drive system. These results complement previous studies which show that drivers prefer visual alerts and find auditory alerts annoying (Donmez et al., 2008). Although this study included a relatively narrow age range—25–50 years old—older drivers found both systems more useful. The effect of age complements other studies indicating that older drivers tend to view in-vehicle technologies positively (Jonsson et al., 2005; Yannis et al., 2010). It is important to note that drivers outside this study's age range, i.e., younger than 25 and older than 75 years old, have higher crash rates (McGwin and Brown, 1999) and might respond differently to feedback systems. These drivers are most likely to benefit from feedback technology, but might not accept it in the same manner as the drivers in this study.

Providing feedback using the concept of social norms can be effective given that drivers trust and accept the system. In contrast, mitigation systems that alert drivers of distraction via flashing lights and auditory alarms can be more detrimental than beneficial given that drivers found them to be less pleasant and less easy to use. After analyzing the responses of the no-feedback group, these findings are confirmed as drivers who did not experience the real-time system found it to be more useful and easier to use than drivers who actually experienced it. This shows that while in theory, real-time systems appear to be effective in preventing distraction, actual implementation of the system does not always produce the desired results and can strongly influence acceptance. The specific frequency, on-set, off-set, and duty cycle of auditory warnings has a strong influence on perceived annoyance (Marshall et al., 2007). Attention to these details of feedback system design might be central to driver acceptance and overall system success.

4.2. Relation between results and the TAM

PEOU was found to be the primary determinant of BI as it had the highest correlation with BI and significantly influenced BI, even in a model that accounted for both PU and unobtrusiveness. PU had a significant, but smaller effect on BI in the model including PEOU, emerging as the secondary determinant of BI. This contradicts previous findings where PU has emerged as the primary predictor and PEOU as the secondary predictor of BI (Davis et al., 1989). However, previous user acceptance studies addressing driving assistance systems agree with the present study, reporting a larger effect for PEOU compared to PU (Chen and Chen, 2011; Xu et al., 2010). These findings collectively suggest that drivers' perception of whether an assistance system is easy to use is a stronger predictor of their intention to use the system, compared to their perception of system's usefulness. PEOU significantly affected PU, as predicted by the TAM. The effect of unobtrusiveness on BI was largely mediated by PU and PEOU—the direct effect of unobtrusiveness on BI was not significant (contrary to hypothesis), but unobtrusiveness did have a substantial influence on both PU and PEOU. This pattern of results suggests that the TAM provides a useful framework for understanding driver acceptance of vehicle technology, but that the particular pattern of influences might differ from other domains and use contexts where TAM has been applied.

4.3. Implications of context of use on acceptance

The use context can substantially influence technology acceptance. In a mandatory use context, applications of the TAM show a stronger PEOU effect (compared to the PU effect) on BI (Brown et al., 2002)—similar to the present study. The distraction mitigation systems in this study were not intended for mandatory use; however, like most experiments, participants were obliged to use the system that was presented to them. This constraint is not representative of most use scenarios that drivers encounter in daily driving. In such situations, PU might become a more important determinant of BI and consequently, acceptance.

Results showed that exposure to distraction mitigation systems can change drivers' perceptions and preferences: drivers in the no-feedback group gave considerably higher ratings to real-time feedback compared to drivers who actually experienced real-time feedback, and lower, although not significantly, ratings to post-drive feedback compared to drivers exposed to post-drive feedback. This is in line with previous studies showing that users' perceptions change as they gain experience with the system (Bajaj and Nidumolu, 1998; Bhattacherjee and Premkumar, 2004; Kim and Malhotra, 2005). These studies demonstrate the importance of accounting for past technology use and presenting users with a representative experience with the actual system when assessing acceptance.

4.4. Future work

Insights and limitations of this study identify several important research directions for future studies. The strong influence of obtrusiveness on perceived ease of use and usefulness is a particularly important insight that suggests different feedback implementations, such as embedding the feedback in the in-vehicle system or combining real-time and post-drive feedback (Donmez et al., 2007, 2008). Varying feedback characteristics, such as content, style (positive or negative), frequency, timing, precision, and delivery methods may also have a profound effect on feedback effectiveness and acceptance (Arroyo et al., 2006; McLaughlin et al., 2006a,b). Specifically, the role of emotion in guiding attention is a worthy topic of investigation given that matching driver emotion to car emotion produces safer driving behavior (Nass et al., 2005). More generally, feedback that includes emotionally salient elements, such as facial expressions of computer agents that provide feedback, can have an unexpectedly strong influence on attention, memory, and decision making and as such, merit careful attention in feedback system design (Breazeal, 2003; Cassell et al., 1999; Lee, 2006).

When evaluating feedback systems, it may be beneficial to gauge participants' acceptance of the feedback system as a whole, as well as each subcomponent. For example, in this study, while the post-drive feedback did provide social norm comparisons, it is not known which aspect of the system (e.g., charts, videos, etc.) was the most effective. In addition, while the real-time feedback was more obtrusive, it is not known which aspect (i.e., visual or auditory alarms) was the most obtrusive. Evaluating each system component would identify which aspects strongly influence behavior and eventually, reduce crashes due to driver distraction.

Because this study included relatively few participants (36 drivers), similar to other simulator-based studies, the relationships among the measures in the Driver Acceptance Model were evaluated using separate linear regression models. A more effective way to evaluate these relationships is structural equation modeling (SEM), which identifies latent variables (here: PU, PEOU, unobtrusiveness, and BI) from survey responses, while at the same time measuring the relationships between latent variables and external variables (for examples, see Dishaw and Strong, 1999; Gefen et al., 2003; Karahanna et al., 2006; Kim and Malhotra, 2005; Venkatesh, 2000; Yi et al., 2006). As such, it is the analytic technique of choice for evaluating models like the Driver Acceptance Model. However, SEM analyses require a large sample—typically a 20:1 ratio of samples per model variable (Kline, 2011). Therefore, the limited sample size of this study would have compromised the conclusions derived from an SEM analysis. Future studies with larger sample sizes might benefit from the power of SEM in evaluating the relationships among acceptance measures.

The current study focused on the perceptions of feedback systems at a single point in time, i.e., after initial exposure or introduction to the system. However, prolonged exposure can change users' perceptions of that system. As such, a longitudinal study that traces system perception over time and as a function of a user's interaction with the system can help identify system elements that shape long-term adoption decisions and shed light on the dynamics of acceptance (Ghazizadeh et al., 2012).

4.5. Conclusion

Designing effective feedback mechanisms represents a crucial challenge in changing distraction-related driver behavior (Gielen and Sleet, 2003). However, for these systems to be effective, drivers must accept them. Extending the Technology Acceptance Model with the construct of unobtrusiveness showed perceived ease of use to be the primary determinant and perceived usefulness to be the secondary determinant of acceptance. The effect of unobtrusiveness was fully mediated by perceived ease of use and perceived usefulness. The results demonstrated an important difference between the attitudes of those drivers who imagined and those who actually used the system. This finding points to the importance of the physical features of the mitigation system in guiding driver acceptance, such as loudness and frequency of auditory alerts. Of particular importance for real-time feedback is that auditory and visual alarms balance alert urgency and annoyance (Marshall et al., 2007). This study also demonstrates the general concept of post-drive feedback to be an effective tool to promote safe driving behavior and shows that informing drivers of their performance using a report card may be more acceptable than warning them of dangerous driving behavior via visual and auditory alarms. In addition, drivers seem willing to accept feedback that include comparison to peers and might influence behavior through social conformism. Overall, this study extends the welldeveloped TAM framework to distraction mitigation systems and provides insight into drivers' acceptance of feedback systems that mitigate driver distraction.

Acknowledgments

The authors thank the two anonymous reviewers and the Cognitive Systems Laboratory members for their comments and suggestions. The authors also gratefully acknowledge the assistance of Tim Brown, Jane Moeckli, and Chris Schwarz in the development of this work. The data presented in this paper were collected as part of a project sponsored by the National Highway Traffic Safety Administration (NHTSA), with technical input from David Band, Eric Nadler, and Eric Traube. Parts of this study were published as a NHTSA technical report. This work was supported by the National Science Foundation through a Graduate Research Fellowship to Shannon C. Roberts.

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