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Using Naturalistic Driving Data to Assess Vehicle-to-Vehicle Crashes Involving Fleet Drivers

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Title

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Author

Cher Carney, Dan McGehee, Karisa Harland, Madonna Weiss, Mireille Raby
University of Iowa

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About the Sponsor

AAA Foundation for Traffic Safety
607 14th Street, NW, Suite 201
Washington, DC 20005
202-638-5944
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Founded in 1947, the AAA Foundation in Washington, D.C. is a not-for-profit, publicly supported charitable research and education organization dedicated to saving lives by preventing traffic crashes and reducing injuries when crashes occur. Funding for this report was provided by voluntary contributions from AAA/CAA and their affiliated motor clubs, from individual members, from AAA-affiliated insurance companies, as well as from other organizations or sources.

Executive Summary

Objective, detailed and accurate data is critically important in the effort to determine the causes and contributing factors of crashes. In the past, the only way to obtain such information for a large number of crashes was to use data collected from police reports. While information gathered this way is helpful, it has many limitations. More recently, in-vehicle event recorders (IVERs) have become a widely accepted means of gathering crash data, both in research and real-world applications.

In this study, we conducted the first-ever large-scale examination of naturalistic crash data. Other naturalistic studies have investigated only a small number of crashes or used near crashes as a proxy for real crashes. In contrast, this project examined hundreds of actual crashes from a naturalistic driving database. The data allowed us to examine behaviors and potential contributing factors in the seconds leading up to the collision, and provided information not available in police reports.

A coding scheme was developed specifically for this study, and video data were coded with the goal of identifying the factors that contributed to crashes—in particular the prevalence of potentially distracting driver behaviors and drowsiness. The study addressed the following research questions:

- What were the roadway and environmental conditions at the time of the crash?
- What were the critical events and potential contributing factors leading up to the crash and did these differ by crash type?
- What driver behaviors were present in the vehicle prior to the crash and did these differ by crash type?
- How did driver response times and eyes-off-road time differ relative to certain driver behaviors and crash types?
- Could drowsy driving be detected using this type of crash data?

Understanding the prevalence of factors that potentially contribute to crashes will provide a significant societal benefit and advance the field of traffic and crash safety. More specifically, information regarding what is happening inside the vehicle during the seconds before a crash can be used to pinpoint automotive safety systems and technologies that might best mitigate certain types of crashes.

METHODS

Lytx, a company that has been collecting data using in-vehicle event recorders (IVERS) for over a decade, provided the crash data. The DriveCam system collects video, audio and accelerometer data when a driver triggers the device by hard braking, fast cornering, or an impact that exceeds a certain *g*-force. Each video is 12 s long, and provides information on the 8 s before and 4 s after the trigger. The system has a wide range of applications—families use them to help young drivers as they begin to drive independently, while over 950 commercial and government fleets employ them for fleet management.

As part of this study, 777 crashes from the fleet driver database were made available for review. In order to eliminate minor curb strikes from the analysis, those crashes in which the vehicle sustained impacts of less than 1g were excluded. Crashes in which the DriveCam-equipped vehicle was struck from behind were also eliminated from this particular analysis. Additional videos were excluded for other reasons (e.g., animal strikes, video problems, or the driver not being a member of the fleet). Consequently, nearly 250 moderate-to-severe vehicle-to-vehicle crashes remained for analysis in the current study. A coding methodology focused on identifying the factors present in the seconds leading up to the crashes was developed specifically for gathering information from the videos.

Development of the coding method began with a thorough review of existing crash coding from government, academic and industry sources. In all, 64 data elements were identified as relevant to the project goals. These were narrowed down according to their relevance to the project and ability to be coded reliably. In the end, 24 data elements were selected for inclusion in the coding methodology. These elements were specific to environmental conditions, contributing circumstances (e.g., inadequate surveillance, running traffic signals), and driver and passenger behaviors. Some of the elements could have multiple data coded (i.e., multiple driver behaviors occurred within one crash segment). Each crash, in particular the 6 s leading up to the crash (this time frame was selected to ensure results were comparable to other naturalistic driving studies), was double coded by two University of Iowa (UI) analysts and mediated by a third when necessary.

RESULTS

For this study, we analyzed 247 moderate-to-severe vehicle-to-vehicle crashes in which the force of the impact was 1.0g or greater. While the extent of any injuries sustained in the crashes was not evident from the videos, it is known that no fatal crashes were included in the analysis. However, it is likely that most, if not all, of the crashes would have resulted in a police report being filed.

The majority of fleet drivers were between the ages of 30 and 64 (73.3%) and nearly 87% were male. Of the crashes coded, the majority were angle (52%) and rear-end (41%) crashes. Approximately 10% of crashes were due to environmental factors, such as poor road conditions. Crashes did not seem more likely to occur on any particular day of the workweek or time of day.

The critical pre-crash event in 97% of rear-end crashes was another vehicle in the driver's lane decelerating or stopping in the roadway. As mentioned above, rear-end crashes in which the DriveCam-equipped vehicle was struck from behind were omitted from the analysis. As to angle crashes, the participant's vehicle crossed the centerline or was turning at an intersection in 45% of crashes, while another vehicle encroaching accounted for 51%. Regardless of fault, in 84% of crashes, the driver contributed to the crash in some way. Recognition errors, such as inadequate surveillance and engaging in a potentially distracting behavior were observed in 71% of crashes. Decision errors, such as following too closely and running stop signs and lights, were coded in 40% of crashes. Performance errors, such as losing control of the vehicle, occurred in only 3% of crashes.

Attending to a location either outside or inside the vehicle that was not relevant to safe operation of the vehicle were the two most frequently coded driver behaviors seen in the six seconds leading up to a crash. These behaviors were associated with recognition errors such as inattentive/engaged in extraneous behaviors and inadequate surveillance.

Cell phone use was the third most frequent driver behavior observed, occurring in 8.3% of crashes. Among crashes with driver cell phone use, the driver was coded as operating/looking at a phone during 53% of these events, talking/listening in 31%, and cell phone use was coded as likely but not visible in 26%. Ninety-six percent of all cell phone-related behaviors happened when the driver was alone in the vehicle. Operating or looking at the phone never occurred when there were passengers present.

When a driver was alone, he/she was seen engaging in potentially distracting behaviors in slightly more than half of crashes (52%). Cell phone use was 3.5 times as likely, and personal grooming and talking to oneself were almost twice as likely when the driver was alone. When passengers were present, having a conversation with the driver was the most common behavior observed, occurring in 21% of crashes.

Drivers involved in a rear-end crash were nearly twice as likely to be seen engaging in non-driving-related activities during the six seconds leading up to the crash compared to drivers of angle crashes. In addition, the average time the driver's eyes were off of the forward roadway was more than 4 times as long for rear-end crashes than for angle crashes (3.2 vs. 0.7s).

There are limitations associated with event-triggered driving data that make detecting drowsy driving extremely difficult. For this study, only four of the 229 fleet crashes examined contained evidence of drowsy driving.

CONCLUSIONS

Use of IVERs in naturalistic driving allows researchers a unique view into the vehicle, and provides invaluable information regarding the behavioral and environmental factors present before a crash. The data gathered offers a much more detailed context relative to police reports and other crash databases, and allows more micro-level analyses to be conducted.

This study examines the roadway and environmental conditions present in different types of crashes. It describes the critical events and contributing factors that lead up to crashes, and how they vary by crash type. It also provides information regarding the effect certain driver behaviors have on reaction time and eyes-off-road time. Finally, it is the first naturalistic study of moderate-to-severe crashes to examine driver and passenger behaviors for a variety of crash types among fleet drivers.

The results of this study indicate that there are different driver behaviors and contributing circumstances present for rear-end vs. angle crashes. The most common driver behavior seen was inadequate surveillance, with attending inside or outside the vehicle to an unknown location being coded most often. However, fleet drivers were more likely to be seen engaging in these potentially distracting behaviors when they were alone in the vehicle. Additionally, drivers involved in a rear-end crash were more likely to engage in a potentially distracting behavior and had total eyes-off-road times that were four times as long as than those involved in angle crashes.

Introduction

In 2012, 42% of occupational fatalities were transportation-related, making it the leading cause of fatal work injuries. Among such fatal crashes, 60% occurred on a roadway, and one in five (22%) occurred in the truck transport and transit/ground passenger transportation industries (Bureau of Labor Statistics, 2012). The highest fatality rate was in the truck transportation industry, with 19.6 fatalities per 100,000 workers (Centers for Disease Control and Prevention, 2011). Among roadway fatalities, almost half were due to collisions with another vehicle (Bunn and Struttmann, 2003; Bureau of Labor Statistics, 2012). In these crashes, males and older occupants were more likely to be victims (Janicak, 2003; Bureau of Labor Statistics, 2012).

Much less is known about non-fatal work-related transportation incidents. An estimated 67,800 emergency room visits associated with such incidents occur every year (Jackson, 2001). Approximately 7% of these emergency room visits result in a hospitalization (Jackson, 2001). Previous studies suggest excess speed (Boufous and Williamson, 2006), fatigue/sleepiness (Bunn and Struttmann, 2003; Boufous and Williamson, 2006; Robb et al., 2008) and driver distraction (Bunn and Struttmann, 2003) contribute to occupation-related crashes. In a study of such crashes in Kentucky, Bunn et al. (2003) found that one in four crashes were due to driver distraction and inattention; in almost one-third of crashes, however, no driver-contributing factor could be determined.

Studying fatigue and driver distraction as a crash cause can be very difficult due to drivers' inability to recall incidents or fear of admitting fault. The Federal Motor Carrier Safety Administration (2006) states that, "Without in-vehicle data recorders or video cameras, driver performance in crash situations must be inferred after the fact from interview data, crash reconstructions, and expert judgment." Over the past 10 years, the traffic safety research community has developed new and increasingly sophisticated means of collecting and analyzing traffic safety data to provide new insights into crash causation. However, naturalistic studies using these in-vehicle (IV) technologies are expensive to conduct, so they typically involve small samples, and therefore, a small number of actual crashes. This is the first study to examine a large set of crashes using IV technology. This study was able to examine the following:

- The roadway and environmental conditions at the time of the crash
- The critical events and contributing factors leading up to the crash
- Driver behaviors present in the vehicle and whether they differed by crash type
- Changes in driver reaction times and eyes-off-road times relative to driver behaviors and crash types
- Whether drowsy driving could be detected using this type of crash data

Methods

A coding methodology focused on crash causation was developed specifically for gathering information from videos of crashes captured on Lytx's Drive Cam cameras for a previous study for the AAA Foundation for Traffic Safety (Carney et al., 2015). Development of the coding method began with a thorough review of existing crash coding from government, academic and industry sources. In all, 64 data elements were identified as relevant to the project goals. These were narrowed down using a modified trade study analysis according to their relevance to the project and ability to be coded reliably. In the end, 24 data elements were selected for inclusion. These were specific to environmental conditions, contributing circumstances (e.g., inadequate surveillance, running traffic signals), and driver and passenger behaviors. Some of the crashes could have multiple data coded (i.e., multiple driver behaviors could occur within one crash segment). For each crash, the 6s leading up to the crash (the time frame selected to ensure results were comparable to other naturalistic driving studies) was double coded by two University of Iowa (UI) analysts, and mediated by a third when necessary.

To find differences in proportions, the Pearson's chi-square test (all cell sizes greater than or equal to 5) or Fisher's exact test (cell size less than 5) was used. To examine differences in means, the student's *t*-test was used. All analyses were completed using SAS 9.4® (Cary, North Carolina).

Review of all fleet-driver crashes

More than 950 commercial and government fleets from all over the world use Lytx's service on a daily basis. As a result, the company has compiled a database of crash events. Crashes from this fleet database were filtered to identify those operating in the U.S., involving two-axle vehicles under 10,000 lbs. gross weight, involved in a vehicle-to-vehicle crash with an impact force 1 g or greater. This included mostly sedans, heavy-duty pickups, large capacity vans and minibuses. The vehicles included taxis, shuttles, government vehicles, and private company vehicles. A total of 777 crash videos were identified and made available to the UI. After review, four were identified as not meeting the criteria of a moderate-to-severe crash, and so were not included in further analyses. A breakdown of the remaining crash videos is presented in Figure 1.

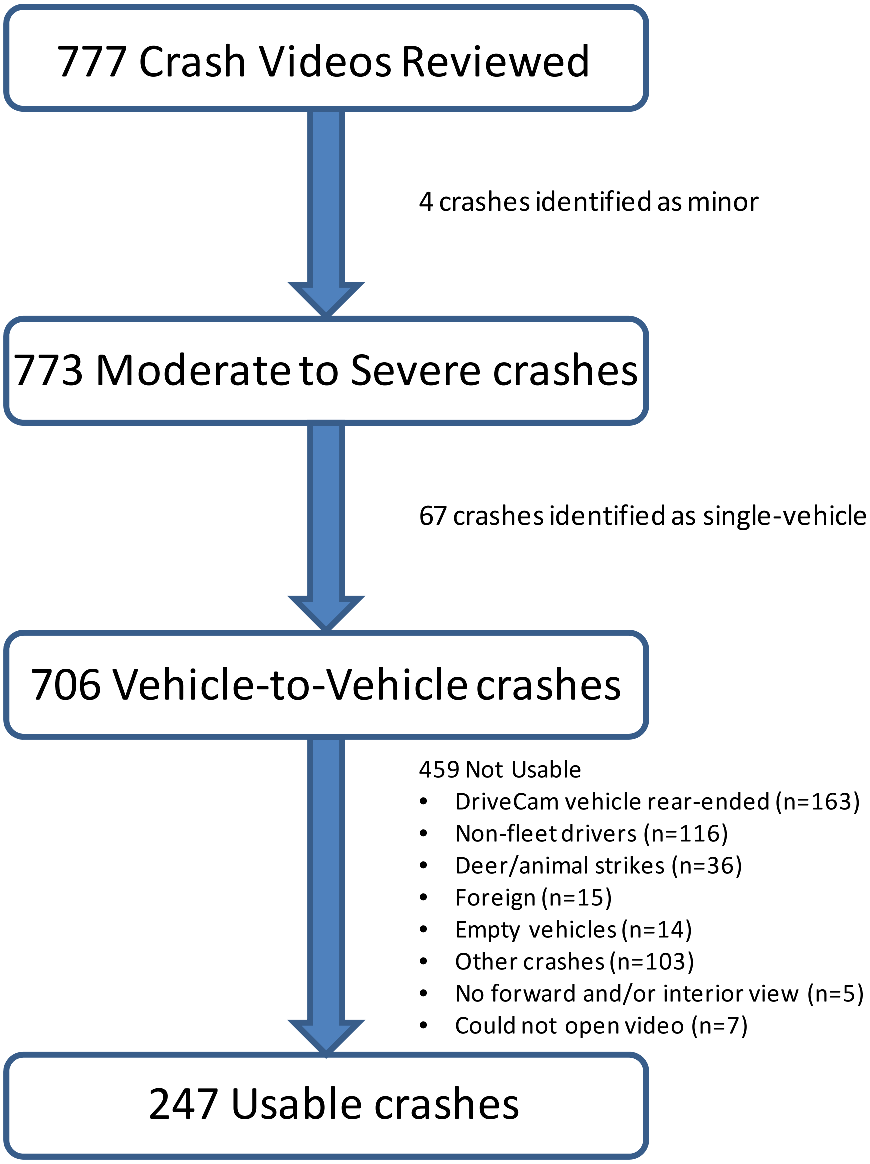

Figure 1. Breakdown of fleet crashes reviewed

Of particular interest were the 247 vehicle-to-vehicle crashes, which comprised approximately 32% of the fleet crashes available to us. Each crash was coded by two independent reviewers using the coding method developed for this project (see Appendix A). The data files were then merged, and any discrepancies were identified. If the discrepancy was due to an error, it was corrected. If it was due to a disagreement, however, the event was turned over to a third reviewer for mediation. Glance durations and reaction times differing by as little as one frame (0.25s) were mediated in an attempt to achieve the highest possible level of accuracy.

Results

Of the crashes coded (n=247), 52% were angle, 41% were rear end, 4% were head-on, 2% were a sideswipe, and 1% were backing crashes. Given the small number of crashes that were not angle or rear-end, the comparison of crash types focused on these two types of crashes (n=229).

Characteristics of drivers and passengers

The characteristics of the 247 drivers are shown in Table 1. The majority of drivers were estimated to be between the ages of 30 and 64 (73.3%), and nearly 87% were male. Most drivers were wearing their seatbelt at the time of the crash (92%). Passengers were seen in less than a quarter of crashes (22%). A single passenger was present in 13% of crashes, two passengers in 6% and three or more passengers in 2%. Most passengers were estimated to be over the age of 20 (95%), and they were split evenly by gender (47.7% male, 46.5% female and 5.8% unknown). In 51% of crashes with passengers present, at least one passenger was unbelted.

Table 1. Characteristics of drivers

Age (estimated)	Male	Female	Total
16-19	4 (1.6%)	0	4 (1.6%)
20-29	37 (15.0%)	7 (2.8%)	44 (17.8%)
30-64	155 (62.8%)	26 (10.5%)	181 (73.3%)
65+	18 (7.3%)	0	18 (7.3%)
	214 (86.6%)	33 (13.4%)	247 (100%)

Characteristics of roadway and environment

Over half of rear-end and angle crashes occurred on arterial roads (52%) or interstates (12%). In 8% of crashes, backed-up traffic was identified during the six seconds before the crash occurred. Almost three-fourths of crashes occurred when there were no adverse weather conditions, and approximately 10% were due to environmental factors such as poor road conditions (Table 2). Crashes did not seem more likely to occur on any particular day of the workweek or time of day.

Characteristics of rear-end and angle fleet crashes

Rear-end crashes were significantly more likely to occur on an interstate, while angle crashes were more likely to happen on arterial roads ($p<.0001$). While no attribution of fault was made, in 84% of crashes the driver contributed to the crash in some way. The most common contributing factors were inadequate surveillance (71.2%), distraction/inattention (50.2%), following too closely (12.2%), and failure to yield right-of-way (12.7%). Recognition errors were present in 81% of the crashes (see Table 3). Decision errors, such as following too closely and running stop signs or lights, were observed in 40% of crashes. Finally, performance errors, such as losing control of the vehicle, accounted for 2% of crashes.

Table 2. Characteristics of roadway and environment by crash type

	Rear-end (n=101)	Angle (n=128)	Total (n=229)
Road type[1]			
Interstate	36 (24.8)	3 (2.3)	28 (12.2)
Arterial	52 (51.5)	66 (51.6)	118 (51.5)
Collector	13 (12.9)	43 (33.6)	56 (24.5)
Local	4 (4.0)	10 (7.8)	14 (6.1)
all other	7 (6.9)	6 (4.7)	13 (5.7)
Weather			
No adverse weather	75 (74.3)	91 (71.1)	166 (72.5)
Fog	1 (1.0)	0	1 (0.4)
Rain	6 (5.9)	9 (7.0)	15 (6.6)
Sleet, hail, freezing rain	0	0	0
Snow	1 (1.0)	2 (1.6)	3 (1.3)
Unknown	18 (17.8)	26 (20.3)	44 (19.2)
Surface condition			
Dry	93 (92.1)	111 (86.7)	204 (89.1)
Gravel	0	1 (0.8)	1 (0.4)
Snow/ice	2 (2.0)	4 (3.1)	6 (2.6)
Wet	5 (5.0)	12 (9.4)	17 (7.4)
Other/unknown	1 (1.0)	0	1 (0.4)
Time of day			
Midnight to 3am	1 (1.0)	2 (1.6)	3 (1.3)
3–5:59 am	1 (1.0)	4 (3.1)	5 (2.2)
6–8:59 am	24 (23.8)	21 (16.4)	45 (19.7)
9–11:59 am	18 (17.8)	21(16.4)	39 (17.0)
Noon to 2:59 pm	19 (18.8)	28 (21.9)	47 (20.5)
3–5:59 pm	24 (23.8)	30 (23.4)	54 (23.6)
6–8:59 pm	12 (11.9)	17 (13.3)	29 (12.7)
9–11:59 pm	2 (2.0)	5 (3.9)	7 (3.1)
Day of week			
Monday	18 (17.8)	17 (13.3)	35 (15.3)
Tuesday	10 (9.9)	19 (14.8)	29 (12.7)
Wednesday	15 (14.9)	35 (27.3)	50 (21.8)
Thursday	21 (20.8)	18 (14.1)	39 (17.0)
Friday	21 (20.8)	15 (11.7)	36 (15.7)
Saturday	10 (9.9)	16 (12.5)	26 (11.4)
Sunday	6 (5.9)	8 (6.3)	14 (6.1)
On a weekend (Fri 5 pm to Sun 11:59 pm)			
Yes	21 (20.8)	26 (20.3)	47 (20.5)
No	80 (79.2)	102 (79.7)	182 (79.5)

	Rear-end (n=101)	Angle (n=128)	Total (n=229)
Light condition			
Daylight	64 (63.4)	81 (63.3)	145 (63.3)
Degraded daylight	11 (10.9)	11 (8.6)	22 (9.6)
Dusk/dawn	8 (7.9)	6 (4.7)	14 (6.1)
Dark, but lighted	14 (13.9)	26 (20.3)	40 (17.5)
Dark, not lighted	4 (4.0)	4 (3.1)	8 (3.5)

[1]p<.0001, [2]p<.01, [3]p<.05

Table 3. Type and frequency of errors made in fleet vehicle-to-vehicle crashes

Error Type	Description	Rear-end (n=101)	Angle (n=128)	All crashes (n=229)
Recognition Errors	Any recognition errors[1]	98 (97.0)	89 (69.5)	187 (81.7)
	Inadequate surveillance[1]	96 (95.1)	67 (52.3)	163 (71.2)
	Inattentive/Engaged in extraneous behaviors[2]	65 (64.4)	50 (39.1)	115 (50.2)
Decision Errors	Any decision errors[2]	28 (27.7)	64 (50.0)	92 (40.1)
	Driving too fast	0	4 (3.1)	4 (1.8)
	Failed to yield ROW - At uncontrolled intersection	0	3 (2.3)	3 (1.3)
	Failed to yield ROW - Entering roadway	0	3 (2.3)	3 (1.3)
	Failed to yield ROW - From driveway	0	0	0
	Failed to yield ROW - From stop sign	0	14 (10.9)	14 (6.1)
	Failed to yield ROW - Making left turn	0	12 (9.4)	12 (5.3)
	Failed to yield ROW - Right on red	0	0	0
	Followed too closely[1]	27 (26.7)	1 (0.8)	28 (12.2)
	Misjudged gap	0	1 (0.8)	1 (0.4)
	Operating in a reckless manner	0	0	0
	Other illegal maneuver	0	1 (0.8)	1 (0.4)
	Ran stop sign/traffic signal[1]	1 (1.0)	25 (19.5)	26 (11.4)
	Travelling wrong way	0	3 (2.3)	3 (1.3)
	Unsafe lane change	0	3 (2.3)	3 (1.3)
	Made improper turn[3]	0	6 (4.7)	6 (2.6)
Performance Errors	Any performance errors	3 (3.0)	4 (3.1)	7 (3.1)
	Crossed centerline	0	1 (0.8)	1 (0.4)
	Lost control	3 (3.0)	3 (2.3)	6 (2.6)
	Overcorrecting/over steering	0	0	0
Non-performance Errors	Any non-performance errors[3]	4 (4.0)	0	4 (1.8)
	Fatigued/tired[3]	4 (4.0)	0	4 (1.8)

[1]p<.0001, [2]p<.01, [3]p<.05

Rear-end crashes were more likely to involve recognition errors, while angle crashes were more likely to be due to decision errors. Rear-end crashes involved recognition errors (97% vs. 70%, p<.0001) significantly more often than angle crashes. The majority (95%) of rear-end crashes had inadequate surveillance, while this was true of only about half of angle crashes (52.3%). In addition, over 60% of rear-end crashes involved driver inattentiveness, while only 40% of angle crashes had such an error. In contrast, half of angle crashes had a decision error, in contrast to approximately one-quarter of rear-end crashes. Angle crashes involved more running stop signs or traffic signals (19.5% vs. 1%) than rear-end crashes. Lastly, the majority of decision errors in rear-end crashes involved the driver following too closely.

The critical pre-crash event in 97% of rear-end crashes was another vehicle in the driver's lane decelerating or stopping in the roadway. For angle crashes, in 45% the participant vehicle was crossing the centerline or turning at an intersection; in 51%, another vehicle encroached into the participant's right-of-way.

Driver behaviors

Analysts made no judgments as to whether drivers were actually distracted by any behavior observed, but simply coded what was occurring inside the vehicle at the time of the crash. In addition, multiple behaviors were sometimes observed in a single crash event.

In a little over half of crashes (50.7%, n=116) potentially distracting driver behaviors were observed (Table 4).The most frequent behaviors seen were attending outside the vehicle to an unknown location (15.3%) and attending inside the vehicle to an unknown location (13.5%). Overall, 8.3% of crashes had a driver using their cell phone, with the most prevalent cell phone activity being operating or looking at their phone.

Driver behaviors differed significantly by crash type (Table 4). In rear-end crashes, drivers were more likely to be seen using their cell phones than in angle crashes (13.9 vs. 3.9%, $p<.01$); specific behaviors included operating or looking at the phone (7.9% vs. 1.6%, $p<0.05$), and attending to an unknown location inside the vehicle (18.8% vs. 9.4%, $p<.05$).

Additionally, driver behaviors were examined by the number of passengers present in the vehicle. Potentially distracting driver behaviors were present in 55% of crashes with one passenger on board, and 41% of crashes with two or more passengers. When passengers were present, attending to a passenger was the most frequent driver behavior, occurring in 21% of crashes with a single passenger (7 of 33) and 14% of crashes with two or more passengers (3 of 22). Several behaviors were observed more frequently when the driver was alone. Engaging in cell phone-related tasks was 3.5 times as likely (10.9% vs. 3.0%); operating/looking at the phone was *only* seen when the driver was alone. Personal grooming and talking to oneself were almost twice as frequent when the driver was alone (5.7% vs. 3.0%, and 5.2% vs. 3.0%, respectively)

Conversation with the driver was the most common passenger behavior, occurring in 20% of crashes and accounting for 57.9% (11 of 19) of all passenger behaviors.

Table 4. Driver behaviors by crash type

Driver Behaviors	Rear-end (n=101)	Angle (n=128)	All crashes (n=229)
Any behaviors[2]	65 (64.4)	51 (39.8)	116 (50.7)
Any cell phone use[2]	14 (13.9)	5 (3.9)	19 (8.3)
Cell use (operating/looking)[3]	8 (7.9)	2 (1.6)	10 (4.4)
Cell use (talking/listening)	2 (2.0)	4 (3.1)	6 (2.6)
Cell use likely but not visible[3]	5 (5.0)	0	5 (2.2)
Eating or drinking	0	3 (2.3)	3 (1.3)
Using electronic device (mp3, iPod, nav)	5 (5.0)	2 (1.6)	7 (3.1)
Attending to a moving object inside vehicle	0	0	0
Attending inside vehicle, unknown[3]	19 (18.8)	12 (9.4)	31 (13.5)
Attending to another vehicle or passenger in other vehicle	1 (1.0)	0	1 (0.44)
Attending outside vehicle, unknown[2]	23 (22.8)	12 (9.4)	35 (15.3)
Attending to passenger(s)	3 (3.0)	4 (3.1)	7 (3.1)
Personal grooming	8 (7.9)	4 (3.1)	12 (5.2)
Reaching for object	7 (6.9)	9 (7.0)	16 (7.0)
Singing/Dancing to music	1 (1.0)	2 (1.6)	3 (1.3)
Smoking related	1 (1.0)	2 (1.6)	3 (1.3)
Talking to self	4 (4.0)	6 (4.7)	10 (4.4)
Operating in-vehicle controls/devices	2 (2.0)	5 (3.9)	7 (3.1)
Attending elsewhere, unknown	0	0	0
Attending to person outside vehicle	0	0	0

[1]p<.0001, [2]p<.01, [3]p<.05

Eyes-off-road time

In crashes where no driver behaviors were coded, the driver had their eyes off the road an average of 0.6 s; in crashes where a driver behavior was coded, this time was significantly longer at 3.0 s. There was a large difference in the average eyes-off-road time when examined by crash type (Table 5). Drivers involved in a rear-end crash had their eyes off the forward roadway more than four times as long as than those involved in an angle crash (3.2 s vs. 0.7 s, $p<.0001$).

Table 5. Eyes-off-roadway time by crash type

	Rear-end	Angle	All crashes
Mean (std dev)[1]	3.2 (2.1)	0.7 (1.3)	1.8 (2.1)
N (%) of crashes with eyes off the road for 6 seconds[1]	8 (9.2)	0	8 (4.0)
N (%) of crashes with eyes off the road for 0 seconds[1]	14 (16.1)	81 (71.7)	95 (47.5)

[1]p<.0001, [2]p<.01, [3]p<.05

Eyes-off-road time differed by behavior as well: for drivers attending outside of the vehicle, the average was 3.3 s, inside of the vehicle 3.8 s, and any cell phone use 3.5 s. Although a small proportion of crashes involved passengers, when a driver was attending to passengers, their eyes-off-road time was lower than when engaged in any of the top three behaviors, at 0.9 s (Table 6).

Table 6. Eyes-off-roadway time by crash type and driver behavior

	Rear-end		**Angle**		**All crashes**	
	N	Mean (std)	N	Mean (std)	N	Mean (std)
No behaviors	36	1.9 (2.1)	77	0.1 (0.3)	113	0.6 (1.4)
Any behaviors	65	3.8 (1.8) [1]	51	1.9 (1.6)[1]	116	3.0 (1.9)[1]
Any cell phone use	14	4.2 (1.4) [2]	5	1.4 (1.8)[3]	19	3.5 (1.9)[1]
Cell phone (operating/looking)	8	4.8 (0.7)[2]	2	2.8 (1.4)[2]	10	4.4 (1.2)[1]
Cell use (talking/listening)	2	2.3 (1.8)	4	0.6 (1.0)	6	1.3 (1.5)
Cell use likely but not visible	5	4.0 (1.2)[3]	0		5	4.0 (1.2)[1]
Eating or drinking	0		3	1.6 (1.8)[3]	3	1.6 (1.8)
Using electronic device (mp3, iPod, nav)	5	5.5 (0.6)[2]	2	2.3 (3.2)[2]	7	4.6 (2.1)[1]
Attending to a moving object inside vehicle	0		0		0	
Attending inside vehicle, unknown	19	4.4 (1.5)[1]	12	2.7 (1.3)[1]	31	3.8 (1.6)[1]
Attending to another vehicle or passenger in other vehicle	1	1.8	0		1	1.8
Attending outside vehicle, unknown	23	3.7 (1.5)[1]	12	2.6 (1.1)[1]	35	3.3 (1.5)[1]
Attending to passenger(s)	3	1.5 (1.6)	4	0.8 (1.4)	7	0.9 (1.4)
Personal grooming	8	3.8 (1.8)[3]	4	1.5 (2.1)[3]	12	3.2 (2.0)[1]
Reaching for object	7	4.4 (1.6)[2]	9	2.7 (1.0)[1]	16	3.4 (1.5)[1]
Singing/Dancing to music	1	3.8	2	1.0 (no std)	3	2.4 (1.9)
Smoking related	1	2.0	2	0	3	1.0 (1.4)
Talking to self	4	2.2 (2.0)	6	0.4 (0.9)	10	1.2 (1.7)
Operating in-vehicle controls/devices	2	3.1 (3.4)	5	1.2 (0.9)[3]	7	1.8 (1.9)
Attending elsewhere, unknown	0		0		0	
Attending to person outside vehicle	0		0		0	

[1]p<.0001, [2]p<.01, [3]p<.05 compared to no behaviors

Compared to rear-end crashes with no driver behaviors, those with any cell phone use (particularly looking and operating the cell phone), using other electronic devices, attending outside the vehicle to an unknown location, personal grooming, and reaching for an object had significantly longer eyes-off-road time. Many of the same relationships existed in angle crashes. In contrast to angle crashes with no driver behaviors, those with cell phone use (in particular, operating/looking), using other electronic devices, attending inside the vehicle to an unknown location, personal grooming, and reaching for an object had significantly longer total eyes-off-road time.

Reaction time

Reaction time was analyzed for rear-end crashes only (Table 7). Among rear-end crashes (n=101), a reaction time was coded for 33 crashes. For the other 68 crashes, the driver had no reaction (i.e., did not apply the brake before impacting the other vehicle). The mean reaction time for crashes with no driver behaviors was 1.9 s; any driver behavior observed increased it to 2.5 s.

Table 7. Reaction time for rear-end crashes by type of driver behavior

	Reaction Time (n=33)		**No Reaction (n=68)**
	N (row %)	Mean (std)	N (row %)
No driver behavior	13 (36.1)	1.9 (0.8)	23 (63.9)
Any driver behavior	20 (30.8)	2.5 (1.3)	45 (69.2)
Any cell phone use	7 (50.0)	3.3 (1.6) [2]	7 (50.0)
Cell phone use (operating/looking)	5 (62.5)	3.7 (1.8)	3 (37.5)
Cell phone use (talking/listening)	2 (100)	3.0 (1.4)	0
Cell phone use likely but not visible	1 (20.0)	3.0	4 (80.0)
Eating or drinking[a]	0		0
Using electronic device (mp3, iPod, nav)[a]	0		5 (100)
Attending to a moving object inside vehicle[a]	0		0
Attending inside vehicle, unknown	2 (10.5)	2.5 (1.1)	17 (89.5)[3]
Attending to another vehicle or passenger in other vehicle[a]	0		1 (100)
Attending outside vehicle, unknown	9 (39.1)	2.1 (1.1)	14 (60.9)
Attending to passenger(s)	2 (66.7)	1.5 (0.4)	1 (33.3)
Personal grooming	3 (37.5)	2.7 (1.2)	5 (62.5)
Reaching for object	2 (28.6)	3.4 (0.9)	5 (71.4)
Singing/dancing to music	1 (100)	3.3	0
Smoking-related	1 (100)	2.8	0
Talking to self	1 (25.0)	3.3	3 (75.0)
Operating in-vehicle controls/devices[a]	0		2 (100)
Attending elsewhere, unknown[a]	0		0
Attending to person outside vehicle[a]	0		0

[1]p<.0001, [2]p<.01, [3] p<.05 compared to reaction time for drivers with no distractions (means) or comparison of proportion with and without time to react, [a] these distractions did not have reaction times

Discussion

Roadway and environmental conditions present in fleet-driver crashes

Very few crashes were due to road surface (10%) or environmental conditions. Over half of crashes occurred on arterial roads (51.5%) or interstates (12.2%). This confirmed the results of a study by Bunn and Struttmann (2003), which found that 44% of fatal crashes occurred on four-lane roads. Almost three quarters of crashes occurred when there were no adverse weather conditions. In 8% of crashes, a traffic back-up was identified during the six seconds prior to the crash.

Critical pre-crash events and contributing factors in fleet-driver crashes

Decision errors, such as following too closely (12.2% of crashes), running a stop sign or traffic signal (11.4%), and failure to yield the right-of-way (12.7%) were observed more frequently here than in previous research (Bunn and Struttmann, 2003). Although performance errors were rare in our study (3.1% of crashes), the proportion was similar to the Bunn and Struttmann study (2003), which found 3-7% of driver errors in crashes were of this type.

In this analysis, driving too fast was observed in very few crashes (1.8%); previous studies, however, suggested 9-15% of crashes were due to speed (Boufous and Williamson, 2006). This difference could be due to actual crash causation, recall bias of self-reports in previous research, or to the difficulty of verifying speed in our videos.

Type and frequency of driver behaviors in fleet-driver crashes

The most common driver behaviors seen were inadequate surveillance (71.2%) and driver distraction or inattention (50.2%). The number of driver distractions coded was more than twice that reported by Bunn and Struttmann (2003) in Kentucky. This was likely due to our more objective measurement of distractions through reviewing naturalistic driving data, rather than through driver self-report or police crash reports. Interestingly, Bunn and Struttmann were unable to determine whether or not the driver contributed to the crash in almost one-third of crashes; using these videos, we were able to report driver contribution in over 80% of crashes. This suggests that naturalistic driving data may offer a more holistic and accurate view of what is occurring inside a vehicle just before a crash.

To the best of our knowledge, this analysis is the first to examine driver behaviors among this population by crash type. As hypothesized, rear-end crashes were more likely to have a driver engaging in a potentially distracting behavior. Rear-end crashes had a higher proportion of the three most common behaviors seen than angle crashes. Drivers exhibiting these behaviors had longer eyes-off-road times, and less time to react to potential crash situations due to inadequate surveillance and distraction.

Driver response time and eyes-off-road time relative to driver behaviors and crash types

Again, to date, no information has been published about the average time fleet drivers' eyes are off the road. As expected, videos with no coded driver behaviors had shorter eyes-off-road time than crashes where a potentially distracting driver behavior was seen. The type of driver behavior also affected the amount of eyes-off-road time and the type of vehicle-to-vehicle crash that occurred. This baseline information regarding driver behaviors, their effect on the amount of time drivers' eyes are off the road, and the crash types that ensue can be used to inform technological interventions to overcome these behaviors.

Drowsy driving and fleet-driver crashes

Here, a small proportion of crashes (1.8%) involved observable evidence of driver fatigue or tiredness. In previous studies, between 4–15% of crashes were attributed to fatigue or sleepiness (Boufous and Williamson, 2006; Bunn and Struttmann, 2003). This discrepancy may be due to actual crash causation, recall bias of self-reports in previous research, or to the difficulty of identifying fatigue/sleepiness (e.g., long eye closures, yawns, blanks stares) in our videos because of the relatively low frame rate of 4 frames per second.

Strengths and Limitations

Naturalistic driving studies allow researchers to examine many aspects of driving, and provide invaluable data that would not be available otherwise. Until now, the only way to obtain large amounts of data regarding driver crashes was through NHTSA's FARS and GES data, obtained from police-reported crashes. While this information is helpful, it has many limitations. One important limitation is the lack information regarding driver distraction, which is limited to what an officer was able to view or a bystander reported. This study allows us to report all driver and passenger behaviors. In addition, the data from this naturalistic study is able to provide a micro-level of detail about a crash, such as eye glances and reaction times—information unavailable in police-reported data.

A major advantage of this study is that it provides data from 229 moderate-to-severe crashes. Having such a large sample makes our findings more generalizable to the fleet-driver population. In addition, we were able to look at different types of crashes within vehicle-to-vehicle crashes (i.e., rear-end vs. angle) by risk factors to provide a more holistic view of these crash subtypes. Understanding the nuances of crash subtypes is vital to the prevention of crashes.

Another major advantage of this particular study, compared to other naturalistic studies, is that we had a view of the entire cab and the ability to hear what was taking place inside the vehicle. This information provided us with a fuller context of what was occurring during the six seconds before a crash. It was particularly important when examining driver distraction. Other naturalistic studies have been limited by the partial view, the inability to see what or who the driver is looking at, or to review audio to examine conversations between drivers and passengers.

In addition, this is the first study to examine risk factors for rear-end or angle crashes among professional drivers. Given that transportation-related death is the leading cause of occupational deaths, this analysis is invaluable in its investigation of driver behaviors among a high-risk group.

As with all naturalistic driving research there are concerns regarding the representativeness of the drivers involved in the study. Since the drivers in these crashes were not recruited, they may be slightly more representative than those who might normally sign up for such studies. However, their employers required that they participate in a program that provided an intervention when unsafe driving behaviors were observed. Drivers knew they were part of the program, and one might argue that this would make them less likely to exhibit risky or aggressive driving behaviors, or to engage in potentially distracting behaviors. If this were true, the frequency of driver behaviors reported may not be generalizable to all drivers, and we hypothesize the proportions reported may underestimate certain behaviors among the general driver population. Nevertheless, more than half of all fleet-driver crashes (50.7%) had a potentially distracting behavior present in the six seconds before the crash.

Another concern is that this particular naturalistic study collected event-triggered data, as opposed to data collected continuously. As a result, we did not have the ability to examine driver or passenger behaviors during non-collision events. Therefore, the true extent to which a driver engages in particular behaviors is unknown. In addition, we cannot give a crash rate by behavior, but can only say that when a crash occurred, certain behaviors were most likely to be present. Again, however, it is notable that given the large study sample, we were able to examine how the presence of such behaviors contributed to different crash types, specifically rear-end and angle. However, prevalence data, such as what was examined in this study, is limited in that we are unable to say anything about causation or associated risk.

For this study, rear-end crashes in which the driver was hit from behind were not examined. Therefore, it is likely that the 84% of vehicle-to-vehicle crashes in which driver error was a contributing factor is inflated. However, the results of this study allow us to describe what types of environments, road conditions, and driver behaviors are present during rear-end crashes in which the fleet driver was the one to collide with the rear of another vehicle.

Finally, there are a few concerns regarding the IVERS used in this study and its ability to detect information that we know to be significant contributors to crashes. Global positioning system (GPS) data was not available, and therefore we could not assess vehicle speed (available for less than 10% of crashes). In addition, drowsy driving and fatigue were difficult to determine due to the low frame rate (4 frames per second), and it is likely that 6 s may not provide enough information to determine fatigue. In addition, the quality of nighttime videos made it difficult to see drivers' eyes, also reducing possible findings of drowsy or fatigued driving.

Conclusion

Use of in-vehicle event recorders in naturalistic driving allows researchers a unique view into the vehicle, and provides invaluable information regarding the behavioral and environmental factors present before a crash. This type of data provides a much more detailed context relative to police reports and other crash databases, and allows more micro-level analyses to be conducted.

This study examined the roadway and environmental conditions present in different types of crashes. It describes the critical events and contributing factors that lead up to crashes, and how they vary by crash type. It also provides information regarding the effect certain driver behaviors have on reaction time and eyes-off-road time. Lastly, it is the first naturalistic study of moderate-to-severe crashes to examine driver behaviors for a variety of crash types.

The results of this study indicate that there are different driver behaviors and contributing circumstances present for rear-end vs. angle crashes. The most common driver behavior seen was inadequate surveillance, with attending inside or outside the vehicle to an unknown location being coded most often. However, fleet drivers were more likely to be seen engaging in these potentially distracting behaviors when they were alone in the vehicle. Additionally, drivers involved in a rear-end crash were more likely to engage in a potentially distracting behavior and had total eyes-off-road times that were four times as long as than those involved in angle crashes.

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