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The influence of daily sleep patterns of commercial truck drivers on driving performance

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ABSTRACT

Fatigued and drowsy driving has been found to be a major cause of truck crashes. Lack of sleep is the number one cause of fatigue and drowsiness. However, there are limited data on the sleep patterns (sleep duration, sleep percentage in the duration of non-work period, and the time when sleep occurred) of truck drivers in non-work periods and the impact on driving performance. This paper examined sleep patterns of 96 commercial truck drivers during non-work periods and evaluated the influence these sleep patterns had on truck driving performance. Data were from the Naturalistic Truck Driving Study. Each driver participated in the study for approximately four weeks. A shift was defined as a non-work period followed by a work period. A total of 1397 shifts were identified. Four distinct sleep patterns were identified based on sleep duration, sleep start/end point in a non-work period, and the percentage of sleep with reference to the duration of non-work period. Driving performance was measured by safety-critical events, which included crashes, near-crashes, crash-relevant conflicts, and unintentional lane deviations. Negative binomial regression was used to evaluate the association between the sleep patterns and driving performance, adjusted for driver demographic information. The results showed that the sleep pattern with the highest safety-critical event rate was associated with shorter sleep, sleep in the early stage of a non-work period, and less sleep between 1 a.m. and 5 a.m. This study also found that male drivers, with fewer years of commercial vehicle driving experience and higher body mass index, were associated with deteriorated driving performance and increased driving risk. The results of this study could inform hours-of-service policy-making and benefit safety management in the trucking industry.

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1. Introduction

According to the Bureau of Labor Statistics (BLS), about 1,701,500 people were employed as heavy and tractor-trailer truck drivers in the United States in 2012 (Bureau of Labor Statistics, 2014). These workers are at an increased risk of occupational fatalities. They were 12 times more likely to die on the job than the U.S. general worker population (Chen et al., 2014). In 2012, 695 heavy and tractor-trailer truck drivers died on the job, the largest number of occupational fatalities in any occupation (Bureau of Labor Statistics, 2013). The majority (488 out of 695, or 70%) of these fatalities were caused by motor vehicle crashes.

Truck driver safety is not only a national occupational safety priority (National Institute for Occupational Safety and Health, 2009), but also a general public health concern because of the high death toll for truck crashes among drivers and occupants of other vehicles and the economic burden of truck crashes on society. In 2012, 3464 large trucks were involved in fatal crashes, 73,000 were involved in injury crashes, and 241,000 were involved in property-damage-only crashes (Federal Motor Carrier Safety Administration, 2014b). In the aggregate, for each large truck driver death, six other persons (persons in other vehicles, pedestrians, or cyclists) died in truck crashes (Federal Motor Carrier Safety Administration, 2014a). Motor vehicle crashes involving large trucks and buses cost the U.S. economy an estimated $99 billion in 2012 (Federal Motor Carrier Safety Administration, 2014b). These costs included productivity

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Table 1
Classification of activities and periods from activity register data.

Activity code	Activity type	Period based on Blanco et al. (2011)	Revised period
1	Driving truck	On-duty work period	Work period
2	Heavy work (loading/unloading)		
6	Light work (waiting, paperwork, vehicle maintenance)		
3	Sleep	On-duty rest period	Non-work period
4	Rest (not asleep)		
5	Eating		
7	Sleep	Off-duty period	
8	Rest (not asleep, watching TV, resting)		
9	Eating		
10	Light housework (dishes)		
11	Heavy housework (mowing lawn)		
12	Light leisure activity (walking, Internet)		
13	Heavy leisure activity (running, sports)		
14	Driving other vehicle (not work-related)		
15	Other		

losses, property damage, medical costs, rehabilitation costs, travel delays, legal and court costs, cost of emergency services (such as ambulance, police, and fire services), insurance administration costs, and the costs to employers (Blincoe et al., 2002).

Fatigued or drowsy driving has been identified as a major cause of truck crashes (Morrow and Crum 2004; Federal Motor Carrier Safety Administration, 2006, Advocates for Highway and Auto Safety, 2011). The National Transportation Safety Board found fatigue to be the most frequently cited probable cause (31%) in fatal-to-the-truck-driver crashes (National Transportation Safety Board, 1990). A primary reason for occupational fatigue is incompatible timing of duty schedules relative to circadian (i.e., 24-h) rhythm and the need for sleep (Satterfield and Van Dongen, 2013). In addition, age and body mass index (BMI) are also contributing factors to fatigue (Schur et al., 2007). A number of studies examined the association between sleep duration and fatigue-related crashes or driving performance. Sweeney et al. (1995) examined 107 single-vehicle heavy truck crashes and classified these crashes as either fatigue-related or non-fatigue-related. The results suggested that drivers who slept less during their last sleep period in the past 24 h and who experienced split sleep periods were more likely to be involved in fatigue-related crashes. Hanowski et al. (2007) reported that drivers who received significantly less sleep than their usual amount prior to trips were more likely to be involved in safety-critical events (SCEs), which include crashes, near-crashes, or crash-relevant conflicts. Blanco et al. (2011) and Soccolich et al. (2013) suggested that breaks (including sleep) preceding driving are beneficial in reducing SCEs, and mitigate the negative effects of time-on-task (i.e. driving performance in the later stage of a work period can be decreased due to tasks occurred earlier in the work period (Soccolich et al., 2013)).

According to circadian rhythm, the time period from 1 a.m. to 5 a.m. is an important natural sleep time (National Sleep Foundation, Butkov and Lee-Chiong 2007; Department of Transportation, 2014, National Institute for Occupational Safety and Health, 2014). In 2013, the Federal Motor Carrier Safety Administration revised the hours-of-service regulations. The revised hours-of-service regulations require the restarting period to cover two night periods occurring between 1 a.m. and 5 a.m. There is a need for examining the association between sleep in the period of 1–5 a.m. and truck drivers' driving performance or driving risk.

The objectives of this study were two fold: (1) to examine truck drivers' sleep patterns in non-work periods, and (2) to evaluate the associations between sleep patterns in the non-work period and driving performance and risk in the immediate subsequent work period adjusted for years of employment, drivers' age, gender, and BMI.

2. Data

2.1. Naturalistic truck driving study data

This study used the Naturalistic Truck Driving Study that recorded approximately 735,000 miles of truck driving by 96 commercial truck drivers (75 long-haul and 21 line-haul truck drivers) (Blanco et al., 2011; Soccolich et al., 2013). Each driver drove a commercial truck equipped with a comprehensive data acquisition system that gathered data from the vehicle network, multiple video cameras, radar, a three-dimensional accelerometer, and a Global Positioning System (GPS). Driving data were collected continuously from ignition-on to ignition-off for approximately one month for each driver. The data were downloaded to a secure data center for analysis after data collection. The project was approved by the Virginia Tech Institutional Review Board.

Abnormal driving events were identified via a combination of kinematic triggers such as longitudinal and lateral acceleration rates and yaw rate, followed by confirmation via visual inspection of videos by trained data analysts. The analysis in this study included the same four types of SCEs used in Blanco et al. (2011): crashes, near-crashes, crash-relevant conflicts, and unintentional lane deviations. Because crashes are rare events, non-crash events are often included in traffic safety analyses to increase sample size and statistical power (Dingus et al., 2006; Fitch et al., 2013; Klauer et al., 2014; Ouimet et al., 2014). It has been illustrated that near-crashes provide useful information on driving risk evaluation (Guo et al., 2010). Crash-relevant conflicts, also known as critical incidents, have been shown to be associated with crash and near-crash risk (Guo and Fang 2013). Unintentional lane deviation events are a measure of driving performance decrement (Van Dongen et al., 2010) and driver fatigue (Hanowski et al., 2008).

The participant drivers recorded their 24-h work and non-work activities using an activity register. As shown in Table 1, drivers' daily activities were subsequently classified using 15 activity codes and divided into three types of periods based on the legal regulations for on- and off-duty driving, working times, and resting times (Blanco et al., 2011). The user recorded activities were cross-referenced with the objectively recorded naturalistic driving data to produce a hybrid register with precise driving period.

2.2. Data processing

To evaluate the impact of sleep on the immediate subsequent driving period, we reclassified the activities into two revised periods: the non-work period and the work period. The classification of the revised periods was based solely on the nature of the daily activities, not on the legal definition from the Federal Motor Carrier Safety Administration (FMCSA) hours-of-service regulations. A *shift* is defined as a non-work period (i.e., off-duty rest period) followed by a work period (i.e., driving duty).

A comprehensive approach was used to operationally identify shift, i.e., a non-work period and work period pair. The complex real-life scheduling and potential in-correct driver input lead to several issues. First, work and non-work activities are mixed together and switched frequently, which leads to excessive number of shifts with very short durations. Second, drivers may not have fully understood the definitive difference between on-duty and off-duty, and thus may have incorrectly entered codes in the activity register (e.g., on-duty sleep for off-duty sleep). Third, the durations of on-duty rest periods vary substantially. As the sleep most likely occurs in long non-work period, it is desired to consolidate short rest periods to avoid an excessive number of very short non-work periods with little sleep.

A three-step process was used to consolidate fragments of activity register periods, as illustrated in Fig. 1. First, off-duty periods less than 3 h were redefined as on-duty rest periods or absorbed into adjacent on-duty rest periods if there were any. The short off-duty periods were often misrecorded by drivers and should be considered as on-duty rest. Second, on-duty rest periods less than 7 h long were absorbed into adjacent on-duty work periods. Third, the new revised periods were created by merging consecutive "off-duty periods" and "on-duty rest periods" together as "non-work periods," and by defining "on-duty work periods" as "work periods". The first two steps considered activity data in the three categories from Blanco et al. (2011) (i.e., on-duty work, on-duty rest, and off-duty), and the third step created the new revised periods.

The operational definition of shift from the above procedure allocate majority of sleep in the non-work period and minimizes the influence of sleep during work periods. Among the 1397 shifts included in the final analysis, sleep duration in work periods is a fraction of the sleep duration in non-work period (0.46%, 53 vs. 11,400 h). Therefore the potential confounding effects of sleep during work period is limited.

After consolidation, 2046 shifts were identified. The duration of 75.6% (1547 out of 2046) of the shifts is less than 27.5 h. The distribution of the remaining 24.4% of shifts with durations over 27.5 h peaks at 48 h and 72 h (Fig. 2). The shifts with durations longer than one day are primarily because (1) the driver did not have sufficient (7 h) on-duty rest between two on-duty work periods, so the short on-duty rest is absorbed into the work period; or (2) the driver had a long off-duty period, such as a restart period. This paper focused on shifts less than 27.5 h to avoid the effects of multiple days. Within shifts less than 27.5 h, 90.3% (1397 out of 1547) contained one period of sleep in the non-work period; 3.7% (57 out of 1547) of the shifts did not include any sleep; and only 6% (93 out of 1547) of the shifts included two or more sleep periods. This study focused on the shifts that are less than 27.5 h long with one period of sleep in the non-work period because they consist of the majority of the shifts. We excluded the shifts that had two or more periods of sleep in a non-work period and the shifts that had no sleep due to the small number of shifts meeting the pre-specified criteria.

The final data used in this study include 1397 shifts, all of which were less than 27.5 h and had one sleep period. The data include 96 drivers, 31,787 shift hours (16,219 non-work-period hours and 15,568 work-period hours), 11,400 sleep hours in non-work periods, 53 sleep hours in work periods, and 11,049 truck-driving hours. These shifts involved 1519 SCEs, including 8 crashes, 28 near-crashes, 728 crash-relevant conflicts, and 755 unintentional lane deviations.

3. Statistical models

3.1. Quantitative measures for sleep pattern

Four quantitative measures were used to describe sleep patterns: sleep duration, sleep start/end point in a non-work period, and the percentage of sleep with reference to the duration of the non-work period. Although sleep duration was determined directly from activity register data, the other three measures were derived based on both the sleep and non-work period, defined as follows and illustrated in Fig. 3.

$$\text{Sleep percentage} = \frac{\text{Sleep duration}}{\text{Duration of non-work period}} \times 100\%$$

$$\begin{array}{c}\text{Sleep start point}\\ \text{within non-work period}\end{array} = \frac{\text{Duration between the start of non-work period and the start of sleep}}{\text{Duration of non-work period}} \times 100\%$$

$$\begin{array}{c}\text{Sleep end point}\\ \text{within non-work period}\end{array} = \frac{\text{Duration between the end of sleep and the end of non-work period}}{\text{Duration of non-work period}} \times 100\%$$

A small value of the sleep start point indicates the sleep started at the early stage of the non-work period. A large value of the sleep end point indicates the sleep ended at the late stage of the non-work period.

3.2. *K*-mean cluster analysis for identifying sleep patterns

K-mean cluster analysis was used to identify sleep patterns. The benefits of using *K*-mean generated cluster variable vs. directly using the original sleep variables include: (1) *K*-mean generated clusters can provide discrete memberships of sleep patterns, which is a primary goal of this study; and (2) *K*-mean generated cluster variables can alleviate multicollinearity issue faced by directly using the original sleep variables in a regression model, and can account for linear and non-linear interactions among the original variables. *K*-mean clustering is an objective approach to classify multidimensional data into groups with certain patterns, and has been used in analysis of naturalistic driving study (Guo and Fang 2013). *K*-mean cluster analysis partitions the data points into a pre-defined number (K) of clusters (Hastie et al., 2009). An observation is assigned to the nearest cluster measured by Euclidian distance. The objective is to identify cluster memberships ($\boldsymbol{S}$) which minimize the within-cluster Euclidian distance as follows;

$$\boldsymbol{S} = \arg\min_{\boldsymbol{S}} \Sigma_{i=1}^{K} \Sigma_{\boldsymbol{x_j} \in S_i} \|\boldsymbol{x_j} - \boldsymbol{\mu_i}\|^2$$

where $\boldsymbol{x_j}$ is the standardized data vector for observation j; $\boldsymbol{S} = \{S_1, S_2, \ldots S_K\}$ is the set of K clusters of observations; $\boldsymbol{\mu}_i$ is the mean vector for the cluster S_i. In the context of this paper, $\boldsymbol{x_j}$ is the standardized data vector for shift j, which includes four original sleep-related variables: sleep duration, sleep percentage, sleep start point and end point within non-work period. We evaluated the clustering results from $K = 2$ to 10 clusters. When $K = 2$ or 3, the patterns of

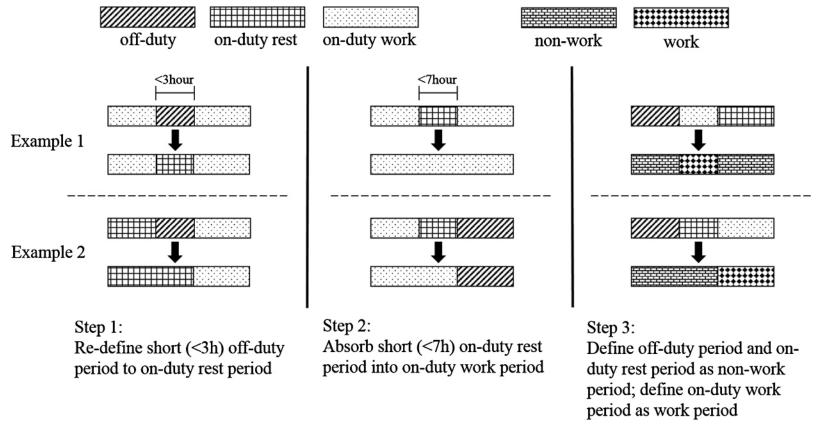

Fig. 1. Graphical illustrations of 3-step data consolidation process.

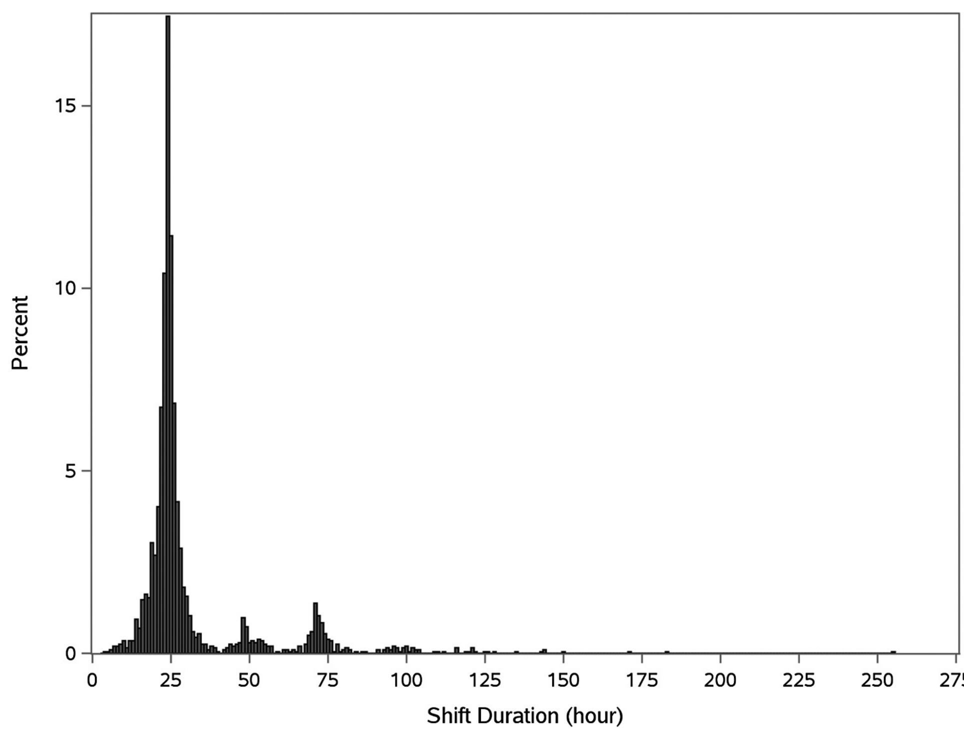

Fig. 2. Distribution of shift durations (2046 shifts).

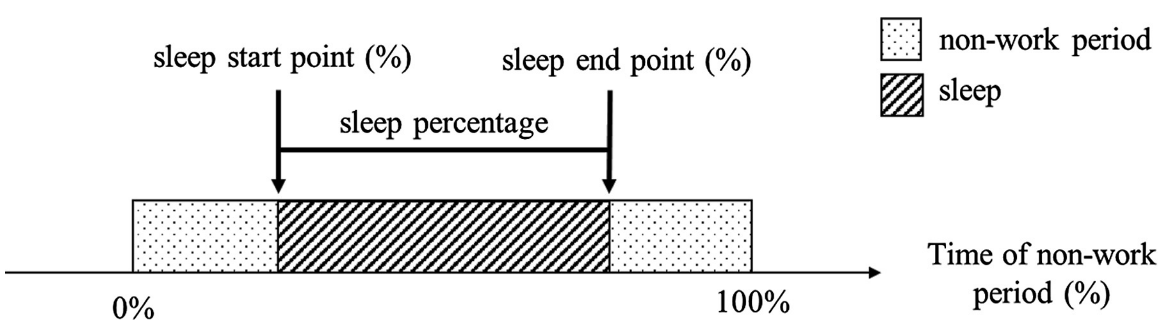

Fig. 3. Definition of sleep pattern metrics.

clusters are not distinct enough; when $K = 5$ or above, some clusters may have very small sample size. Through a combination of the parsimonious principle and engineering meaningful difference between clusters, $K = 4$ were selected for the subsequent analysis.

3.3. Negative binomial regression for impact of sleep pattern on driving risk

We used a negative binomial (NB) regression to model the association between SCEs and sleep patterns adjusted for driver demographics. NB regression can accommodate the variance over-dispersion issue commonly presented in safety event data and has been used to analyze naturalistic driving data (Guo and Fang 2013; Guo et al., 2014, 2015). The event count Y_i is assumed to follow an NB distribution:

$$Y_i \sim NB(E_i^{\beta_e}\lambda_i, \gamma)$$

where λ_i is the expected event rate for shift *i*, measured by number of events per hour driven; E_i, the exposure, is the hours driven in shift *i*; β_e is the regression parameter for the exposure; γ is the dispersion parameter. Parameter β_e provides flexibility for the baseline event rate over the exposure; if we set $\beta_e \equiv 1$, the baseline event rate is constant across different exposures. The expected event rate is linked with a set of covariates as:

$$\log(\lambda_i) = \beta_0 + \sum_{k=1}^{p} \beta_k x_{ik}$$

where x_{ik}'s are the covariates and β_k's are regression coefficients. In this study, we included sleep pattern clusters, years of commercial vehicle driving, age, gender, and body mass index (BMI) as covariates. Although multiple shifts come from the same driver, this drivers-specific correlation, however, could potential confound with cluster-effect and thus not included in the model.

4. Results

4.1. Demographic information

The demographic information for the 96 drivers (91 male, 5 female) in the analysis is listed in Table 2. The mean age of all drivers was 44.4 years; the ages ranged from 21 to 73 years. The mean number of years of commercial vehicle driving was 9.3 years, the median was 5.4 years, with a range from 0.1 to 54 years.

4.2. Cluster analysis results

Cluster analysis results (Fig. 4) demonstrate the distributions of the identified clusters with respect to the four sleep pattern measures used in *K*-mean clustering as well as the duration of the non-work period. The clusters can be distinguished by certain characteristics as shown in Fig. 4. Cluster 4 has the highest sleep percentage and sleep duration, followed by Cluster 3. Cluster 1 and 2 have similar sleep percentage and sleep duration; while the sleep in Cluster 2 happened in the first half of the non-work period and the sleep in Cluster 1 happened in the second half of the non-work period.

The quantitative characteristics of clusters are summarized in Table 3. As can be seen in Table 3, Cluster 2 includes the lowest percentage of shifts (6%) and the lowest average age (42.7 years old).

Tables 4 and 5 and Fig. 5 show the characteristics of sleep patterns and driving during work and non-work periods. Shifts in Cluster 1 and Cluster 2 show shorter sleep durations (about 6 h) and moderate sleep percentage (about 50%). The main difference between Cluster 1 and Cluster 2 is the sleep start time in Cluster 1 was later than Cluster 2 (0.41 vs. 0.10). In contrast, Cluster 3 and Cluster 4 have longer sleep durations (about 8–9 h) and higher sleep percentage (about 70% and 90%). The sleep periods in Cluster 4 occupied almost the entire non-work period, and the sleep periods in Cluster 3 occupied two-thirds of the non-work period. Moreover, Clusters 3 and 4 have longer average work periods and driving durations than Clusters 1 and 2. Combined with the longer sleep periods in Cluster 3 and 4, these results suggest that, drivers tend to work and drive longer if they sleep longer before work or they tend to sleep longer before work if they know to have to work and drive longer than usual. These results suggest an association but does not demonstrate causality.

4.3. Involvement of sleep between 1 a.m. and 5 a.m

In this study, we also evaluated sleep involvement between 1 a.m. and 5 a.m. by clusters using the numbers and proportions of the shifts with a non-work period, sleep, and a full 4-h sleep between 1 a.m. and 5 a.m. A shift with a non-work period between 1 a.m. and 5 a.m. is defined as a shift with some portion of the non-work period occurring between 1 a.m. and 5 a.m. A shift with sleep between 1 a.m. and 5 a.m. is defined as a shift with some portion of the non-work-period sleep occurring between 1 a.m. and 5 a.m.

The results for 1–5 a.m. sleep involvement in sleep patterns are shown in Table 6. As can be seen, Cluster 2 has a significantly lower proportion (53%) of shifts with a non-work period between 1 a.m. and 5 a.m. compared with Cluster 1 (88%), Cluster 3 (86%), and Cluster 4 (89%). Cluster 2 also has a dramatically lower proportion (35%) of shifts with sleep between 1 a.m. and 5 a.m., as compared with Cluster 1 (86%), Cluster 3 (83%), and Cluster 4 (89%). For those shifts with sleep between 1 a.m. and 5 a.m., Cluster 2 has the lowest proportion (33%) of shifts with a full 4-h sleep at dawn, followed by Cluster 1 (48%); Cluster 3 and Cluster 4 have about 80% of shifts with a full 4-h sleep between 1 a.m. and 5 a.m. These results suggest that when taking shifts in Clusters 3 and 4 the drivers were more likely to sleep between 1 a.m. and 5 a.m. than in Cluster 2.

4.4. Assessing the impact of sleep pattern on driving performance and risk

A summary of SCEs and driving durations is shown in Table 7.

The NB regression results are shown in Tables 8 and 9. Sleep patterns, years of commercial vehicle driving, gender, and BMI are associated with SCE risk. Sleep pattern Cluster 2 has about 1.8 and 1.6 times the SCE rate as Cluster 3 and Cluster 4 respectively, indicating that a shorter sleep at the early stage of a non-work period was associated with a higher SCE risk compared to a longer sleep. Moreover, male drivers have an SCE rate about 2 times that of female drivers. More years of commercial vehicle driving is associated with a decreased SCE risk, and higher BMI is associated with a higher SCE risk.

5. Conclusions and discussion

In this study, we analyzed the Naturalistic Truck Driving Study data to study the sleep patterns of commercial truck drivers and their impacts on truck-driving performance and risk. Using *K*-mean cluster analysis, we identified four sleep patterns/clusters in a workday shift, each with distinctive sleep-related characteristics. Using an NB regression model, we showed the shifts with shorter-duration sleep in the early stage of the non-work period (Cluster 2) had a higher SCE risk than the shifts with a longer-duration sleep that occupied the majority of non-work periods (Cluster 3 and 4). When the sleep duration was short, sleep in the late stage of non-work period (Cluster 1) might be more beneficial for driving performance than sleep in the early stage (Cluster 2). Results from this study also showed that shifts with more sleep time between 1 a.m. and 5 a.m. (Cluster 1, 3, 4) were involved with a lower driving risk and better driving performance than shifts with less sleep time between 1 a.m. and 5 a.m. (Cluster 2). Moreover, the study revealed that increased years of commercial vehicle driving experience were associated with a decreased SCE risk, and increased BMI was associated with an increased SCE risk.

Results of the study show the importance of drivers' receiving adequate sleep the night prior to their driving (workday shift) and underscore the importance of providing drivers with sufficient

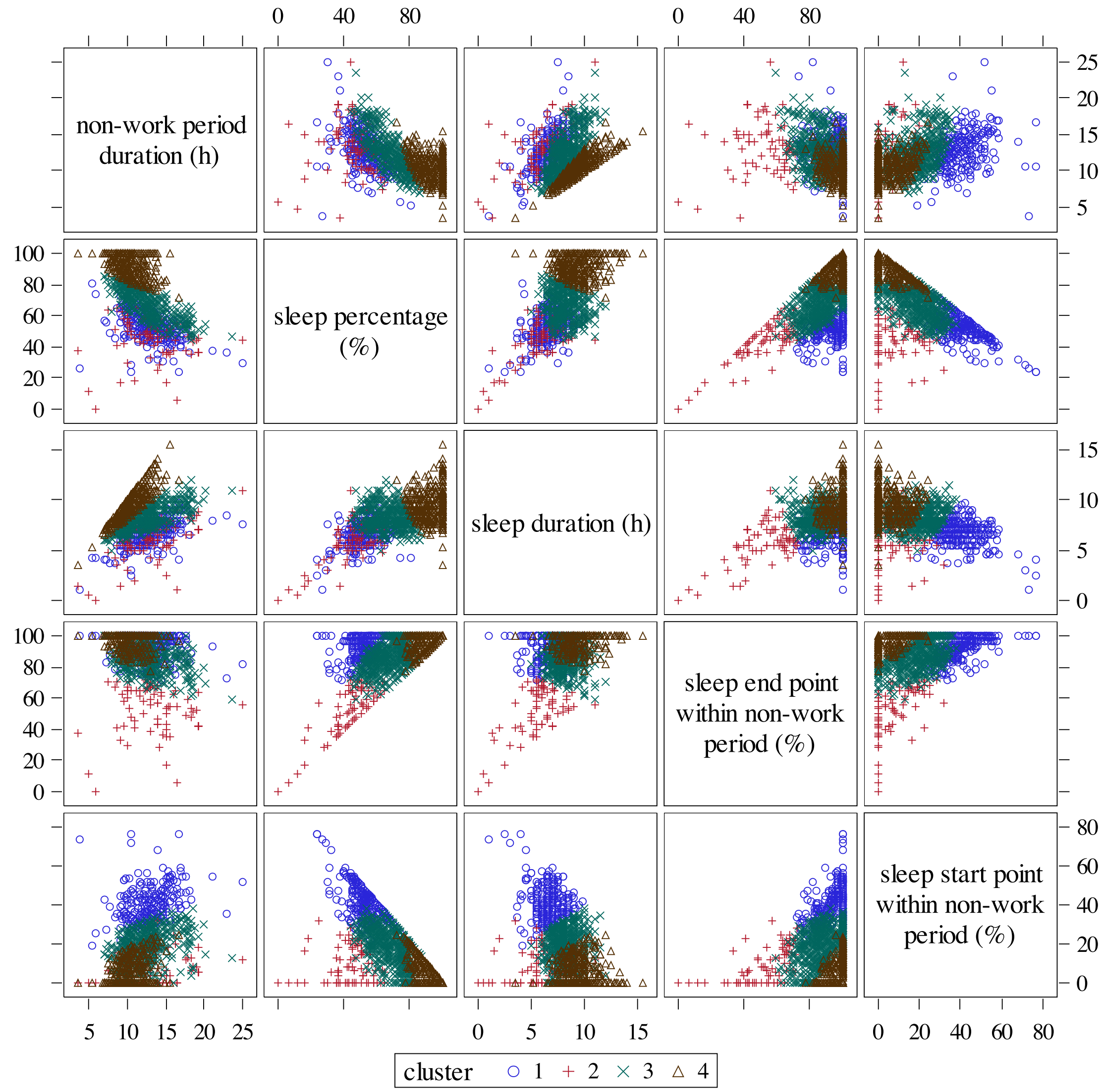

Fig. 4. Distributions of sleep pattern clusters.

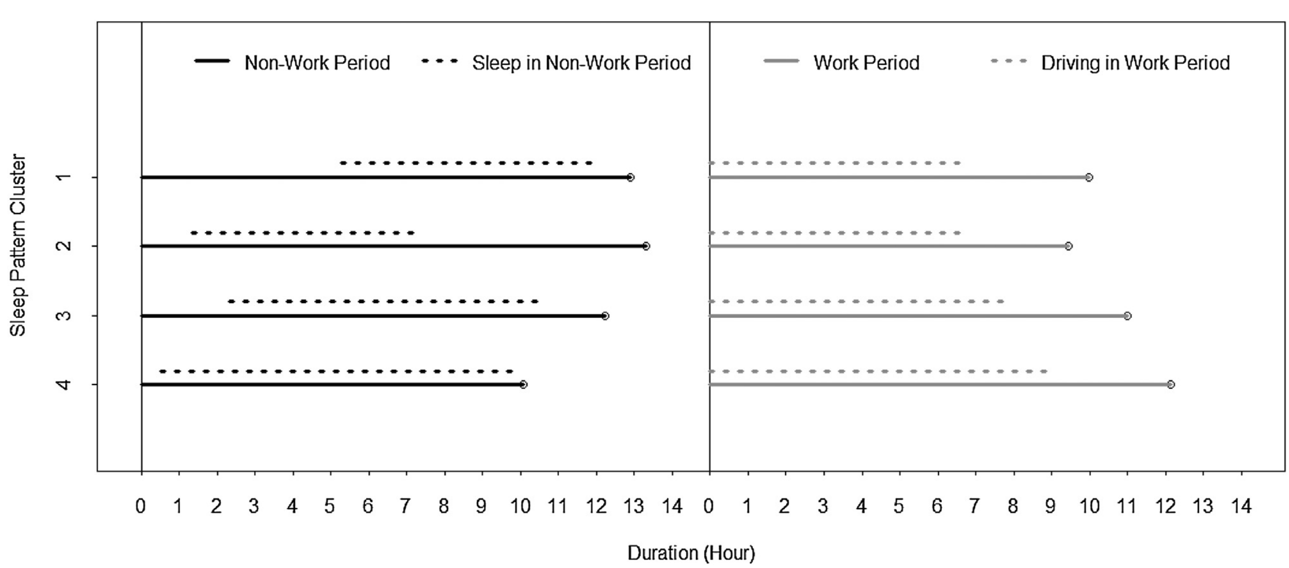

Fig. 5. Demonstration of average sleep and driving durations in a work shift.

Table 2
Driver demographic information.

# Drivers		Male	Female	All
	N	91	5	96
Age	Mean (sd)	44.6 (11.9)	41.2 (12.8)	44.4 (11.9)
	Median (range)	44 (21–73)	46 (26–53)	44 (21–73)
Height (in.)	Mean (sd)	69.4 (2.5)	66.1 (2.9)	69.2 (2.6)
	Median (range)	69.3 (65–75)	65.1 (63–71)	69.1 (63–75)
Weight (lb.)	Mean (sd)	218.6 (44.7)	190.5 (71.6)	217.1 (46.3)
	Median (range)	215.8 (120–384)	171.4 (128–314)	214.2 (120–384)
BMI	Mean (sd)	31.9 (6.2)	30.2 (8.8)	31.8 (6.3)
	Median (range)	31.2 (18–48)	29.4 (21–44)	30.7 (18–48)
Years of commercial vehicle driving	Mean (sd)	9.3 (10.6)	9.3 (11.4)	9.3 (10.6)
	Median (range)	5.6 (0.1–54)	4.4 (0.8–28)	5.4 (0.1–54)

Table 3
Driver demographic characteristics by sleep pattern clusters.

Cluster				By shifts			
	# of Drivers	# of Shifts	% Shifts	Average age*	% Male*	Average BMI*	Average years of commercial vehicle driving*
1	66	250	18	46.9	92.4	32.3	10.5
2	31	86	6	42.7	97.7	30.9	10.6
3	81	544	39	45.1	96.7	31.7	9.5
4	66	517	37	43.1	89.6	32.0	6.8

* Averages are calculated based on shifts, not individual driver.

Table 4
Characteristics of non-work periods by sleep pattern clusters.

Cluster	Avg. non-work period (h)	Avg. sleep (h)	Avg. sleep %	Avg. sleep start point (%)	Avg. sleep end point (%)	Avg. sleep start time (h)	Avg. sleep end time (h)
1	12.9 (2.6)	6.7 (1.2)	52.5 (8.9)	40.8 (9.1)	93.3 (7.3)	5.3 (1.9)	12.0 (2.5)
2	13.3 (3.6)	5.8 (1.9)	43.9 (12.2)	9.9 (8.7)	53.8 (15.4)	1.3 (1.2)	7.1 (2.4)
3	12.2 (2.6)	8.1 (1.0)	68.1 (9.0)	18.8 (8.8)	86.8 (9.0)	2.4 (1.4)	10.5 (2.0)
4	10.1 (1.7)	9.3 (1.5)	92.9 (7.0)	4.8 (6.4)	97.6 (4.4)	0.5 (0.7)	9.8 (1.7)

Numbers in parenthesis are standard deviation of the data.
Abbreviation. Avg. = Average; h = hours.

Table 5
Characteristics of work periods by sleep pattern clusters.

Cluster	Avg. work period (h)	Avg. driving hour (h)	Avg. driving %	Avg. at-work hour* (h)	Avg. at-work %*
1	10.0 (3.1)	6.8 (2.7)	68.6 (19.5)	9.4 (2.7)	95.1 (9.1)
2	9.4 (3.1)	6.8 (2.4)	73.4 (15.7)	9.1 (2.9)	97.2 (7.1)
3	11.0 (3.0)	7.7 (2.7)	70.8 (17.5)	10.3 (2.7)	93.6 (10.0)
4	12.1 (3.4)	8.8 (2.9)	73.7 (17.8)	11.2 (3.3)	92.7 (10.2)

Numbers in parenthesis are standard deviations of the data.
Abbreviation. Avg. = Average; h = hours.
* At-work includes driving truck, heavy work, and light work (i.e., activity codes 1, 2, and 6).

Table 6
Non-work period and sleep between 1 a.m. and 5 a.m. by clusters.

Cluster		# Shifts	Non-work period, 1–5 a.m.		Sleep, 1–5 a.m.		Full 4-hour sleep, 1–5 a.m.	
			No	Yes	No	Yes	<4 h	=4 h
1	Count	250	30	220	35	215	111	104
	Proportion		12%	88%	14%	86%	52%	48%
2	Count	86	40	46	56	30	20	10
	Proportion		47%	53%	65%	35%	67%	33%
3	Count	544	76	468	92	452	89	363
	Proportion		14%	86%	17%	83%	20%	80%
4	Count	517	55	462	58	459	95	364
	Proportion		11%	89%	11%	89%	21%	79%
(Total)	Count	1,397	201	1,196	241	1,156	315	841
	Proportion		14%	86%	17%	83%	27%	73%

sleep opportunities. Previous research that evaluated the impact of a change in the 2003 revised hours-of-service regulations, where off-duty time was changed from 8 to 10 h, found that drivers may sleep more when provided with 10 h of off-duty time as compared with the previous regulations requiring only 8 h off duty (Hanowski et al., 2007). The analysis of SCE risk in current study suggests that longer sleep duration has a measurable safety benefit as well, whereby more sleep reduces the SCE risk in the following shift.

Table 7
Summary of SCEs by sleep pattern clusters.

Cluster	Total driving duration (hours)	SCEs	SCE rate (per 100 h driven)
1	1705.9	279	16.4
2	582.5	127	21.8
3	4197.4	502	12.0
4	4563.4	611	13.4
Total	11,049.2	1519	13.7

This study took a step further than the previous study(Hanowski et al., 2007) that examined the association between sleep duration and SCE risk by considering the sleep time between 1 a.m. and 5 a.m., which is relevant to a change in the current hours-of-service regulations (the 2013 revision) that require the restarting period to cover two night periods occurring between 1 a.m. and 5 a.m. (Federal Motor Carrier Safety Administration, 2013). It is noteworthy this study only examined a workday shift and did not study the restart period. Further research is required to study the safety benefit of the change in the current hours-of-service (2013 revision).

The finding that increased BMI is associated with increased SCE risk is consistent with previous studies that suggested the association between driver BMI and truck crash risk (Wiegand et al., 2009, Anderson et al., 2012). A national survey of long-haul truck drivers suggested that 66% of long-haul truck drivers were obese compared to 30% in the U.S. adult working population (Sieber et al., 2014). The average BMI (32 kg/m^2) among truck drivers in this study is similar to the average BMI (33 kg/m^2) in both Sieber et al. (2014) and Guan et al. (2012) studies.

Limitations of our analysis included the relatively small samples of study participants and workday shifts; thus, confidence intervals were relatively wide, even with the combination of crashes, near-crashes, crash-relevant conflicts, and unintentional lane deviations. Another limitation is the small number ($n = 5$) of female drivers in this study population. In preliminary analysis, two regression models were conducted; one with gender as a covariate and the other without. The results of the two models were similar for covariates other than gender. We chose the model with gender as a covariate in order to control for the gender effect. However, the gender effect should be regarded with caution due to the small sample size of female drivers. The 5% (5/96) of female drivers in this study is similar to the 7% of female drivers among U.S. long-haul truck drivers and U.S. heavy truck driver and delivery/sales workers (Sieber et al., 2014). The self-reported activity register in this study were subject to human error and recall bias. This study only examined sleep patterns on specific workday shifts (a non-work period followed by a work period in a time period less than 27.5 h and there was only one sleep in the non-work period). On the basis of pre-specified criteria, this study excluded the workday shifts that had two or more periods of sleep in a non-work period and the restart period due to the small sample size.

Table 9
SCE rate ratios by clusters and demographics.

	Rate ratio	95% LCL	95% UCL	p-Value
Cluster 1 vs. 4	1.25	0.90	1.73	0.187
Cluster 2 vs. 4	1.62	1.01	2.59	0.044*
Cluster 3 vs. 4	0.91	0.70	1.18	0.465
Cluster 1 vs. 3	1.38	0.99	1.90	0.054
Cluster 2 vs. 3	1.79	1.12	2.84	0.014*
Cluster 1 vs. 2	0.77	0.47	1.27	0.309
Years of commercial vehicle driving	0.98	0.97	0.99	0.010*
Age	1.00	0.99	1.01	0.644
Gender (M vs. F)	1.98	1.21	3.26	0.007*
BMI	1.03	1.01	1.04	0.005*

* Indicates the p-value < 0.05.

This study examined the impact of sleep patterns (considering sleep duration, sleep percentage in the duration of non-work period, and the time when sleep occurred especially in the time window between 1 a.m. and 5 a.m.), years of commercial vehicle driving, driver age, gender, and BMI on driving performance and risk. Findings from this study have implications on driver training and crash prevention, for example, educating new drivers on the safety benefits of adequate sleep and sleep in the time period of 1–5 a.m., and arranging sleep in the late stage of non-working period if possible. NIOSH (2014) recommended the following sleep tips for truck drivers: "Try to get 7–9 h of sleep each day; most people need this amount. Be aware of your body's natural feelings of sleepiness. When you are driving, try to plan your stops and sleep breaks to match your natural sleep times. Sleeping at about the same times every day helps improve sleep. Getting sufficient and regular sleep actually will help you fall asleep faster and sleep better in the future. Better sleep will lead to better health and increased alertness. Remember, any exercise during the day that does not take away from sleep time improves sleep." Company safety policies should also consider incorporating health and wellness programs addressing truck driver obesity, along with other countermeasures to address behind-the-wheel drowsiness (e.g., hours-of-service compliance, allow drivers to rest when needed, etc.) that must be considered for improving safety in commercial motor vehicle operations.

Disclaimer

The findings and conclusions in this report are those of the author(s) and do not necessarily represent the views of the National Institute for Occupational Safety and Health.

Table 8
Negative binomial regression parameter estimation.

Parameter	Estimate	Std. dev.	95% LCL	95% UCL	p-Value
Intercept	−3.94	0.49	−4.91	−2.98	<0.001
Exposure (Hours Driven)	1.20	0.14	0.92	1.48	<0.001
Cluster 1 vs. 4	0.22	0.17	−0.11	0.55	0.187
Cluster 2 vs. 4	0.48	0.24	0.01	0.95	0.044*
Cluster 3 vs. 4	−0.10	0.13	−0.36	0.16	0.465
Years of commercial vehicle driving	−0.02	0.01	−0.03	−0.01	0.010*
Age	0.00	0.01	−0.01	0.01	0.644
Gender (M vs. F)	0.69	0.25	0.19	1.18	0.007*
BMI	0.03	0.01	0.01	0.04	0.005*
Dispersion	3.23	0.23	2.81	3.72	
Chi-square/DF	1.43				
Deviance/DF	0.75				

* Indicates the p-value < 0.05.

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References

Advocates for Highway and Auto Safety, 2011. Truck driver fatigue fact sheet. http://www.saferoads.org/∼saferoad/truck-driver-fatigue.
Anderson, J.E., Govada, M., Steffen, T.K., Thorne, C.P., Varvarigou, V., Kales, S.N., Burks, S.V., 2012. Obesity is associated with the future risk of heavy truck crashes among newly recruited commercial drivers. Accid. Anal. Prevent. 49, 378–384.
Blanco, M., Hanowski, R.J., Olson, R.L., Morgan, J.F., Soccolich, S.A., Wu, S.C., Guo, F., 2011. The Impact of Driving, Non-driving Work, and Rest Breaks on Driving Performance in Commercial Motor Vehicle Operations No. Fmcsa-rrr-11-017. Department of transportation, Federal Motor Carrier Safety Administration.
Blincoe, L., Seay, A., Zaloshnja, E., Miller, T., Romano, E., Luchter, S., Spicer, R., 2002. The Economic Impact of Motor Vehicle Crashes, 2000 (dot hs 809 446). U.S. Department of Transportation, National Highway Traffic Safety Administration, Washington, D.C.
Bureau of Labor Statistics, 2013. Fatal occupational injuries resulting from transportation incidents and homicides by occupation, all united states, 2012. http://stats.bls.gov/iif/oshwc/cfoi/cftb0273.pdf.
Bureau of Labor Statistics, 2014. Occupational outlook handbook: heavy and tractor-trailer truck drivers. http://www.bls.gov/ooh/transportation-and-material-moving/heavy-and-tractor-trailer-truck-drivers.htm.
Butkov, N., Lee-Chiong, T.L., 2007. Fundamentals of Sleep Technology. Lippincott Williams & Wilkins, Philadelphia, PA.
Chen, G.X., Amandus, H.E., Wu, N., 2014. Occupational fatalities among driver/sales workers and truck drivers in the united states, 2003–2008. Am. J. Ind. Med. 57 (7), 800–809.
Department of Transportation, 2014. Why we care about truck driver fatigue. https://www.dot.gov/fastlane/why-we-care-about-truck-driver-fatigue.
Dingus, T., Klauer, S., Neale, V.L., Petersen, A., Lee, S.E., Sudweeks, J., Perez, M., Hankey, J., Ramsey, D., Gupta, S., Busher, C., Doerzaph, Z., Jermeland, J., Knipling, R., 2006. The 100-car naturalistic driving study, phase ii—results of the 100-car field experiment. National Highway Safety Administration (NHTSA), Washington, D.C, pp. 422.
Federal Motor Carrier Safety Administration, 2006. Report to congress on the large truck crash causation study. http://www.fmcsa.dot.gov/sites/fmcsa.dot.gov/files/docs/ltccs-2006.pdf.
Federal Motor Carrier Safety Administration, 2013. Maximum driving time for property-carrying vehicles (code of federal regulations: 49 cfr 395.3). http://www.fmcsa.dot.gov/regulations/title49/section/395.3.
Federal Motor Carrier Safety Administration, 2014a. Large Truck and Bus Crash Facts 2012. US Department of Transportation, Federal Motor Carrier Safety Administration http://www.fmcsa.dot.gov/safety/data-and-statistics/large-truck-and-bus-crash-facts-2012-pdf.
Federal Motor Carrier Safety Administration, 2014b. Pocket guide to large truck and bus statistics—October 2014 update 2. http://www.fmcsa.dot.gov/safety/research-and-analysis/2014-pocket-guide-large-truck-and-bus-statistics.
Fitch, G.M., Soccolich, S.A., Guo, F., Mcclafferty, J., Fang, Y., Olson, R.L., Perez, M.A., Hanowski, R.J., Hankey, J.M., Dingus, T.A., 2013. The impact of hand-held and hands-free cell phone use on driving performance and safety-critical event risk. (DOT HS 811 757).
Guan, J., Hsiao, H., Bradtmiller, B., Kau, T.-Y., Reed, M.R., Jahns, S.K., Loczi, J., Hardee, H.L., Piamonte, D.P.T., 2012. US truck driver anthropometric study and multivariate anthropometric models for cab designs. Hum. Factors 54 (5), 859–870.
Guo, F., Fang, Y., 2013. Individual driver risk assessment using naturalistic driving data. Accid. Anal. Prevent. 61, 3–9.
Guo, F., Fang, Y., Antin, J.F., 2014. Evaluation of older driver fitness-to-drive metrics and driving risk using naturalistic driving study data. Report no. 15-um-036. National Surface Transportation Safety Center for Excellence.
Guo, F., Fang, Y., Antin, J.F., 2015. Older driver fitness-to-drive evaluation using naturalistic driving data. J. Safety Res. 54, 49–54.
Guo, F., Klauer, S.G., Hankey, J.M., Dingus, T.A., 2010. Near crashes as crash surrogate for naturalistic driving studies. Transp. Res. Rec. 2147 (1), 66–74.
Hanowski, R.J., Bowman, D., Alden, A., Wierwille, W.W., Carroll, R., 2008. Perclos+: moving beyond single-metric drowsiness monitors. (no. 2008-01-2692). SAE Technical Paper.
Hanowski, R.J., Hickman, J., Fumero, M.C., Olson, R.L., Dingus, T.A., 2007. The sleep of commercial vehicle drivers under the 2003 hours-of-service regulations. Accid. Anal. Prevent. 39, 1140–1145.
Hastie, T., Tibshirani, R., Friedman, J., 2009. The Elements of Statistical Learning: Data Mining, Inference, and Prediction, 2nd ed. Springer.
Klauer, S.G., Guo, F., Simons-Morton, B.G., Ouimet, M.C., Lee, S.E., Dingus, T.A., 2014. Distracted driving and risk of road crashes among novice and experienced drivers. N. Engl. J. Med. 370, 54–59.
Morrow, P.C., Crum, M.R., 2004. Antecedents of fatigue, close calls, and crashes among commercial motor-vehicle drivers. J. Saf. Res. 35 (1), 59–69.
National Institute for Occupational Safety and Health, 2009. National occupational research agenda: National transportation, warehousing, and utilities agenda. http://www.cdc.gov/niosh/nora/comment/agendas/transwareutil/pdfs/TransWareUtilAug2009.pdf.
National Institute for Occupational Safety and Health, 2014. Quick sleep tip for truck drivers. http://www.cdc.gov/niosh/docs/2014-150/pdfs/2014-150.pdf.
National Sleep Foundation, http://sleepfoundation.org/sleep-topics/sleep-drive-and-your-body-clock.
National Transportation Safety Board, 1990. Safety study: fatigue, alcohol, other drugs, and medical factors in fatal-to-the-driver heavy truck crashes (volume 1). National Transportation Safety Board. Report No. NTSB/SS-90/01, Washington, D.C.
Ouimet, M.C., Brown, T.G., Guo, F., Klauer, S.G., Simons-Morton, B.G., Fang, Y., Lee, S.E., Gianoulakis, C., Dingus, T.A., 2014. Higher crash and near-crash rates in teenage drivers with lower cortisol reactivity: an 18-month longitudinal, naturalistic study. JAMA Pediatr. 168 (6), 517–522.
Satterfield, B.C., Van Dongen, H.P., 2013. Occupational fatigue, underlying sleep and circadian mechanisms, and approaches to fatigue risk management. Fatigue: Biomed. Health Behav. 1 (3), 118–136.
Schur, E.A., Noonan, C., Smith, W.R., Goldberg, J., Buchwald, D., 2007. Body mass index and fatigue severity in chronic fatigue syndrome. J. Chron. Fatigue Syndr. 14 (1), 69–77.
Sieber, W.K., Robinson, C.F., Birdsey, J., Chen, G.X., Hitchcock, E.M., Lincoln, J.E., Nakata, A., Sweeney, M.H., 2014. Obesity and other risk factors: the national survey of us long-haul truck driver health and injury. Am. J. Ind. Med. 57 (6), 615–626.
Soccolich, S.A., Blanco, M., Hanowski, R.J., Olson, R.L., Morgan, J.F., Guo, F., Wu, S.-C., 2013. An analysis of driving and working hour on commercial motor vehicle driver safety using naturalistic data collection. Accid. Anal. Prevent. 58, 249–258.
Sweeney, M.M., Ellingstad, V.S., Mayer, D.L., Eastwood, M.D., Weinstein, E.B., Loeb, B.S., 1995. The need for sleep: discriminating between fatigue-related and nonfatigue-related truck accidents. Proc. Hum. Factors Ergon. Soc. Ann. Meet. 39 (17), 1122–1126.
Van Dongen, H.P., Jackson, M.L., Belenky, G., 2010. Duration Restart Period Needed to Recycle with Optimal Performance: Phase ii. Federal Motor Caarrier Safety Administration, USDOT, Washington, DC.
Wiegand, D.M., Hanowski, R.J., Mcdonald, S.E., 2009. Commercial drivers' health: a naturalistic study of body mass index, fatigue, and involvement in safety-critical events. Traffic Inj. Prev. 10 (6), 573–579.