The Prevalence of Driver Fatigue in an Urban Driving Environment: Results from the 100-Car Naturalistic Driving Study.

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INTRODUCTION

Commonly cited crash statistics and case studies indicate that driver fatigue is a major cause of long-haul truck crashes (e.g., NTSB, 1990 (1); NTSB, 1995 (2); Haworth, Triggs, and Grey, 1988 (3)). Campbell, Smith, and Najm (2003) (4) used data existing in the General Estimates System (GES) crash database and the Crashworthiness Data System (CDS) database to examine the primary contributing factors of single vehicle run-off road (SVOR), rear-end (RE), and lane change (LC) crashes. Their results suggest that fatigue (sleepy/drowsiness) contributed to 6% of SVOR crashes (property damage only) and only 1% to rear-end collisions (property damage only). Wang, Knipling, and Goodman (1995) (5) reviewed data from the CDS and found similar results in that fatigue contributed to 1.3% of all crashes.

A review of the fatigue-related driver literature indicated that very little research has been done on fatigue and younger drivers. Ferguson (2003) (6) reported serious concerns about the effects of fatigue among younger drivers, given that adolescents’ sleep patterns shift to later hours. However, younger drivers’ school start times rarely cooperate with their new sleep patterns and therefore increase daytime sleepiness. Secondly, fatigue, in combination with alcohol use, is a serious combination given adolescent’s lack of driving experience and inability to compensate. Williams (2003) (7) briefly discussed fatigue in combination with nighttime driving and alcohol use. He reported data indicating that younger drivers fatal crash involvement was 3 times higher during the night than during the day which is probably a combination of alcohol use and fatigue.

An instrumented vehicle study investigating truck driver fatigue indicated that fatigue may contribute to more crashes than crash database results suggest. Dingus, Neale, Garness, Hanowski, Keisler, et al. (2001) (8) conducted an instrumented vehicle study investigating the impact of fatigue on truck drivers. The results from this study indicated that fatigue contributed to over 20% of all near-crashes and crashes. While there were only 2 crashes and 22 near-crashes, this finding does suggest a strong influence of fatigue involvement in crashes and near-crashes.

Possible reasons for the conflicting results between epidemiological research and empirical research include: 1) the lack of a specific check box for fatigue on some state police report forms; 2) the lack of firm evidence on which to base a police finding of fatigue; 3) the lack
of awareness on the part of the driver of his/her own fatigue; and 4) the significant number of crashes involving “drift out of lane,” of which are not cited as drowsiness related (Wang, Knipling, & Goodman 1996) (5). Empirical research has significantly fewer cases upon which to base results.

A large-scale naturalistic data collection could serve as an alternative to these traditional methods. The “scale” is typically much smaller than epidemiological requirements, but still requires substantial data to be collected and analyzed. This has several advantages. First, the data can be analyzed via a near-crash/crash approach since these occur with enough frequency to maintain statistical power. Second, there is growing evidence that true near-crashes provide a valid safety surrogate relative to many traditional empirical measures (Dingus, Hetrick and Mollenhauer, 1999) (9). Third, the collection of “natural” driver behavior provides important information about the complex circumstances and scenarios that lead to crashes. This “natural” behavior information could be useful for mitigating crashes.

**METHOD**

**Subjects**

One-hundred drivers who commuted into or out of the Northern Virginia/Washington, DC metropolitan area were initially recruited as primary drivers to have their vehicles instrumented or receive a leased vehicle for this study. Drivers were recruited by placing flyers on vehicles as well as by placing newspaper announcements in the classified section. Drivers who had their private vehicles instrumented (78) received $125.00 per month and a bonus at the end of the study for completing necessary paperwork. Drivers who received a leased vehicle (22) received free use of the vehicle, including standard maintenance, and the same bonus at the end of the study for completing necessary paperwork. Drivers of leased vehicles were insured under the Commonwealth of Virginia policy.

As some drivers had to be replaced for various reasons (for example, a move from the study area or repeated crashes in leased vehicles), 109 primary drivers were included in the study. Since other family members and friends would occasionally drive the instrumented vehicles, data were collected on 132 additional drivers.

A goal of this study was to maximize the potential to record crash and near-crash events through the selection of subjects with higher than average crash- or near-crash risk exposure.
Exposure was manipulated through the selection of a larger sample of drivers below the age of 25, and by the selection of a sample that drove more than the average number of miles. The age by gender distribution of the primary drivers is shown in Table 1. The distribution of miles driven by the subjects during the study appears as Table 2. As presented, the data are somewhat biased compared to the national averages in each case, based on TransStats. Nevertheless, the distribution was generally representative of national averages when viewed across the distribution of mileages within the TransStats data.

Table 1. Driver age and gender distributions.

<table>
<thead>
<tr>
<th>Age</th>
<th>N</th>
<th>Gender</th>
<th></th>
<th></th>
<th>Grand Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of total</td>
<td></td>
<td>Female</td>
<td>Male</td>
<td></td>
<td></td>
</tr>
<tr>
<td>18-20</td>
<td>9</td>
<td>8.3%</td>
<td>7</td>
<td>6.4%</td>
<td>14.7%</td>
</tr>
<tr>
<td>21-24</td>
<td>11</td>
<td>10.1%</td>
<td>10</td>
<td>9.2%</td>
<td>19.3%</td>
</tr>
<tr>
<td>25-34</td>
<td>7</td>
<td>6.4%</td>
<td>12</td>
<td>11.0%</td>
<td>17.4%</td>
</tr>
<tr>
<td>35-44</td>
<td>4</td>
<td>3.7%</td>
<td>16</td>
<td>14.7%</td>
<td>18.3%</td>
</tr>
<tr>
<td>45-54</td>
<td>7</td>
<td>6.4%</td>
<td>13</td>
<td>11.9%</td>
<td>18.3%</td>
</tr>
<tr>
<td>55+</td>
<td>5</td>
<td>4.6%</td>
<td>8</td>
<td>7.3%</td>
<td>11.9%</td>
</tr>
<tr>
<td>Total N</td>
<td>43</td>
<td>39.4%</td>
<td>66</td>
<td>60.6%</td>
<td>100.0%</td>
</tr>
<tr>
<td>Total Percent</td>
<td>39.4%</td>
<td>60.6%</td>
<td>100.0%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2. Actual miles driven during the study.

<table>
<thead>
<tr>
<th>Actual miles driven</th>
<th>Number of Drivers</th>
<th>Percent of Drivers</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-9,000</td>
<td>29</td>
<td>26.6%</td>
</tr>
<tr>
<td>9,001-12,000</td>
<td>22</td>
<td>20.2%</td>
</tr>
<tr>
<td>12,001-15,000</td>
<td>26</td>
<td>23.9%</td>
</tr>
<tr>
<td>15,001-18,000</td>
<td>11</td>
<td>10.1%</td>
</tr>
<tr>
<td>18,001-21,000</td>
<td>8</td>
<td>7.3%</td>
</tr>
<tr>
<td>More than 21,000</td>
<td>13</td>
<td>11.9%</td>
</tr>
</tbody>
</table>

One demographic issue with the 100-Car data sample that needs to be understood is that the data were collected in only one area (i.e., Northern Virginia/Metro Washington, DC). This
area represents primarily urban- and suburban driving conditions, often in moderate to heavy traffic. Thus, rural driving, as well as differing demographics within the U.S., are not well represented.

**Vehicles**

Since 100 vehicles had to be instrumented with a number of sensors and data collection hardware, and since the complexity of the hardware required a number of custom mounting brackets to be manufactured, the number of vehicle types had to be limited for this study. Six different vehicle models were selected based upon their prevalence in the Northern Virginia area. These included five sedan models (Chevrolet Malibu and Cavalier, Toyota Camry and Corolla, and Ford Taurus) and one SUV model (Ford Explorer). The model years were limited to those with common body types and accessible vehicle networks (generally 1995 to 2003). The distribution of these vehicle types was:

- Chevy Cavalier – 17%
- Chevy Malibu – 21%
- Ford Taurus – 12%
- Ford Explorer – 15%
- Toyota Camry – 17%
- Toyota Corolla – 18%

**Apparatus**

The data acquisition system (DAS) used for the 100-Car Study was developed by engineers at the Virginia Tech Transportation Institute (VTTI). The DAS distributed data acquisition method provided a very flexible and maintainable hardware data collection system. The sensors used for this DAS included five video channels, forward and rearward Vorad radar units, accelerometers, lane tracking software (developed in-house), and an in-vehicle network sensor.

The main unit was mounted in the trunk under the “package shelf” (Figure 1) using bolts. Wiring was run though the existing wire chases to all the various network nodes as well as to the cameras. The cameras were mounted unobtrusively in order to facilitate naturalistic driving
behavior. All of the microprocessor boards, including the firmware and data collection software, were developed at VTTI.

![Figure 1. The main Data Acquisition System (DAS) unit mounted under the package shelf of the trunk.](image)

The DAS for the 100-Car Study collected data continuously from the time that the driver turned the ignition on until the ignition was turned off. MPEG 1 compression software was used to assist in compressing and storing the video data. Approximately 6.4 TB of data was collected for this study.

**Procedure**

Participants were recruited via newspaper advertisements and fliers placed on appropriate vehicles in parking lots located near the Virginia Tech Northern Virginia Center. Drivers who responded to these recruiting methods were informed of the study details (e.g., data collection system, five video channels, and 12 month data collection period).

During data collection, four VTTI employees (chase vehicle drivers) drove to each of the instrumented vehicles to download the data approximately once every 2-3 weeks. Data were stored on multiple copies of DVDs. One copy was sent to VTTI researchers in Blacksburg and one copy was kept in Northern Virginia.

**Data Reduction Process**

As stated previously, data were collected continuously to optimize the trigger criteria values after driving performance data were collected. If the triggers had been set prior to data
collection, valuable events may have been lost without any method of recovery. One method of efficiently establishing trigger criteria is to perform a sensitivity analysis.

A sensitivity analysis was performed by setting the trigger criteria to a very liberal level, reducing the chance of a missed valid event to a minimal level while allowing a high number of invalid events (false alarms) to be identified. Data reductionists then viewed all of the events produced from the liberal trigger criteria and classified each event as valid or invalid. The number of valid events and invalid events that resulted from this baseline setting was recorded.

The trigger criteria for each dependent variable was then set to a slightly more conservative level and the resulting number of valid and invalid events was counted and compared to the first frequency count. The trigger criteria were made more and more conservative and the number of valid and invalid triggers counted and compared until an optimum trigger criteria value was determined (a level which results in a minimal amount of valid events lost and a reasonable amount of invalid events identified). The goal in this sensitivity analysis was to obtain a miss rate of less than 10% and a false alarm rate of less than 30 percent.

Based on data from past VTTI studies, it was originally hypothesized that as many as 26 crashes, 520 near-crashes, and over 25,000 incidents (crash-relevant conflicts and proximity conflicts) would be collected; however many of these early estimates were based on long-haul truck driving data. It was soon discovered, after the sensitivity analysis process began, that the variability in light vehicle drivers’ braking, acceleration, and steering behavior is much larger than with truck drivers. It is likely that this is due to differences in vehicle dynamics and the more uniform driving skill of commercial truck drivers.

Given the large variability in light vehicle driving performance, the sensitivity analysis proved to be challenging. VTTI researchers determined that the best option was to accept a very low miss rate while accepting a fairly high false alarm rate to ensure that few valid events were missed. This resulted in viewing over 110,000 events in order to validate 10,548 events. The distribution of the total number of reduced events by severity is shown in Table 3.
Table 3. The total number of events reduced for each severity level.

<table>
<thead>
<tr>
<th>Event Severity</th>
<th>Total Number</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crash</td>
<td>69 (plus 13 without complete data)</td>
</tr>
<tr>
<td>Near-Crash</td>
<td>761</td>
</tr>
<tr>
<td>Incidents (Crash-relevant Conflicts and Proximity Conflicts)</td>
<td>8,295</td>
</tr>
<tr>
<td>Non-Conflict Events</td>
<td>1,423</td>
</tr>
</tbody>
</table>

Once the trigger criteria were set for Phase II, data reductionists watched 90 s epochs for each event (one minute prior to and 30 s after), reduced and recorded information concerning the nature of the event, driving behavior prior to the event, the state of the driver, the surrounding environment, etc. The specific variables recorded in the data reduction process are described in detail in the data reduction software framework section of this chapter.

**Recruiting and Training Data Reductionists**

The data reductionists performed two general tasks for this project. On the first 10-15% of the data, they performed a preliminary data reduction task in which they viewed events to determine whether the event was valid or invalid and to determine the severity of the event. After the trigger criteria for Phase II was set using the results from the sensitivity analysis, the data reductionists then validated the data, determined severity, and performed a full data reduction. For the full data reduction, they recorded all of the required variables for the event type. For a complete description of all variables recorded, please refer to Dingus, Klauer, Neale, Petersen, Lee, (in press) (10).

**RESULTS**

The total number of subjects who were involved in fatigue-related crashes and near-crashes was 38 with the most frequent offenders (11 drivers) accounting for 58% of all the fatigue-related crashes and near-crashes. The range of fatigue-related crash and near-crash involvement is shown in Figure 2. As has been found in previous research, there appears to be high variability among subjects who tend to drive fatigued and those who are able to avoid it.
Figure 2. Frequency of Fatigue-Related Crashes and Near-crashes by Subject Number.

Figure 3 shows the percent of crashes and near-crashes where fatigue was marked as a contributing factor. Note that 12% of crashes were considered to be caused at least in part by fatigue. This percentage is much higher than current epidemiological research suggests.
The data in the 100 Car Naturalistic Driving Study were collected continuously which provides a means to sample randomly and estimate exposure. In order to estimate exposure, 20,000 randomly selected 6 second segments of video were viewed and reduced by trained data reductionists. Moderate to severe driver fatigue was recorded if observed, providing an estimate of the amount of time drivers were fatigued but were not involved in a crash or near-crash event. Using these estimates of exposure to fatigue and the occurrence of fatigue-related crashes and near-crashes, relative risk calculations and population attributable risk calculations were conducted.

Relative risk calculation can be estimated from an odds ratio and is calculated by counting the frequency of crashes and near-crashes that were and were not fatigue-related as well as the number of baseline events that were and were not fatigue-related. This calculation provides an estimate for crash risk of driving fatigued as compared to normal driving.

Population attributable risk also takes into account the baseline data (estimate of exposure) and calculates how this result applies to the population at-large. Therefore, based on this data, how many crashes in the population are then fatigue-related.

Figure 3. Percent of all crashes and near-crashes where fatigue was considered to be a contributing factor.
The relative risk and population attributable risk, calculated using the 100 Car data, are shown in Table 4. These results suggest that drivers are at a 4 times greater risk of a crash or near-crash if they choose to drive while fatigued. The population attributable risk calculation suggests that between 11.5% and 12.5% of all crashes and near-crashes in the population are attributable to fatigue.

<table>
<thead>
<tr>
<th>Crash Risk Measure</th>
<th>Calculated Value</th>
<th>Lower Confidence Interval</th>
<th>Upper Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relative Risk</td>
<td>4.6</td>
<td>3.6</td>
<td>5.8</td>
</tr>
<tr>
<td>Population Attributable Risk</td>
<td>12.2</td>
<td>11.9</td>
<td>12.5</td>
</tr>
</tbody>
</table>

In order to determine whether age played a role in the high variability among subjects, an ANOVA was conducted to determine if age significantly affected involvement in fatigue-related crashes and near-crashes. Figure 4 shows the mean number of fatigue-related events per million vehicle miles traveled per age group. The main effect of age was significant ($F (5, 95) = 4.47, p = 0.001$); therefore, a Tukey post-hoc test was conducted to determine which age groups were significantly different from each other. This result indicated that the youngest age group, 18- to 20-year-olds, were significantly different from all other age groups at $p < 0.01$. No other significant differences were observed among any other groups.
Figure 4. The rate of occurrence of fatigue-related crashes and near-crashes per million vehicle miles traveled by age group.

To further understand the differences associated with the youngest age group versus the rest of the age groups, driver involvement in fatigue-related crashes and near-crashes was compared to driver responses on several questions from the Walter Reed Sleep Hygiene Questionnaire. This questionnaire was administered to the drivers prior to data collection.
The two questions that were used were the following:

1.) To what extent do you currently experience daytime sleepiness?

   1 = Never
   5 = Moderate
   10 = Severe

2.) How many hours of actual sleep do you usually get?

Two-way ANOVA’s were calculated to determine if age and daytime sleepiness ratings affected driver’s involvement in fatigue-related events. Neither test showed statistical significance for either main effects or interaction.

**CONCLUSIONS**

Fatigue may contribute to a higher percentage of crashes than was thought in previous studies (Wang, Knipling, & Goodman, 1996, Campbell, Smith, & Najm, 2003) (5, 4). The data collected in The 100 Car Naturalistic Driving Study shows that driving while fatigued increases a driver’s risk of involvement in a crash or near-crash by nearly four times. Also, fatigue contributes to 12.2% of all crashes in the population.

Younger drivers are over-represented in the fatigue-related crashes and near-crashes as well which is interesting considering the lack of research on this topic. Analyses of the questionnaire responses regarding levels of daytime sleepiness or number of hours slept on average indicated there are no significant differences between age groups. This result may indicate that the problem of fatigue may rest primarily with lack of driver experience. It may be that younger drivers do not have sufficient experience to cope with even moderate fatigue and still maintain their basic skill level.

While younger driver research has looked extensively at the relationship between time of day and alcohol use with regard to crashes (both of which may be associated with fatigue), driver fatigue for younger drivers is an area of research that needs to be explored and better understood. Future analyses with the 100-Car database will further investigate this question and it is hoped that future naturalistic driving studies will involve younger drivers (16- to 18-years-old) and
further analyze the issues of fatigue and alcohol use and their impact on crash and near-crash involvement.

Acknowledgements

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