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The National Surface Transportation Safety Center for Excellence

Identifying High-Risk Commercial Truck Drivers Using a Naturalistic Approach

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Lighting | Technology
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EXECUTIVE SUMMARY

Several research reports suggest that some people are characterologically more inclined to have more crashes than other people. It appears that individual differences in personality and performance may predispose some people to a greater risk of being involved in a crash. This document serves as the final report for a National Surface Transportation Safety Center for Excellence (NSTSCE) research project that assessed the concept of high-risk commercial motor vehicle (CMV) drivers and the characteristics associated with these drivers. The current study used naturalistic data collected during the Federal Motor Carrier Safety Administration (FMCSA)-funded Drowsy Driver Warning System Field Operational Test (DDWS FOT) and Naturalistic Truck Driving Study (NTDS) projects.

METHODS

The rates of at-fault and non-fault safety-critical events (SCEs) per mile were calculated for each participant. A cluster analysis using the flexible beta method was performed on the participants' rates of at-fault and non-fault SCEs/mile to assess group membership (i.e., risky, average, and safe drivers). Questionnaires completed by these drivers during the DDWS FOT and NTDS were re-coded (i.e., to a common coding system), and the clusters were compared to identify differences in drivers' anthropometric and demographic variables. A regression model using the anthropometric and demographic variables was also explored to predict group membership.

RESULTS

Three distinct clusters of CMV drivers (safe, average, and risky) emerged in the cluster analysis. The safe cluster comprising 119 drivers accounted for 75.9 percent of the total miles traveled and 24.8 percent of the SCEs. The average cluster comprising 50 drivers accounted for 17 percent of the total miles traveled and 24.9 percent of the SCEs. The risky cluster comprising 31 drivers accounted for 7.1 percent of the total miles traveled and more than 50.3 percent of the SCEs. The health conditions of head injury, inner ear problem, arthritis, and motion sickness were reported significantly more in the risky group compared to the safe and average groups. However, the relationship between these health variables and driver risk is likely to be exaggerated due to low cell counts and the small size of the risky group of CMV drivers. The regression analysis was inconclusive as the models were misleading and difficult to interpret due to non-significant interactions between the variables once the hierarchical principle was applied.

DISCUSSION

A small percentage of CMV drivers was responsible for a disproportionately large percentage of SCEs, whereas the vast majority of CMV drivers were safe drivers. It would appear that interventions that target the risky group of drivers would yield the largest impact on crash reduction. Although the data set used in the current study was rich, the small sample size created limitations in the analyses and associated interpretations. Future studies with a larger sample size would address some of the limitations in the current study and would allow a principal component analysis, which could lead to a better understanding of the individual differences in the different clusters of CMV drivers.

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LIST OF ABBREVIATIONS AND SYMBOLS

ANOVA	Analysis of variance
BMI	Body mass index
CMV	Commercial motor vehicle
DDWS FOT	Drowsy Driver Warning System Field Operational Test
FMCSA	Federal Motor Carrier Safety Administration
ND	Naturalistic driving
NSTSCE	National Surface Transportation Safety Center for Excellence
NTDS	Naturalistic Truck Driving Study
SCE	Safety-critical event
USDOT	U.S. Department of Transportation
VTTI	Virginia Tech Transportation Institute

CHAPTER 1. OVERVIEW OF THE NATIONAL SURFACE TRANSPORTATION SAFETY CENTER FOR EXCELLENCE

The National Surface Transportation Safety Center for Excellence (NSTSCE) at the Virginia Tech Transportation Institute (VTTI) was established by the Federal Public Transportation Act of 2005 to develop and disseminate advanced transportation safety techniques and innovations in both rural and urban communities. Using state-of-the-art facilities, including the Virginia Smart Road, the Center conducts the necessary research to improve driver safety at the local, state, and national levels in both rural and urban communities.

One major component of the NSTSCE mission is to develop a greater understanding of driver decision making and performance during normal driving through imminent crash situations in various driving environments. This document serves as the final report for an NSTSCE research project that assessed the concept of high-risk commercial motor vehicle (CMV) drivers and the characteristics associated with these drivers. The current study used naturalistic data collected during the Federal Motor Carrier Safety Administration (FMCSA)-funded Drowsy Driver Warning System Field Operational Test (DDWS FOT) and Naturalistic Truck Driving Study (NTDS) projects.

CHAPTER 2. BACKGROUND

At any given time a multitude of interacting factors influence crash involvement. Drivers are influenced by fatigue-related factors (e.g., amount of prior sleep, time of day, hours driving), situational stressors (e.g., pressure to deliver on time, recent events causing anger or anxiety), and varying environmental conditions (e.g., weather, the actions of other motorists). All these can contribute to crash involvement.[1,2] As such, CMV driver behavior is likely to be a product of these interacting factors.

The notion that some people are characterologically more inclined to have more crashes than other people has been referred to as “accident proneness.” The concept was first proposed by Greenwood and Woods.[3] When Greenwood and Woods analyzed the incident records of similarly exposed and experienced munitions workers in Britain they found that a small percentage of the workers accounted for the majority of incidents.[3] The idea of accident proneness spawned much research, and many studies have been conducted about the subject since Greenwood and Woods’ seminal study.

It certainly appears that individual differences in personality and performance predispose some people to a greater risk of being involved in a crash. Driver errors can include violations of rules, mistakes of judgment, inattention errors, or inexperience errors. Common driver errors that result in crashes include recognition errors (failure to perceive a crash threat) and decision errors (risky driving behavior such as tailgating).[4] When the concept that some people are more likely to be involved in an incident was first proposed it generated enormous interest because of its practical implications. If CMV fleets could identify certain traits or behaviors of CMV drivers who are likely to be involved in crashes (high-risk) they could be intervened, thereby preventing future crashes and associated injuries.

EVIDENCE OF HIGH-RISK CMV DRIVERS

Knipling et al.[4] surveyed fleet safety managers and other CMV safety experts regarding high-risk CMV drivers and effective safety management techniques. The authors also reviewed concepts about driver risk, factors related to driver risk, and safety management techniques that address driver risk. Perhaps the most fundamental question about high-risk CMV drivers is whether the problem is genuine and significant and not just an artifact of chance or factors uncontrollable by CMV drivers and their fleets. The majority of both respondent groups in Knipling et al. believed the worst 10 percent of drivers were associated with 50 percent or more of fleet crash risk.[4] Moreover, approximately two-thirds of both respondent groups believed there was a “strong tendency” for individual differences in crash risk to be consistent and enduring over time.[4] Empirical data partially corroborate these views held by fleet safety managers and other CMV safety experts. An FMCSA-sponsored study conducted by Hanowski et al.[5] observed 42 instrumented local/short-haul trucks that covered a total of 28,000 vehicle miles. The study identified 249 critical incidents of which 77 were primarily related to the behaviors of truck drivers. Common critical incidents included running red lights or crossing traffic with insufficient gaps (i.e., approaching vehicles too close for safe crossing). The 42 truck drivers were responsible for 77 critical incidents during 1,376 hours of driving. Figure 1 displays the frequency of critical incidents per hour among the 42 drivers.

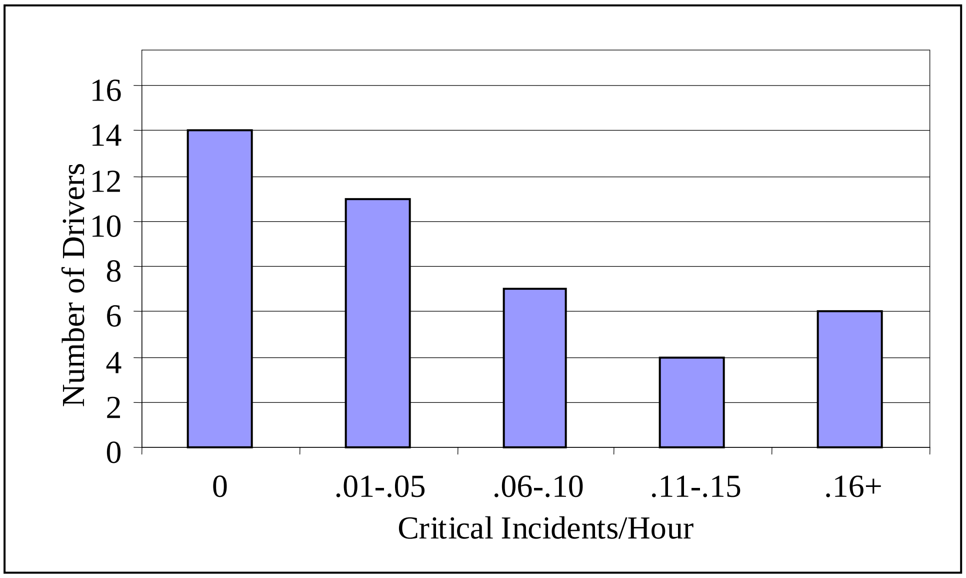

Figure 1. Graph. Frequency distribution of drivers' critical incident rates in Hanowski et al.[(5)]

As can be seen in Figure 1, six drivers had rates of critical incidents per hour greater than 0.15. These six drivers accounted for 12 percent of the total driving hours in the study but were responsible for 38 percent of all the truck driver critical incidents (29 of 77). In contrast, the 25 best drivers (the first two bars in Figure 1) accounted for 63 percent of the hours driving but were only responsible for 16 percent of the critical incidents.

Figure 2 illustrates the exposure-risk relationship for the worst (high risk), moderate (moderate risk), and best (low risk) drivers in Hanowski et al.[(5)]

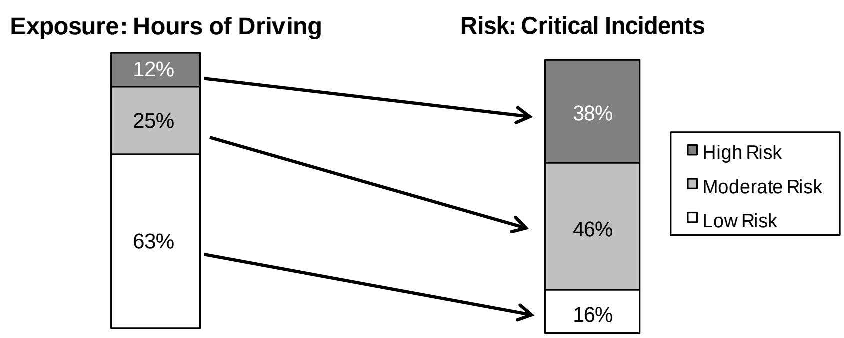

Figure 2. Illustration. Relationship between exposure and critical incidents in Hanowski et al.[(5)]

Hickman et al.[(6)] found similar results in a preliminary analysis of the DDWS FOT. These data were collected from instrumented long-haul and line-haul CMV drivers making their normal delivery runs. The drivers were classified into three groups (worst, middle, and best) based on the rate of safety-critical events (SCEs)/hour. SCEs are safety-related traffic events, including crashes, near-crashes, and crash-relevant conflicts. The worst 15 drivers accounted for 11 percent of the total driving hours and 38 percent of the total at-fault SCEs; the middle 40 drivers accounted for 47 percent of the total driving hours and 54 percent of the total at-fault SCEs; and the best 40 drivers accounted for 42 percent of the total driving hours and 8 percent of the total at-fault SCEs. Similar results were found when assessing drivers' rates of non-fault and high-drowsiness SCEs.

SUMMARY

Most CMV drivers are both conscientious and safe, as evidenced by the fact that most two-vehicle crashes involving CMVs are precipitated by the other vehicle.[7] Nevertheless, there is a widespread industry belief [4] and empirical evidence[5,6] that a relatively small percentage of CMV drivers are associated with a significant and inordinate percentage of the overall motor carrier crash risk.

We currently have kernels of knowledge that suggest certain factors are associated with high-risk drivers; however, we do not have a comprehensive model to ascertain how these factors interact with each other. Further, all these factors have not been included in one study, nor have they been studied under naturalistic driving (ND) conditions. It is certainly possible that some unknown determinant is associated with high-risk drivers; thus, an ND study seems most appropriate to answer these questions. The finding of differential crash risks among CMV drivers along many safety-related personal dimensions presents a key opportunity to the trucking industry and government safety officials. If 15 percent of the CMV drivers represent 50 percent of the crash risk, then efforts directed at those 15 percent of drivers could yield significant safety benefits. Improved safety selection procedures could ensure that many of the worst drivers are intervened or never hired. Improved safety management procedures, onboard safety monitoring devices, and other safety technologies could ensure that high-risk drivers are identified early so that effective safety management interventions can be implemented to reduce these safety-related driving behaviors.

PURPOSE OF THE STUDY

Various studies have indicated that crash, incident, and violation risks are disproportionately distributed among CMV drivers, with a relatively small percentage (e.g., 10 to 15 percent) of drivers being associated with disproportionate risk (e.g., 30 to 50 percent). The Hickman et al.[6] study was a preliminary analysis of the DDWS FOT, and the drivers assigned to each grouping (i.e., worst, middle, and best) were not mutually exclusive (e.g., a driver in the worst group for at-fault SCEs may not have been in the worst group for non-fault or high-drowsiness SCEs). Specifically, the groupings for at-fault, non-fault, and high-drowsiness drivers were based on the rate of SCEs/hour within each category (e.g., the worst group of at-fault drivers was selected by the rate of at-fault SCEs/hour, the worst group of non-fault drivers was selected by the rate of non-fault SCEs/hour, and so on). The present study improved upon the Hickman et al.[6] study in several fundamental ways, including:

- Use of the entire DDWS FOT data set and the recently completed NTDS data set. This resultant data set included a total of 203 CMV drivers.
- The identification of groupings (safe, average, and risky) was based on statistical techniques (cluster modeling) rather than arbitrarily selecting the worst 15 percent of drivers based on the rate of SCEs/hour.

- Data were presented about individual risk factors (or predictors) such as education, age, body mass index (BMI), years of CMV driving experience, sleep, etc. that could be used to identify differences between these groups of drivers.

OVERVIEW OF THE DATA SETS USED IN THE CURRENT STUDY

Large-Truck Naturalistic Driving Data Sets

Two large-truck ND data sets were included in the current study: the DDWS FOT and the NTDS. In total, approximately three million miles of driving data and 250,000 hours of actigraphy data were collected during these two ND studies. The DDWS FOT was the largest ND commercial vehicle study ever conducted by the U.S. Department of Transportation (USDOT) with more than 12 terabytes of kinematic and video data. The DDWS FOT involved three CMV fleets across eight locations and 103 drivers. The study used continuous data collection in 46 trucks that were instrumented to gather kinematic and video data. Each driver in the study was also asked to wear an actigraphy device in order to collect sleep quantity and quality data. The resulting database contains approximately 2.3 million miles traveled and more than 8,000 days' worth of actigraphy data. See Hanowski et al.(5) for a complete description of the DDWS FOT.

The NTDS was another ND study using instrumented heavy trucks that collected more than 4 terabytes of kinematic and video data. The NTDS involved four CMV fleets across seven locations and 100 drivers. As in the DDWS FOT, the NTDS collected continuous driving data from nine instrumented trucks (including kinematic and video data). However, unlike the DDWS FOT, an additional channel of video was installed in the instrumented trucks that allowed a view over the driver's shoulder. Actigraphy devices were also worn by participants in the NTDS. The resulting NTDS database contained approximately 735,000 miles of driving data and 65,000 hours of actigraphy data. See Blanco et al.(8) for a complete description of the NTDS.

During the DDWS FOT and NTDS participants completed various questionnaires. The DDWS FOT questionnaires included items regarding demographic characteristics, health, personal feelings about driver performance, alertness, work schedule, and drivers' opinions of the DDWS. The NTDS questionnaires included items about demographic characteristics, health and sleep hygiene. Please see Hanowski et al.(5) and Blanco et al.(8) for a complete list of the questionnaires used in the DDWS FOT and NTDS, respectively.

CHAPTER 3. METHODS AND ANALYSIS APPROACH

RETRIEVAL AND ORGANIZATION OF EXISTING DATA

Prior to analyses, the data were formatted and merged into one data set. The questionnaires used during the DDWS FOT and NTDS were not identical, although the studies gained similar information from the questionnaires. As the drivers in the DDWS FOT and NTDS completed different questionnaires, it was important to identify the data elements common in both studies. In addition, the analysis required the data elements to have identical response options. The common data elements from the questionnaires in the DDWS FOT and NTDS included both categorical items (listed in Table 1, Table 2, and Table 3) and continuous items (height, weight, experience driving a CMV, BMI, and sleep quantity measured via an Actigraph watch). The coding keys for each questionnaire were compared to ensure common coding methods were used. If the responses for a particular item were coded differently, the data were re-coded to a common coding system. For example, in both studies drivers were asked, “What time do you prefer to go to bed when you have no commitments the following day.” To answer this question, drivers in the DDWS FOT chose a time interval from a given list of responses (see Table 3). However, drivers in the NTDS wrote their preferred time in a blank space rather than responding to a forced choice (as in the DDWS FOT). In the current study, the responses were re-coded by matching the NTDS driver responses to their corresponding forced choice response in the DDWS FOT questionnaire. Table 1, Table 2, and Table 3 describe the final coded response options for each categorical item. Continuous items were did not contain forced-choice response options; thus, these items did not require coding. However, some continuous items were converted into identical units. For example, height was measured in feet and inches in the DDWS FOT, but only in inches in the NTDS; thus, the current study converted height into inches to maintain identical units. Once the coding keys were verified, each driver was assigned a unique driver identification number and the data were merged into a single data set.

Table 1. Categorical demographic items and response options.

Demographic Item	Response Options
Gender	(i) Male (ii) Female
Physical build	(i) Small (ii) Medium (iii) Large
Highest level of education	(i) Didn’t complete high school (ii) High school graduate (iii) Didn’t complete technical school (iv) Technical school graduate (v) Didn’t complete college (vi) College graduate
Is English your preferred language for reading?	(i) No (ii) Yes
Is English your preferred language for speaking?	(i) No (ii) Yes

Table 2. Categorical health items and response options.

Health Item	Response Options
Health conditions	(i) Yes, had or currently have this condition (ii) No, have not had this condition
Medication	(i) Yes, I am currently using medication (ii) No, I am not currently using medication
Alcohol use	(i) Never (ii) Once a month or less (iii) A few times a month (iv) Once per week (v) More than once per week (vi) Every day
Tobacco use	(i) Yes, I smoke cigarettes, cigars, pipe, chew, tobacco, or use snuff (ii) No, I do not use tobacco
Caffeine use	(i) Yes, I drink caffeinated beverages (ii) No, I do not drink caffeinated beverages

Table 3. Categorical sleep hygiene items and response options.

Sleep Hygiene Item	Response Options
Sleep difficulties (snoring, difficulty falling asleep, difficulty staying asleep, difficulty waking up)	Numbers 1 through 10, with 1 being "none" and 10 being "severe"
Time to bed	(i) 8pm-9pm (ii) 9pm-10:15pm (iii) 10:15pm-12:30am (iv) 12:30am-1:45am (v) 1:45am-3am (vi) 3am or later
Wake time	(i) 5am-6:30am (ii) 6:30am-7:45am (iii) 7:45am-9:45am (iv) 9:45am-11am (v) 11am-12pm (vi) 12pm or later
Sleep conditions (narcolepsy, sleep apnea, periodic limb movement, restless leg syndrome, and insomnia)	(i) Yes, I have been diagnosed with or suffered from this disorder at some point (ii) No, I have never been diagnosed with or suffered from this disorder

The number of SCEs and the mileage during the course of the driver's participation in the DDWS FOT or NTDS were also recorded for each driver. The SCEs included crashes, near-crashes, crash-relevant conflicts, and unintentional lane deviations. Each is defined as:

- Crash: Any contact with an object, either moving or fixed, at any speed. Included another vehicle, roadside barrier, object on or off of the roadway, pedestrian, pedalcyclist, or animal.

- Near-crash: Any circumstance that required a rapid, evasive maneuver (e.g., hard braking, steering) by the subject vehicle or any other vehicle, pedestrian, pedalcyclist, or animal in order to avoid a crash.
- Crash-relevant conflict: Any circumstance that required a crash-avoidance response on the part of the subject vehicle, any other vehicle, pedestrian, pedalcyclist, or animal that is less severe than a rapid evasive maneuver (as defined above) but greater in severity than a normal maneuver. A crash-avoidance response can include braking, steering, accelerating, or any combination of control inputs.
- Unintentional lane deviation: Any circumstance where the subject vehicle crossed over a solid lane line (e.g., onto the shoulder) where no hazard (e.g., guardrail, ditch, vehicle, etc.) was present.[9]

SCEs were coded as at-fault or non-fault. If the participant was judged to be responsible for the SCE it was considered at-fault. If the participant was judged to not be responsible for the SCE it was considered non-fault. The total number of at-fault plus non-fault SCEs per driver is called all SCEs in the current study (i.e., the total number of SCEs irrespective of fault). The methods used to identify SCEs and mileage can be found in Hanowski et al.[(5)] and Blanco et al.[(8)] The current study calculated a rate of all, at-fault, and non-fault SCEs/mile for each driver by dividing the driver's SCE count by his or her total mileage from the DDWS FOT or NTDS.

STATISTICAL METHODS

The current project involved two phases: Phase I identified high-risk, moderate-risk, and low-risk drivers in the ND data set, and Phase II determined which driver characteristics predicted group membership. In Phase I a cluster analysis was conducted to identify groupings of drivers (e.g., those drivers with a low rate of SCEs/mile, a high rate of SCEs/mile, etc.). Cluster analysis is a statistical technique during which data are grouped depending on similarity across designated characteristics of interest. Within each cluster the values of the characteristics should be homogeneous, and between each cluster the values of the characteristics should be heterogeneous.[(10)]

Many different clustering methods exist. These methods differ in how they define the distance between any two points and whether the clusters are formed by minimizing or maximizing distances between points. In a hierarchical clustering algorithm, the clusters are formed by minimizing the distance between points in each cluster. In the first iteration, the distance between every two points is calculated according to the particular distance method used, and these distances are stored in a distance matrix.[(11)] The two points with the shortest distance between them become part of the first cluster. In each successive iteration, a distance matrix is created between unassigned points and existing clusters. If two clusters have the shortest distance, they can be joined together. Iterations continue until only one cluster remains or until the preferred number of clusters is reached.

In the current study, a flexible beta cluster analysis was used with $\beta = -0.7$. In the flexible beta clustering method, the distance between any two points or clusters was defined as:

$$\delta_{k(ij)} = ((\delta_{ki} + \delta_{kj}) \times (1-\beta)/2) + \beta\delta_{ij}$$

In the distance formula, $\delta_{k(ij)}$ is the distance between cluster, or point, k and the newly formed group (ij) comprising clusters, or points, i and j. The other distances, δ_{ki}, δ_{kj}, and δ_{ij}, represent the distances between the particular points, or clusters, referenced in the subscripts. The value of β is a weight assigned to the distances between the points, or clusters, being joined.[10] Although β can range from -1 to 1, β values below zero cause the distance between clusters to grow as the size of the clusters grows.[12] As the data in the current study contained extreme values, a $\beta = -0.7$ was used in the cluster analysis. In this analysis the participants were the drivers in the ND data set, and the characteristics of interest were the rate of at-fault SCEs and non-fault SCEs.

After identifying three groupings of drivers an analysis of variance (ANOVA) was conducted to test for significant differences between the groupings for the rate of all SCEs/mile, at-fault SCEs/mile, and non-fault SCEs/mile. A significant difference would indicate that at least one cluster, with 95 percent confidence, was indeed a distinct group (safe, average, and risky).[13] Tukey-Kramer tests of the three clusters were used to identify which of the three clusters were significantly different from each other in the rate of all SCEs/mile, at-fault SCEs/mile, and non-fault SCEs/mile.[12] The Tukey-Kramer procedure was preferred as it allows for multiple comparisons between means of groups with unequal sample sizes, and controls the type I error rate and power.[14, 15]

Once distinct clusters were identified, the analysis assessed drivers' anthropometric and demographic characteristics common in each cluster. Characteristics with continuous values were tested for significant differences using an ANOVA. An ANOVA tested each characteristic across the three clusters. For characteristics with discrete or categorical values, contingency tables were used to visually demonstrate where the differences existed between clusters. To statistically test these differences, a Fisher's test was conducted.[16,17] To model the relationship between multiple characteristics and the rate of all SCEs/mile, a stepwise regression model was created. The stepwise regression went beyond an ANOVA that assessed univariate predictors and included individual variables as well as the interactions between these variables. Before the regression analysis could be performed, the data was modified in two ways. The rate of all SCEs/mile had inconsistent variance as the rates went from small to large; thus, a natural log transformation was performed to normalize the data. In the second modification, the categorical variables were converted to dichotomous values and modeled as indicator or predictor variables. Variables with two response options, such as gender, health conditions, alcohol use, caffeine use, tobacco use, and sleep conditions, were converted from text values into an indicator variable format (0, 1). Variables with more than two response options, such as physical build, time to bed, wake time, and sleep hygiene, were first converted into dichotomous variables by splitting the response options into unique variables and then converted into indicator (0, 1) variables. For example, physical build became two variables: small and medium physical build. If a participant had a small physical build, the participant would be marked as "1" in the small physical build variable and as "0" in the medium physical build variable. A participant with a large physical build would be marked as "0" in the small physical build variable and as "0" in the medium physical build variable.

CHAPTER 4. RESULTS

PHASE I: CLUSTER ANALYSIS

Below are the results of the cluster analysis. The drivers were clustered by the rate of at-fault and non-fault SCEs/mile using a flexible beta method with $\beta = -0.7$. Three of the 203 drivers in the data set had missing SCE data and were not included in the cluster analysis.

Figure 3 is a scatter plot with the rate of non-fault SCEs/mile plotted against the rate of at-fault SCEs/mile. The two points circled in orange in

Figure 3 are two drivers with extreme rates of at-fault SCEs/mile or non-fault SCEs/mile. Although these drivers could be considered extreme values, they represent a high level of risk that is essential to examine. Therefore, these drivers were not removed from the data set. The recommended cluster analysis method when using data that may include extreme values is the flexible beta clustering method.[10]

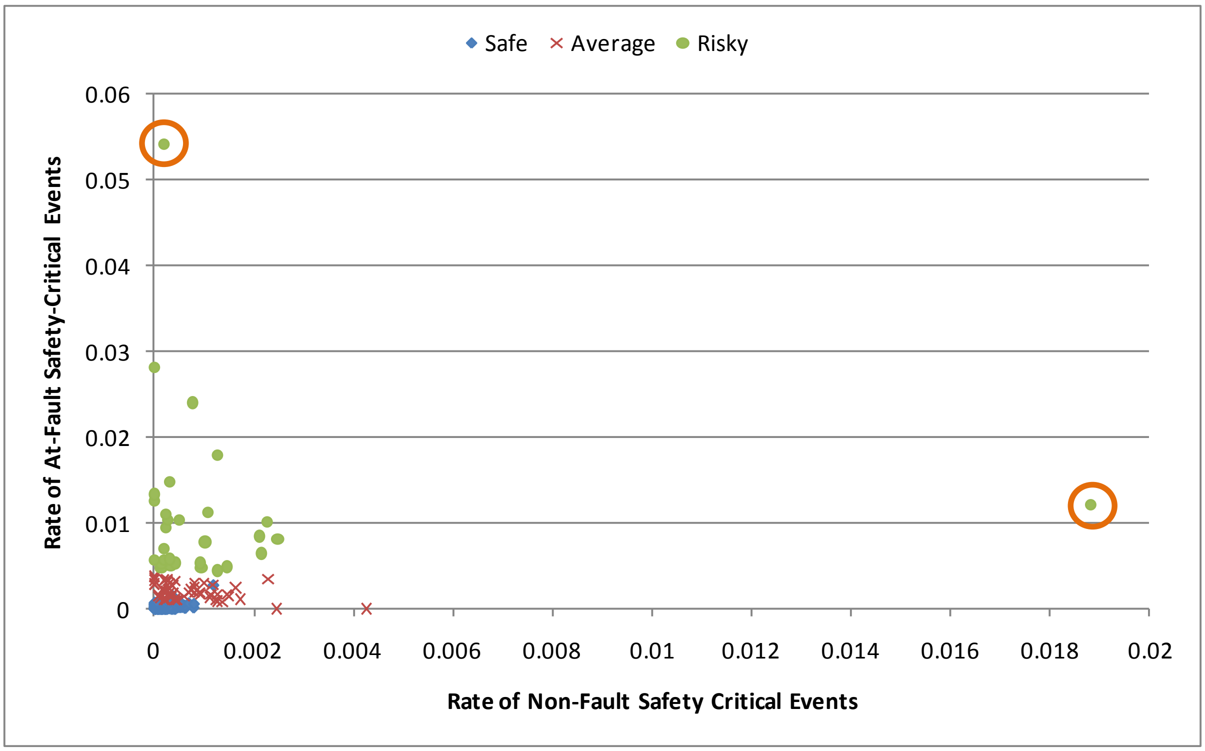

Figure 3. Graph. Scatter plot of the non-fault SCEs/mile and at-fault SCEs/mile.

Three distinct clusters were detected using the flexible beta clustering method with the rate of at-fault and non-fault SCEs/mile. In Figure 4 the results of the cluster analysis are shown in a scatter plot by the rate of non-fault and at-fault SCEs/mile. The drivers in Cluster 1 (i.e., safe drivers) had a low rate of at-fault and non-fault SCEs/mile. The drivers in Cluster 2 (i.e., average drivers) had a slightly higher rate of at-fault and non-fault SCEs/mile compared to Cluster 1. The drivers in Cluster 3 (i.e., risky drivers) had a much higher rate of at-fault and similar non-fault SCEs/mile compared to Cluster 2.

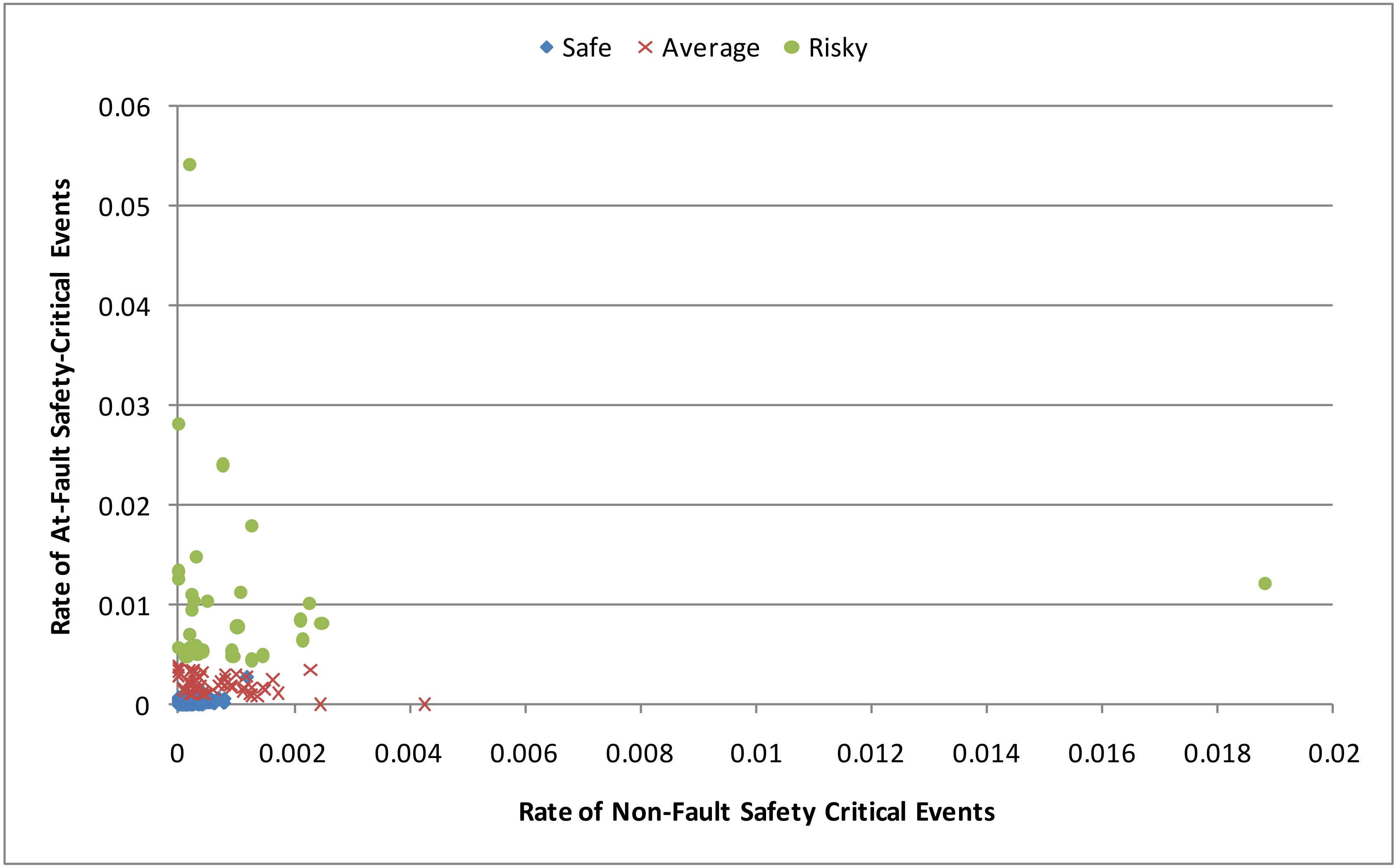

Figure 4. Graph. Scatter plot of clusters by non-fault SCEs/mile and at-fault SCEs/mile.

Table 4 shows the number of SCEs, mileage, and driver count in each cluster. The safe group had the majority of miles (75.9 percent) and drivers (59.5 percent), yet the smallest percentage of SCEs (24.8 percent). The risky group had the least number of miles (7.1 percent) and drivers (15.5 percent), yet the highest percentage of SCEs (50.3 percent). The average group had nearly a similar percentage of SCEs as the safe group but less than a quarter of the miles traveled. Figure 5 shows a stacked bar chart that demonstrates the imbalance in the percentage of SCEs and mileage between each cluster. It is important to note that driver routes were not evaluated for equivalency in terms of factors that might affect risk (e.g., night driving, rural roads, etc.).

Table 4. Number and percentage of SCE, mileage, and drivers in each cluster

Cluster	SCE Count	Percentage of Total SCEs	Mileage Count	Percentage of Total Miles	Driver Count	Percentage of Total Drivers
Safe	1,092	24.8%	2,035,035.8	75.9%	119	59.5%
Average	1,097	24.9%	455,582.7	17.0%	50	25.0%
Risky	2,220	50.3%	189,226.6	7.1%	31	15.5%

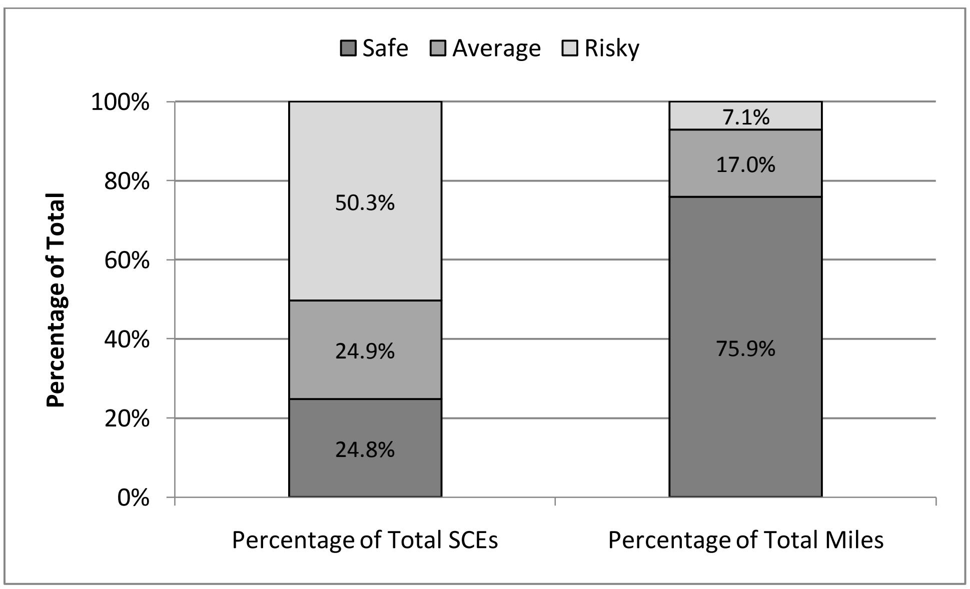

Figure 5. Graph. Percentage of total SCEs and total miles per cluster.

To test if the clusters were significantly different an ANOVA was performed on the rates of all, at-fault, and non-fault SCEs/mile. Table 5 displays the results from each ANOVA. As shown in Table 5, all three ANOVAs were significant. Thus, simple effects tests (e.g., Tukey's t-tests) were calculated to determine which of the clusters differed from the others.

Table 5. ANOVA of all, at-fault, and non-fault SCE rates across clusters.

Comparison Across Clusters	Numerator df	Denominator df	ANOVA SS	Mean Square	F Value	*p*
All SCE Rate*	2	197	0.00337	0.00169	101.82	<.0001
At-fault SCE Rate*	2	197	0.00279	0.00139	93.27	<.0001
Non-fault SCE Rate*	2	197	0.00003	0.00002	8.58	.0003

* Indicates significant result ($p < 0.05$)

Figure 6 visually displays the results of the Tukey t-tests for all pair-wise group (safe, average, risjy) by rate of SCE/mile (all, at-fault, and non-fault) comparisons. In Figure 6, the red line indicates the level of significance (i.e., $p < 0.05$). Comparisons that extend beyond the red line in Figure 6 were not significant (i.e., $p > 0.05$). The exact p-value for each comparison is listed at the end of the corresponding bar. As shown in Figure 6, two of the nine comparisons were not significant: (1) non-fault SCEs: mile safe vs. average ($p = 0.06$), and (2) non-fault SCEs: mile average vs. risky ($p = 0.184$). This may be due to the limited variance in the rate of non-fault SCEs/mile (from 0 to 0.02; see Figure 3.

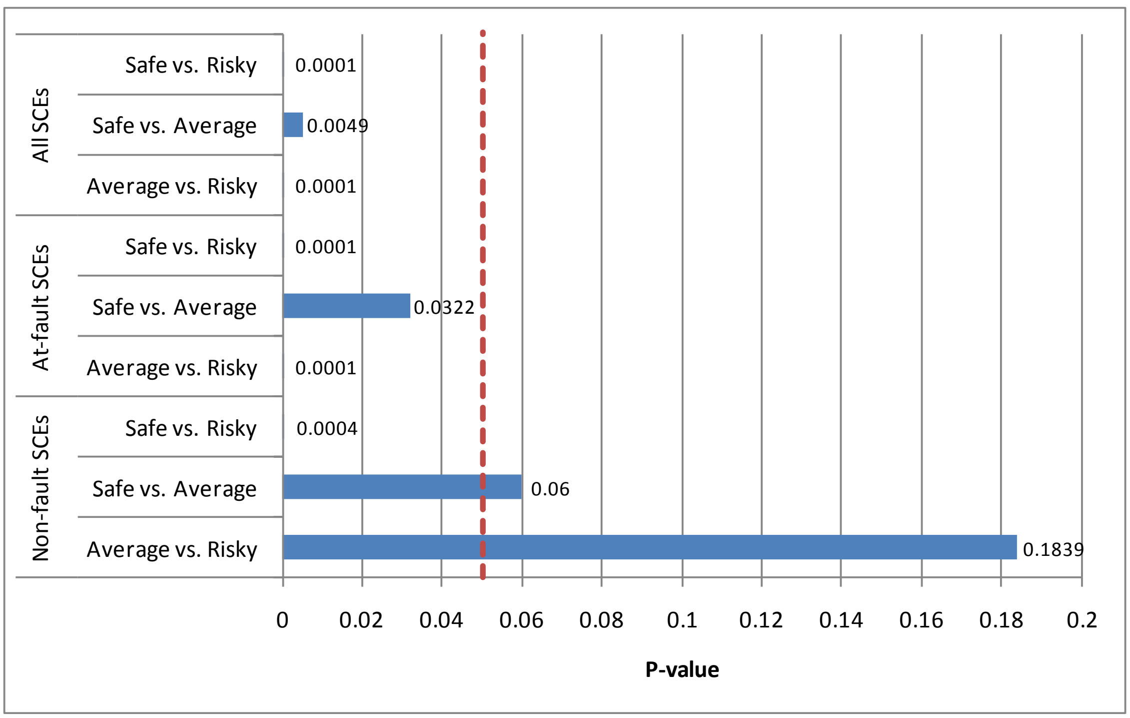

Figure 6. Graph. Results of Tukey's t-tests.

PHASE II: ANALYSIS OF ANTHROPOMETRIC AND DEMOGRAPHIC DIFFERENCES IN CLUSTERS

Analysis of Individual Variables

The characteristics, or variables, investigated in Phase II were age; CMV driving experience; height; weight; gender; build; BMI; highest level of education; mean sleep per day during the study; having had or currently having various health conditions (such as stroke or high blood pressure); alcohol, caffeine, or tobacco use; and sleep habits and conditions (such as experiencing difficulty falling asleep or having restless leg syndrome). The variables fell into two categories of data, including continuous and numerical or categorical. The continuous variables were analyzed using an ANOVA, and the categorical variables were analyzed using Fisher's tests. These analyses were conducted on one variable at a time to assess if and how an individual variable differed in distribution across the three groups of drivers.

Continuous Variables

The continuous variables in the current study were driver age, mean sleep per day during the study (via Actigraph watch), CMV driving experience, BMI, height, and weight. Driver age and CMV driving experience were self-reported and measured in years. Mean sleep per day during the study was calculated using data collected from the driver's Actigraph watch, which recorded drivers' hours of sleep each day. Driver height (in inches) and weight (in lbs) were measured by a member of the research team when the driver completed the questionnaires. Driver height and weight were used to obtain BMI using the follow formula: (weight/height^2) X 70.[18]

In Table 6 the mean values for the continuous variables are shown for each cluster. An ANOVA was used to test if the variables were significantly different in value across the clusters. Table 7 shows the results of the ANOVA for each of the continuous variables in Table 6. As shown in Table 7, no variables were significantly different across clusters.

Table 6. Mean values of continuous variables across clusters.

Cluster	Mean Age	Mean Sleep per Day	Mean CMV Experience	Mean BMI	Mean Height	Mean Weight
Safe	42.40	6.34	10.53	30.15	70.47	213.26
Average	39.64	6.11	7.96	31.00	70.27	218.28
Risky	45.52	6.67	10.32	30.60	70.11	213.97

Table 7. Results of an ANOVA for the continuous variables.

Variable	df Numerator	df Denominator	MS_{model}	MS_{error}	*F*	*p*
Age	2	197	336.54	111.44	3.02	0.051
Mean Sleep	2	112	2.45	1.24	1.98	0.143
CMV Experience	2	197	120.72	89.94	1.34	0.264
BMI	2	197	13.25	34.45	0.38	0.681
Height	2	197	1.93	8.20	0.23	0.791
Weight	2	197	451.45	2044.47	0.22	0.802

Categorical Variables

The discrete or categorical variables in the current study were gender, physical build, highest level of education, various health conditions, alcohol use, caffeine use, tobacco use, and sleep habits and conditions. All categorical items were self-reported except physical build. Table 8 and Table 9 show how physical build was calculated for each driver using measured height and wrist size (both in inches).

Table 8. Physical build calculation for females.

Height (inches)	Wrist (inches)	Physical Build
Shorter than 62	Smaller than 5.5	Small
	5.5 to 5.75	Medium
	Larger than 5.75	Large
62 to 65	Smaller than 6	Small
	6 to 6.25	Medium
	Larger than 6.25	Large
Taller than 65	Smaller than 6.25	Small
	6.25 to 6.5	Medium
	Larger than 6.5	Large

Table 9. Physical build calculation for males.

Wrist (inches)	Physical Build
5.5 to 6.5	Small
6.5 to 7.5	Medium
More than 7.5	Large

Each of the health conditions and sleep habits was analyzed as a single variable. Due to the dimensions of the contingency tables, which were always 3 x 2 or larger, Fisher's tests were used to check for differences among the groups. Fisher's tests were also used when cells in the table had an expected count less than five (due to missing data and/or low numbers of certain health conditions).[13,14]

The first categorical variables tested were driver gender, physical build, and highest level of education. Table 10 displays the results of the Fisher's tests for highest level of education, gender, and build. As seen in Table 10, the demographic categorical variables were not statistically significant.

Table 10. Results of contingency table analysis using Fisher's test on demographic variables.

Variable	Levels	Fisher Statistic	*p*
Education	7	9.854E-08	0.4278
Gender	2	0.0773	0.4956
Build	3	0.0004	0.5312

The second set of categorical variables tested was information about drivers' health conditions (past or present). Table 11 shows the results of the Fisher's tests for each health condition. The percentage of drivers reporting a current or past head injury, inner ear problem, arthritis, or motion sickness were significantly different (p's < 0.05) in at least one group.

Table 11. Results of contingency table analysis using Fisher's test on health variables.

Variable	Levels	Fisher Statistic	*p*
Head Injury*	2	0.0002	0.0002
Inner Ear Problems*	2	0.0067	0.0300
Arthritis*	2	0.0033	0.0336
Motion Sickness*	2	0.0219	0.0444
Dizziness, Vertigo, or Balance Problems	2	0.0139	0.0569
Anxiety	2	0.0158	0.0622
Migraine or Tension Headache	2	0.0064	0.0865
Medication	2	0.0031	0.1178
Stroke	2	0.1667	0.1667
Chronic Stress	2	0.1667	0.1667
Depression	2	0.0338	0.2033
Heart Arrhythmias	2	0.0822	0.2712
Diabetes	2	0.0459	0.6983
Respiratory Disorder	2	0.0897	0.7839
High Blood Pressure	2	0.0340	0.9251
Other Psychological Disorders	2	0.5655	1.000

* Indicates significant result ($p < 0.05$)

Figure 7 and Figure 8 show the proportion of drivers in each cluster reporting a head injury and inner ear problem, respectively. The risky cluster had the largest proportion of drivers reporting a head injury or inner ear problem (17.9 percent and 10.7 percent, respectively). The safe cluster had the smallest proportion of drivers reporting a head injury or inner ear problem (0 percent and 1 percent, respectively).

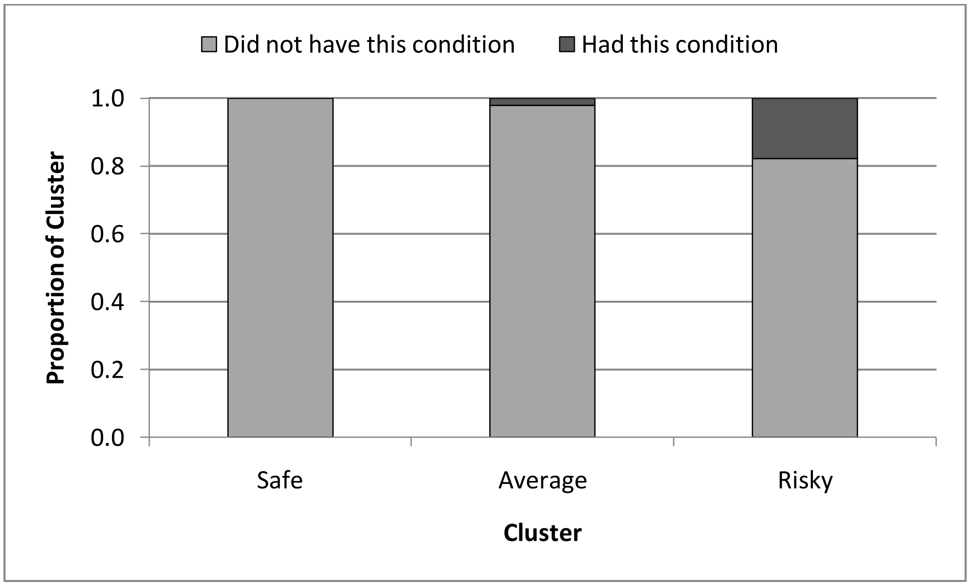

Figure 7. Graph. Proportion of drivers in each cluster reporting a head injury.

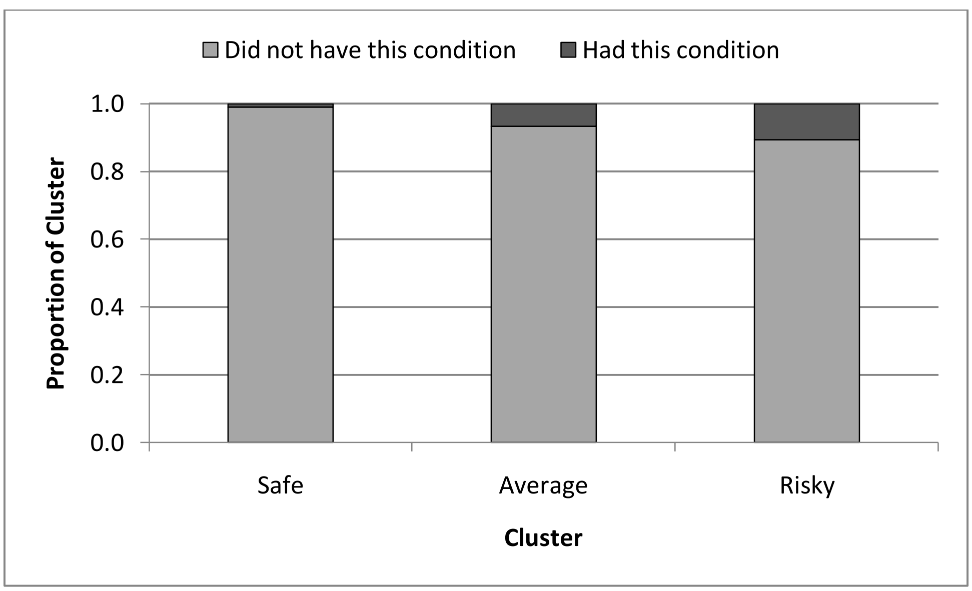

Figure 8. Graph. Proportion of drivers in each cluster reporting an inner ear problem.

Figure 9 and Figure 10 show the proportion of drivers in each cluster that reported arthritis and motion sickness, respectively. The distribution of driver arthritis and motion sickness was similar to those reported for driver head injury and inner ear problems. The risky cluster had the largest proportion of drivers reporting arthritis and motion sickness (21 percent and 7 percent, respectively). The safe cluster had the smallest proportion of drivers reporting arthritis and motion sickness (5 percent and 0 percent, respectively).

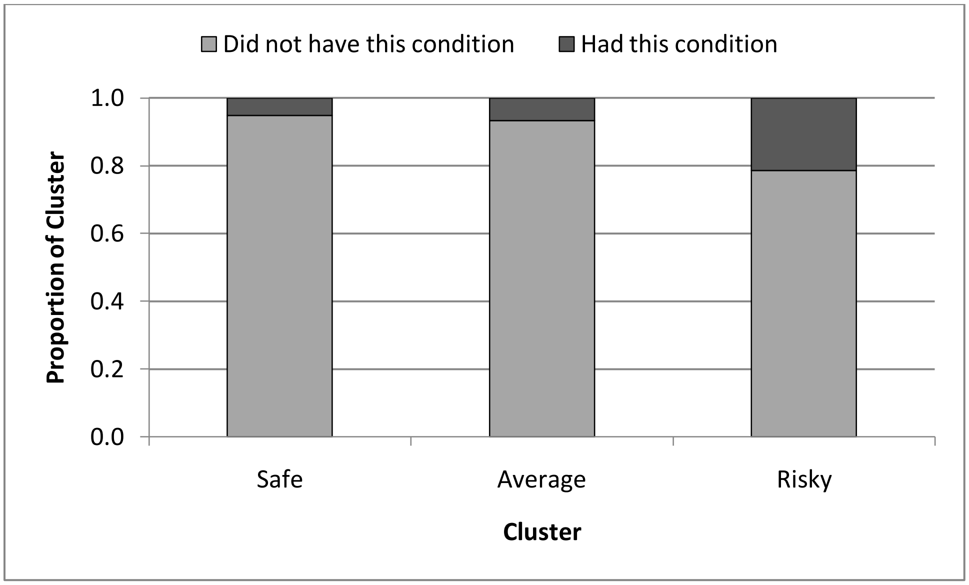

Figure 9. Graph. Proportion of drivers in each cluster reporting arthritis.

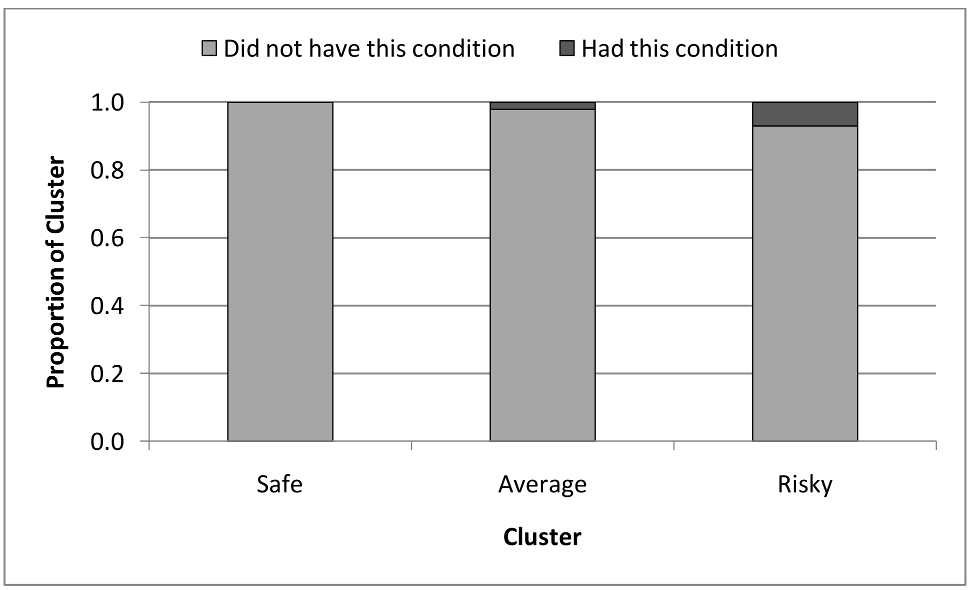

Figure 10. Graph. Proportion of drivers in each cluster reporting motion sickness.

Some of the significant health variables had very low cell counts. Inner ear problems were reported by a total of seven drivers (one in the safe cluster, three in the average cluster, and three in the risky cluster). Motion sickness was reported by a total of three drivers (one in the average cluster and two in the risky cluster). As the risky cluster had only 31 drivers, these low counts could potentially exaggerate the relationship between these health variables and driver risk.

The last set of variables measured sleep hygiene. The sleep hygiene variables included self-reports of regular snoring, difficulty falling asleep, difficulty staying asleep, and difficulty waking up. Drivers indicated their preferred times to go to bed and to wake up when they had no other responsibilities. Drivers were also asked if they had sleep-related health conditions such as sleep apnea or restless leg syndrome. Alcohol, caffeine, and tobacco use were also self-reported. The questionnaire item asking about alcohol use had six response options. When each option was analyzed separately, the results were misleading as to how the three clusters differed. The ambiguous results for alcohol use were due to the lack of direction when comparing those who reported a middle response option (once a month or less, a few times a month, once per week, or more than once per week) to those that did not report the same option. In the analysis it was not possible to tell whether the group that did not report a middle option instead chose alcohol consumption less or more frequently. Clearly distinguishing how the groups differed was important in order to draw sound conclusions on the association between alcohol consumption and risky driving. To gain more insight, the responses were combined into two choices: drinks alcohol once a month or less and drinks alcohol more than once a month. Table 12 lists the results of the Fisher's tests on the sleep hygiene variables. One variable was found to be significant: drinking alcohol once a month or less.

Table 12. Results of contingency table analysis using Fisher's test on sleep hygiene variables.

Variable	Levels	Fisher Statistic	*p*
Drinks Alcohol Once a Month or Less*	2	<0.0001	0.0138
Restless Leg Syndrome	2	0.0682	0.0955
Wake Time of 9:45am-11am	2	0.0069	0.1013
Wake Time of 5am-6:30am	2	0.0081	0.1862
Snoring (high or low)	2	0.0063	0.2144
Bedtime of 8pm-9pm	2	0.0630	0.4237
Sleep Apnea	2	0.0875	0.4506
Drinks Caffeine Beverages	2	0.0389	0.4510
Bedtime of 1:45am-3am	2	0.0340	0.4573
Difficulty Falling Asleep (high or low)	2	0.0219	0.4628
Bedtime of 10:15pm-12:30am	2	0.0113	0.4713
Smokes Tobacco	2	0.0142	0.5856
Bedtime of 9pm-10:15pm	2	0.0239	0.6008
Bedtime of 3am or later	2	0.0936	0.6167
Insomnia	2	0.3016	0.6779
Wake Time of 6:30am-7:45am	2	0.0213	0.7309
Difficulty Waking Up (high or low)	2	0.0313	0.7557
Difficulty Staying Asleep (high or low)	2	0.0247	0.7646
Bedtime of 12:30am-1:45am	2	0.0462	0.7862
Wake Time of 12pm or later	2	0.0788	0.8336
Wake Time of 7:45am-9:45am	2	0.0240	0.9237
Wake Time of 11am-12pm	2	0.2549	1.0000

* Indicates significant result ($p < 0.05$)

Figure 11 shows the proportion of drivers in each cluster that reported alcohol consumption of once a month or less. The proportion of drivers that reported drinking alcohol once a month or less was 77.7 percent in the safe cluster, 52.4 percent in the average cluster, and 75 percent in the risky cluster. For this particular variable, the safe and risky clusters had almost identical percentages of drivers choosing to drink alcohol once a month or less, and the average cluster had a much smaller percentage of drivers selecting this response.

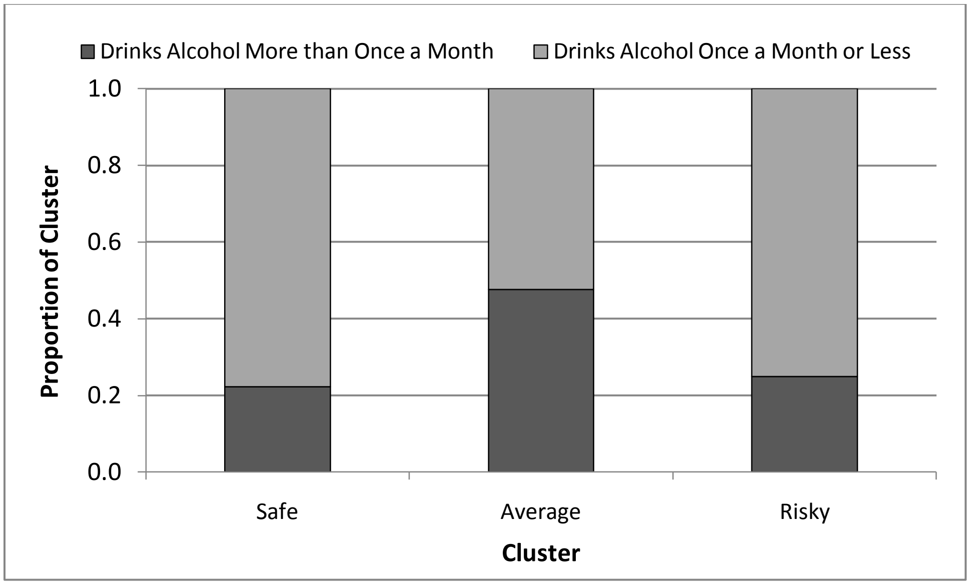

Figure 11. Graph. Proportion of drivers in each cluster reporting alcohol consumption of once a month or less.

The univariate analyses provided information about how the three clusters differed with respect to drivers' personal characteristics; however, possible interactions between variables were unknown. Many of the health variables are likely to interact with each other (e.g., motion sickness and head injury) and with age. To examine the relationships between the variables and the rate of SCEs/mile, a follow-up analysis was conducted using regression modeling.

Regression Analysis

The rate of all SCEs/mile was shown to be significantly different across the three clusters. Regression analyses were conducted to predict the rate of all SCEs/mile using the univariate demographic, health, and sleep hygiene variables as well as interactions between these variables. Figure 12 displays the rate of all SCEs per driver in ascending order. As described earlier, the rate of all SCEs/mile had inconsistent variance as the rates went from small to large; thus, a natural log transformation was performed to normalize the data. Figure 13 shows the natural log transformation of the rate of all SCEs/mile per driver.

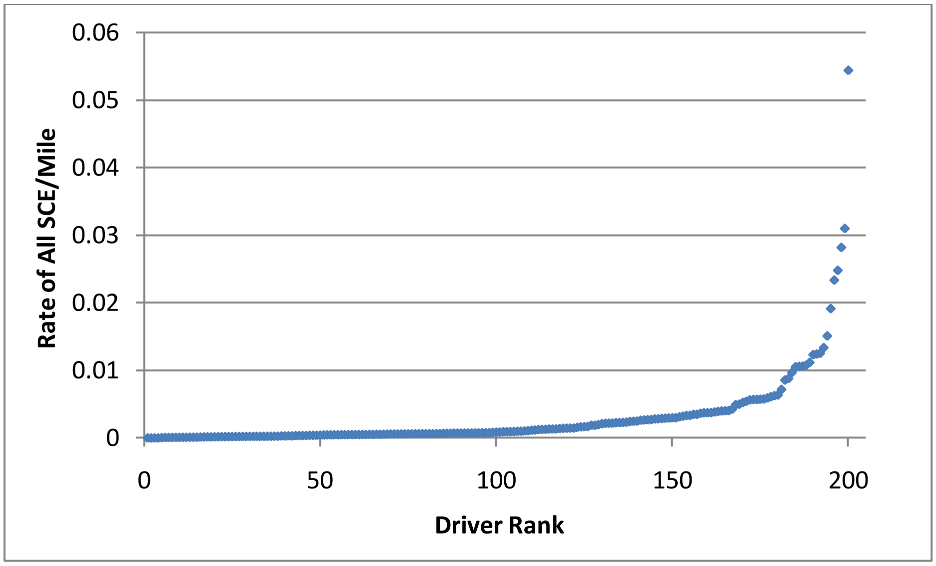

Figure 12. Graph. Scatter plot of all SCEs/mile for each driver in ascending order.

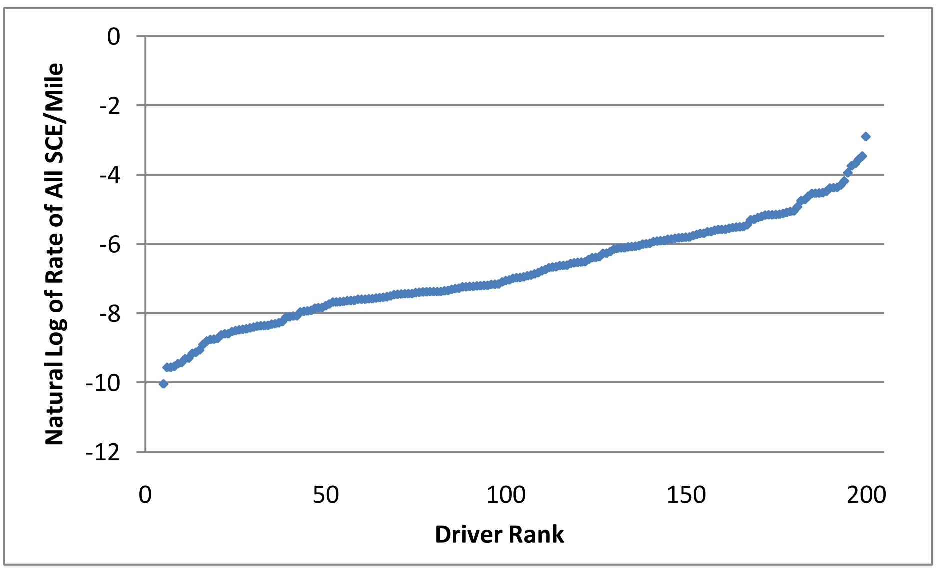

Figure 13. Graph. Scatter plot of natural log transformation of all SCEs/mile for each driver in ascending order.

Although the nature of the data was suitable for a principal component analysis or factor analysis, missing data in the health and sleep hygiene surveys made these approaches inappropriate. Instead, a stepwise method was used. Interaction terms were included in the initial variables set. Many different models and interactions were tested in the stepwise regression. Interactions between predictors consistently tested as significantly calculating the rate of all SCEs/mile. Significant interactions showed interesting relationships between the variables; however, the model became hard to interpret and less meaningful when the hierarchical principle was applied. For these reasons the results of the regression analyses are not displayed in the current study. The findings from the stepwise regression indicated that a larger data set is required in order to use a principal component analysis. A principal component analysis could paint a clearer picture of the intricate relationships between variables and the rates of SCEs/mile.

CHAPTER 5. CONCLUSIONS

DISCUSSION

The goal of the current study was to determine if different risk-level groups of CMV drivers existed and if these groupings could be distinguished based on individual driver attributes such as anthropometric, demographic, and other personal qualities. To achieve these goals the research team used cluster analysis, ANOVA, Fisher's tests, and regression modeling. The cluster analysis using the rates of at-fault and non-fault SCEs/mile found three distinct groups of drivers. The safe group had the lowest rates of all, at-fault, and non-fault SCEs/mile; the high-risk group had the highest rates of all, at-fault, and non-fault SCEs/mile; and the average group had rates of all, at-fault, and non-fault SCEs/mile that fell between the safe and risky group values.

The results of the cluster analysis support conclusions drawn from other naturalistic studies. A naturalistic study by Hanowski et al.(5) using local/short-haul drivers found that six drivers accounted for 12 percent of the total driving hours and 38 percent of the SCEs. In Hickman et al.(6) the worst 15 drivers accounted for 11 percent of the total driving hours and 38.2 percent of the at-fault SCEs, with comparable results found for non-fault and high-drowsiness SCEs. A recent study reported by SmartDrive indicated that a review of more than 13.8 million video events found 5 percent of drivers accounted for 67 percent of the distracted driving incidents.(19)

Each study noted above employed a different technique to identify risky drivers, yet each found that a small group of drivers was responsible for a disproportionate number of at-risk driving events (even after controlling for exposure). Similar to other naturalistic studies,(5,6,7,19) the current study strongly supports the "high-risk" driver concept. What does the existence of three different risk levels existing in the CMV driver population mean to future training programs and safety interventions? In the current sample, if the average and risky driver groups were to drive as safely as the safe group, the number of SCEs would drop from 4,409 SCEs to 1,438 SCEs (a reduction of over 66 percent). If risky drivers can be changed into safe drivers, a tremendous drop in the number of crashes is expected. Thus, training and safety interventions that target the risky group of drivers are likely to have the greatest net safety benefit. Training and intervention methods need to be examined thoroughly in future studies to identify safety management techniques and tools proven to be successful in producing lasting safety performance in this group of drivers.

The current study attempted to identify the personal qualities (e.g., anthropometric, demographic, sleep, etc.) of risky drivers using various statistical techniques. The statistically significant variables that differed between the risky group of drivers and the safe and average groups of drivers were head injury, motion sickness, inner ear problems, arthritis, and choosing to drink alcohol once a month or less. It is important to note that some of the significant variables in the current study were reported by few drivers (i.e., low cell counts). As the high-risk cluster had only 31 drivers, the relationship between the variables and SCE risk could potentially be inflated.

Drivers were not instructed to record the type of head injury or the date of the head injury; thus, this makes the relationship between this variable and group membership tenuous. However, studies have linked head injuries of all degrees to severe after-effects, including symptoms that would have a significant impact on driving performance.[20,21] A head injury can result in a concussion, and even mild concussions can result in dizziness and motion sickness (one of the other health variables found to be significant in the individual variable analyses) as well as concentration difficulties. These symptoms can manifest and persist for days, weeks, months, or even years after the head injury.[20,22] Shekleton et al.[23] found that patients with brain injuries also experience poor sleep habits (such as less sleep efficiency) more often than patients without these injuries. Concentration difficulties or drowsiness from poor sleep may lead to driver involvement in SCEs, either through impaired driving or decreased reaction times.

The relationship between dizziness and driving has not been extensively studied. However, dizziness is a common symptom of inner ear problems and motion sickness, and can be associated with feelings of lightheadedness, fainting, or falling.[24] Cohen et al. (2003) found that drivers with dizziness caused by inner ear disorders reported having greater difficulty than control subjects in many driving situations, including driving in the rain, at night, or on the freeway. Compared to the control subjects, drivers with dizziness also reported having more difficulty staying in their driving lane and changing lanes.[24] Several of the driving situations and tasks listed above are experienced daily by CMV drivers. In particular, difficulty staying in a driving lane could certainly lead to an SCE. Due to the small sample size of the current study it is difficult to precisely determine the degree to which dizziness and inner ear problems were associated with high-risk driving.

Additional studies have found links between driving performance and arthritis, one of the significant health variables found in the current study. In a survey taken by older drivers, arthritis was listed as one of the top illnesses believed to significantly interfere with driving tasks.[25] McGwin et al. (2000) found that female drivers with arthritis who were over 65 years old had significantly higher odds of being involved in an at-fault crash.[26] The symptoms of arthritis, including joint stiffness and loss of physical strength, could cause diminished response capabilities and lead to a higher risk of SCE involvement, as evidenced in the results of Gilhotra et al. (2001), McGwin et al. (2000), and Merat et al. (2005).[25,26,27] The small sample in the current study could have inflated the link between arthritis and high-risk drivers. Due to the high correlation of age and arthritis, studies not directly examining arthritis may have trouble determining whether arthritis alone is a cause for high SCE rates.

If the statistically significant health variables are indeed indicators of driver group membership, drivers should be regularly screened for head injuries, inner ear problems, motion sickness, and arthritis, and be made aware of the ways in which these particular conditions can affect driving performance. Particular care should be taken with drivers who have experienced a head injury. Drivers should be encouraged to seek follow-up care after experiencing a head injury, as effects from the head injury may last or appear long after the incident.[20,21] The statistical significance of health variables indicates that risky driving may not necessarily be a result of personality traits; instead, risky driving may be related to diminished motor skills due to conditions beyond a driver's control. However, this is a tenuous conclusion based on the small sample size in the current study.

The significance of drinking alcohol once a month or less is particularly complicated as drivers in the safe and risky groups reported similar responses on this question. Drivers in the average group, on the other hand, most frequently reported drinking alcohol more than once a month.

Frequent drinking has been shown to be associated with risk-favoring personality traits.[28,29] However, the current study did not show this association. The weak association of alcohol consumption and driving risk may be due to the wording of the original survey question and response choices. The consumption patterns of non-social drinkers or heavy drinkers could not be identified given the response choices. Moreover, drivers were not instructed to report when they consumed alcohol (e.g., off-duty, on-duty, social occasions, etc.). Thus, it is difficult to make an association between group membership and self-reported drinking behavior.

LIMITATIONS

The current study had several limitations. 1.) The participants were volunteers; therefore, a voluntary response bias is possible. Although the videos were not shared with employers, risky drivers may have been more reluctant to participate in the DDWS FOT and the NTDS for fear of reprisal. 2.) Self-reported data may be less accurate than observed data as participants may not be aware of their personal habits or may be reluctant to share personal information. For example, some drivers might not be aware of their sleep habits (e.g., if they snore); thus, their responses might not be accurate. Drivers may have been hesitant to report poor sleep hygiene or other health conditions out of fear of repercussions. 3.) Driving routes and schedules were not addressed in the current study. Although the data were normalized for exposure (in terms of mileage), some driving routes or schedules may have been more dangerous than others (thereby affecting the rate of SCEs/mile). 4.) As previously mentioned, the current study had a small sample size. In the individual variable analysis, relationships between variables and SCE risk could be exaggerated due to the small group sizes and low cell counts in several of the variables (e.g., health variables).

FUTURE WORK

Although the current study included a rich data set, it suffered from a small sample size. Having a small data set in this study limited the analyses and interpretation of the results. As more ND studies are conducted, data sets can be combined to increase the size of the data set (thereby increasing the statistical power). Individual variable analyses would be more stable and not vulnerable to small differences between groups. A larger data set would allow exploratory factor analysis or principal component analysis to model the rate of SCEs/mile. These methods are preferred when predictor variables are correlated (i.e., multicollinearity).

In the current study, usable data had to be consistent across the two original studies (DDWS FOT and NTDS) from which the data were gathered. Due to differences in coding and response choices on the questionnaires in the two studies, many questions could not be combined to examine their relationship with driver group membership. If future studies included the identical measures used in the DDWS FOT and the NTDS, these surveys could be combined to better identify variables that predict risky drivers. The evidence for risky drivers is strong. Future studies may also look into the existence of two different types of risky drivers: those who are risky due to personal attitudes and choices, and those who are risky due to health conditions that interfere with driving tasks. Safety management techniques would need to be tailored to the needs of each group. Studies investigating how the safe, average, and risky groups respond to different training and intervention methods will help identify which safety management techniques are most effective in reducing unwanted or risky behavior that leads to crash involvement.

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