IISE Transactions on Occupational Ergonomics and Human Factors

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/uehf21

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To cite this article: Alec Smith, Anthony D. McDonald & Farzan Sasangohar (2021) The Impact of Commutes, Work Schedules, and Sleep on Near-Crashes during Nurses' Post Shift-Work Commutes: A Naturalistic Driving Study, IISE Transactions on Occupational Ergonomics and Human Factors, 9:1, 13-22, DOI: 10.1080/24725838.2021.1945708

To link to this article: https://doi.org/10.1080/24725838.2021.1945708

IISE TRANSACTIONS ON OCCUPATIONAL ERGONOMICS AND HUMAN FACTORS
2021, VOL. 9, NO. 1, 13–22
https://doi.org/10.1080/24725838.2021.1945708

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ORIGINAL RESEARCH

The Impact of Commutes, Work Schedules, and Sleep on Near-Crashes during Nurses' Post Shift-Work Commutes: A Naturalistic Driving Study

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OCCUPATIONAL APPLICATIONS

Driving and survey data were collected from nurses following the night-shift and analyzed with logistic regression and frequency analysis. The analyses showed that prior near-crashes and drive length contributed significantly to near-crashes. The frequency analysis showed that most near-crashes occurred on major roadways, including principal arterials, major collectors, and interstates, within the first 15 minutes of the drive. These results highlight the urgent need for countermeasures to prevent drowsy driving incidents among night-shift nurses. Specifically, nurses and hospital systems should focus on countermeasures that encourage taking a break on the post work commute and those that can intervene during the drive. This may include the use of educational programs to teach nurses the importance of adequate rest or taking a break to sleep during their drive home, or technology that can recognize drowsiness and alert nurses of their drowsiness levels, prompting them to take a break.

TECHNICAL ABSTRACT

Background: Night-shift nurses are susceptible to drowsy driving crashes due to their long working hours, disrupted circadian rhythm, and reduced sleep hours. However, the extent to which work, sleep, and on-road factors impact the nurses' commutes and the occurrence of near-crash events is not well documented.
Purpose: A longitudinal naturalistic driving study with night-shift nurses from a large hospital in the United States was conducted to measure these factors and analyze the occurrence and location of near-crashes during post-shift commutes.
Methods: An on-board data recorder was used to record acceleration, speed, and GPS coordinates continuously. Nurses also completed daily surveys on their sleep, work, and ***commute***. Near-crashes were identified from the data based on acceleration thresholds. Data from a total of 853 drives from 22 nurses and corresponding surveys were analyzed using Poisson and negative binomial regressions for swerve and hard brake near-crash events, respectively.
Results: Swerve events were increased by the length of the drive (RR = 2.59, LL = 1.62, UL = 4.16), and the occurrence of hard brakes (RR = 1.69, LL = 1.45, UL = 1.99), while hard brake events were increased by the occurrence of swerves (RR = 1.55, LL = 1.28, UL = 1.88). The majority of near-crashes occurred on principal arterials ($n = 293$), minor arterials ($n = 71$), and interstates ($n = 51$).
Conclusions: The results demonstrate the high risk of near-crashes during post-shift commutes, which may present danger to nurses and other drivers, and highlight the need for countermeasures that address shift structures, sleep quality, and taking breaks.

ARTICLE HISTORY
Received 10 March 2021
Accepted 16 June 2021

KEYWORDS
Naturalistic driving study; drowsy driving; shift-work; near-crash; nurse

1. Introduction

Drowsy driving has contributed to over 800 deaths and 29,000 injuries each year from 2011 to 2015 (National Center for Statistics & Analysis, 2017). Shift-workers such as night-shift nurses are especially prone to drowsy driving due to long working hours, poor sleep, and disrupted circadian rhythm (National Sleep Foundation, 2009). In one study, nearly 80% of night-shift nurses reported drowsy driving at least once (Scott et al., 2007). In another study, drowsy driving was cited as a factor in 95% of driving crashes and incidents involving nurses (Gold et al., 1992). The

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prevalence of drowsy driving among more than three million registered nurses in United States is even more concerning given the expected 7% growth in nursing jobs over the next decade (Bureau of Labor Statistics, 2020). It is expected that the rate of drowsy driving-related crashes will continue to rise without significant interventions. Indeed, several regulatory agencies have issued renewed calls for implementing interventions (Caruso et al., 2017; Higgins et al., 2017). A theme across these recommendations is the need for detailed understanding of the process and effects of drowsy driving.

Drowsy driving among nurses has primarily been studied using qualitative methods such as logbooks and interviews to document crashes and near-crashes—a conflict requiring an evasive maneuver (Dingus et al., 2006). A logbook study of 895 nurses found crashes and near-crashes during nurses' post-work commutes were associated with working at night, alertness at work, shift durations of 12.5 hours or more, and reduced sleep (Scott et al., 2007). A second logbook study of Australian nurses found struggles to stay awake at work, exhaustion, and consecutive shifts as contributors to extreme drowsiness during the post-work commute (Dorrian et al., 2008). The study also found that struggling to stay awake was predicted by exhaustion, prior sleep, and shift length. Our recent analysis of interviews with night-shift nurses aligned with the findings from the logbook studies, but also found that most nurses report peak drowsiness immediately prior to or during their post-work commute (Smith et al., 2020).

Drowsy driving has also been studied in driving simulator, closed-test track, and observational driving studies (Åkerstedt et al., 2005; Ftouni et al., 2013; Lee et al., 2016; Mulhall et al., 2019). A simulator study with shift-workers, the majority of whom were nurses, found a relatively high number of incidents as well as an increasing level of subjective sleepiness on the drive following shift-work (Åkerstedt et al., 2005). More recently, Lee et al. (2016) evaluated the driving behavior of night-shift nurses following the shift in a closed-test track driving study and found increased rates of lane excursions, emergency braking maneuvers, and drive terminations due to drowsiness after a night-shift compared to a non-shift day baseline. Further, the rate of near-crash events increased dramatically after 45 minutes of continuous driving (Lee et al., 2016). Ftouni et al. (2013) and Mulhall et al. (2019) conducted observational driving studies with night-shift nurses and found higher levels of subjective and objective sleepiness (e.g., Jones Drowsiness Score) following shift-work. Mulhall et al. (2019) found that extended periods of wakefulness (16 hours or more) increased the occurrence of self-reported near-crash events. While these studies illuminate the attributes of nurse shifts, sleep, wakefulness, and driving duration that may lead to drowsy driving crashes, there is a gap in studies that comprehensively evaluate the effect of these conditions alongside of countermeasures (e.g., breaks). Furthermore, self-report measures and closed-test track and simulator studies are limited in their ability to assess the impacts of these factors on objective driving outcomes (i.e., crashes and near-crashes). Naturalistic driving studies that measure vehicle location, speed, and accelerations directly can address these gaps and limitations (Dingus et al., 2006).

Prior naturalistic driving studies have demonstrated the effectiveness of naturalistic driving data for assessing driver distraction (Klauer et al., 2014), changes in behavior due to sleep apnea (McDonald et al., 2017; McLaurin et al., 2018), interactions with automated vehicles (Fridman et al., 2019), and general driving behavior among special populations such as teenagers and professional truck drivers (Dingus et al., 2006; Lee et al., 2011). Beyond their objectivity and unobtrusiveness, naturalistic driving studies directly link driver characteristics and safety outcomes. While crashes are the best indicator of driving safety, they are rare—the 100-Car Study observed only 69 crashes in over 43,000 hours of driving (Dingus et al., 2006). Near-crashes can be used as an effective surrogate safety measure (Dingus et al., 2006; Perez et al., 2017). Despite their potential for informing the links between drowsy driving and driving behavior, we are unaware of published naturalistic driving studies on night-shift nurses documenting objective indicators of near-crashes. This study addresses that gap, with a longitudinal naturalistic driving study and daily survey methodology that links nurses' sleep, occupational behavior, and commute metrics to near-crashes.

2. Material and Methods

The naturalistic driving study was conducted over a 4-month period using a mixed-methods approach involving in-vehicle data collection and daily log surveys to capture information about commutes, sleep quality, and shifts. The study was approved by the Texas A&M University and the host site's Institutional Review Boards (IRB2018-0895) and complied with the American Psychological Association Code of Ethics. Participation in the study was voluntary, and all participants were provided with informed

Table 1. Participant demographics compared to the nation (Data USA, 2018).

Demographic variable		Nation (Data USA, 2018)	Participants
Age (SD)		43.7	33.4 (7.2)
Race (%)	White	74.5	15.6
	Black	11.9	28.1
	Asian	9.3	50
	Two or more	2.2	6.3
Ethnicity (%)	Hispanic	7.4	3.1
	Not Hispanic	92.6	84.4
Education level (%)	Associates	2.5	0.0
	Bachelors	81.5	86.4
	Masters	15.1	13.6
	Doctoral	0.9	0.00
Unit (%)	Medical / Surgery	–	37.5
	Intensive / Critical Care	–	28.1
	Cardiovascular	–	12.5
	Orthopedic/Neurology	–	9.4
	Oncology	–	3.1
	Operating Room	–	3.1
	Rehabilitation	–	3.1
	Transplant	–	3.1
Marital status (%)	Single	–	53.1
	Married	–	43.8
	Widowed	–	3.1

consent documentation and consented to their participation.

2.1. Participants

Thirty-two participants from a large hospital located in Houston, Texas were recruited using emails and flyers. To be included in the study, nurses had to be full-time (at least 3 shifts per week) on the night-shift (starting at 19:00 h and ending at 07:00 h for a total of 12 hours), hold a valid driver's license, have car insurance, and own a smartphone. Nurses were excluded if they had a medical condition or used medication that increased drowsiness. Table 1 summarizes the demographics of the participants alongside national averages. The participants were about 10 years younger than the national average and more racially diverse, with a greater percentage of participants who identified as Asian or Black and a lower percentage of participants who identified as White. The education levels of the participants were similar to the national average (note that no participants held an associate or a doctorate degree). Most nurses worked in medical/surgery or intensive/critical care units.

2.2. Data Collection

Driving data were collected with an OBDLink MX + device (OBDLink) paired with the participants' cellular phone. The OBDLink MX + device is a commercially-available On-Board Diagnostic II (OBD-II) data recorder that can access the car's computer, connect to cellular devices via Bluetooth, and transmit information from the car's on-board computer to the connected device. The OBDLink MX + device was connected to the OBD-II port in participants' vehicles and transmitted data to the participants' phones via Bluetooth. The paired OBDLink MX + and phone collected speed, three axis acceleration, and GPS location data at 2 Hz throughout the drive. Data were stored in separate files created each time the vehicle's ignition was turned on and closed when the vehicle was turned off. Following each drive, the data were automatically stored to cloud-based storage. In addition to the driving data, participants completed daily online surveys after their commute on their cellular phones. The surveys contained questions related to the participants' work schedule, sleep, and how they felt during their drive (see Appendix A). The participants were instructed to complete the questions pertaining to work about their most recently completed shift, and the questions pertaining to sleep about their most recent time of extended sleep. A personalized quick response (QR) code card was provided to each participant to facilitate the data collection. Upon completion of the survey, the responses were stored on the cloud and integrated with the driving data.

2.3. Data Pre-Processing

Data from a total of 1,217 drive files from 32 nurses were collected. Ten nurses were excluded from the

Table 2. Criteria for identifying near-crashes (Adapted from Perez et al., 2017).

Measure	Direction	Acceleration (g)	Speed (mph)
Swerve	lateral (left-to-right)	(+/−) 0.92	>15
Hard brake	longitudinal (braking)	−0.75	>15

analysis because they had fewer than 15 drives (98 drives total), which was deemed insufficient to establish driving patterns. Post-hoc analysis showed that this removal did not affect the significance observed in the regression. In addition, 155 drive files were removed for the following reasons: 13 occurred more than three hours outside of the post-work commute time; 24 were empty due to device failures; 53 were shorter than five minutes, a normal trip length classified by travelers (Bricka & Bhat, 2006); and 65 had some missing information needed for the analysis including speed, acceleration, or GPS coordinates. Two hundred twenty-two (222) drive files occurred on the same day as another drive by the same participant. GPS data in these files were reviewed, and the data were consolidated into a single drive file if the additional driving instance occurred as part of a planned stop (e.g., gas station). After this consolidation, a total of 853 drives from 22 nurses were included in the analysis.

2.4. Identification of Near-Crashes

No crashes were observed over the duration of the experiment. Near-crashes were identified based on the thresholds validated in Perez et al. (2017), which were derived from analysis of the Strategic Highway Research Program 2 (SHRP 2) dataset. The SHRP-2 dataset includes data from over 3,400 instrumented vehicles across the United States representing over 4,300 person years of driving data across participants (Hankey et al., 2016). Two types of near-crashes were identified in the current study, swerves and hard brakes. Thresholds used to identify these events are presented in Table 2. While these thresholds reduce false positive rates relative to other commonly used thresholds (Dingus et al., 2006), they may still include incidents that do not represent evasive maneuvers. For this reason, all near-crash events identified in the dataset were reviewed manually. This review consisted of analyzing the speed of the vehicle during the near-crash, the vehicle trajectory prior to the near-crash, and the location of the near-crash event. In this review, near-crashes that occurred when the vehicle was traveling less than 15 miles per hour for one minute prior to the event, and events that occurred in designated parking zones or structures, were removed from the dataset. The final dataset included 462 events: 169 swerves and 293 hard brakes.

Functional classification of the roadways where the events occurred were identified through ArcGIS Online software. ArcGIS Online software (ESRI, 2020) leverages a database of layers and maps that include classification of roadways based on the Federal Highway Administration's (2013) (FHWA) definitions maintained by the Texas Department of Transportation (TxDOT, 2020). The functional classification categories included: principal arterials, minor arterials, major collectors, and interstates. Roadways not labeled by TxDOT were reviewed manually and labeled as commercial roads (close proximity to businesses and areas of commerce), rural roads, or residential (close to housing and noncommercial property). Near-crashes were normalized by driver exposure to each road type. Each near-crash was captured in a 0.5 s time frame and was normalized by dividing the total number of near-crashes on a roadway by the total number of 0.5 s segments spent on the same roadway. The normalized rate was then converted into events per minute, by multiplying the rate by 120 seconds (as there are 120 half seconds in a minute) for greater clarity in interpretation.

2.5. Data Analysis

The driving data, demographics, and surveys were combined for each study day and analyzed in R software using Poisson regression for swerves and negative binomial regression for hard brakes. The use of Poisson and negative binomial regressions is consistent with prior naturalistic driving studies estimating the impact of independent variables and covariates (e.g., demographics, road conditions, time) on drowsy driving (Lee et al., 2016; Owens et al., 2018). The choice of regression approach was guided by a Chi-square goodness of fit test (Bol'shev & Mirvaliev, 1979). Participants were added to the models as random variables to account for individual differences. Rate ratios and 95% confidence intervals were used to assess the impact of the independent measures on near-crashes. A p-value <0.05 was selected to determine significance. The occurrence of near-crashes is expected to increase or decrease by the rate ratio for each one unit increase in the associated factor. For example, an increase in drive length by one minute, while holding all other factors constant, would show a proportionate increase in the occurrence of swerves by 1.02, the rate ratio. Beyond the regression modeling, the locations and the time-into-the drive when

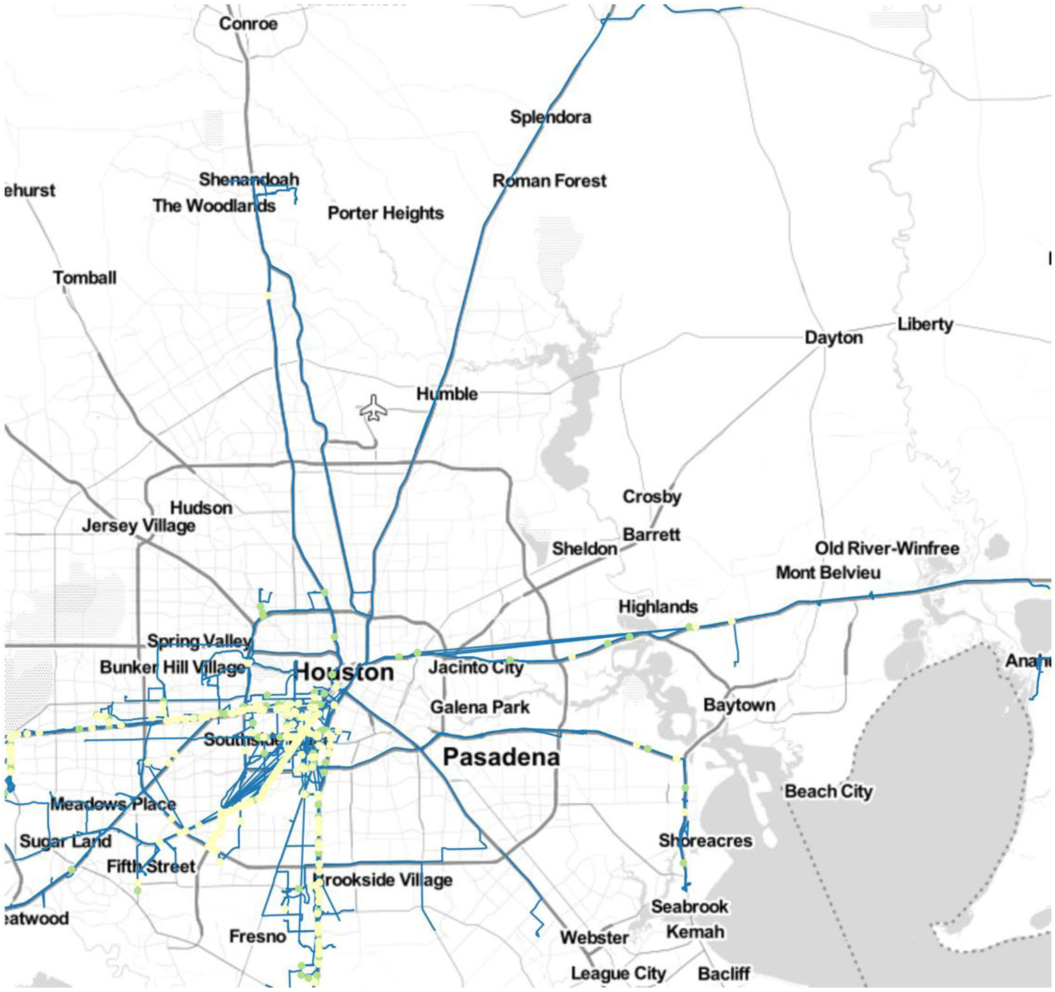

Figure 1. Map with locations traveled (blue lines) and near-crashes (yellow points as hard brakes and green points as swerves).

the near-crashes occurred were investigated with frequency analyses.

The regression analyses included 15 independent measures: consecutive and total weekly shifts, sleep duration, four sleep quality measures, prior near-crashes, taking breaks during the drive, the drive length, and demographics including age, marital status, education level, and unit. The shift (Geiger-Brown et al., 2012; Smith et al., 2020; Steege et al., 2015), sleep (Ftouni et al., 2013; Geiger-Brown et al., 2012; Mulhall et al., 2019), drive duration factors (Lee et al., 2016), and units (Scott et al., 2006) were included, based on findings in prior work that related these factors to increases in self-reported driving incidents or increases in fatigue. Age, marital status, and education level were included, based on our prior findings from an interview study that suggested experience and familial obligations could impact drowsy driving frequency (Smith et al., 2020). The occurrence of prior near-crashes and breaks were included to provide novel understanding of the impact of these factors on driving incidents.

3. Results

The range of the driving data and corresponding locations of the near-crashes are shown in Figure 1. Participants drove a mean of 495.6 (SD = 447.9, Median = 290.5) miles and spent a mean of 1,124.8 (SD = 613.2, Median = 980.1) minutes on the road during the study. The mean drive duration was 29 minutes (SD = 19.2, Median = 25.7) and participants drove a mean of 12.8 (SD = 10.85, Median = 11.6) miles. The majority of participants (19/22; 89.4%) experienced at least one near-crash; however, no crashes were observed. Across participants, there was a mean of 7.7 (SD = 10.9, Median = 4) swerves and a mean of 13.3 (SD = 24.5, Median = 5) hard brakes.

Table 3. Results of the Poisson (Swerve) and Negative Binomial (Hard Brake) regression including the rate ratio and 95% confidence intervals for each factor.

	Swerve			Hard Brake		
Factors	Rate ratio	(LL, UL)	*p*-value	Rate ratio	(LL, UL)	*p*-value
Consecutive shifts	1.00	(0.81, 1.24)	0.98	0.94	(0.78, 1.12)	0.51
Total shifts	1.06	(0.87, 1.29)	0.54	1.05	(0.89, 1.25)	0.50
Hours slept	0.99	(0.90, 1.08)	0.84	0.99	(0.93, 1.07)	0.98
Hours awake before sleeping	0.99	(0.88, 1.12)	0.98	0.98	(0.90, 1.08)	0.79
Times awakened	0.93	(0.79, 1.09)	0.44	1.02	(0.93, 1.12)	0.61
How rested	0.91	(0.82, 1.02)	0.11	1.00	(0.92, 1.08)	0.95
How easily fell asleep	0.86	(0.57, 1.29)	0.48	0.88	(0.65, 1.19)	0.42
Hard brakes	**1.69**	**(1.45, 1.99)**	**5.12E-11**	–	–	
Swerves	–	–	–	**1.55**	**(1.28, 1.88)**	**5.15E-06**
Stopped during drive	0.72	(0.37, 1.39)	0.33	1.17	(0.76, 1.81)	0.45
Drive length (Time)	**2.59**	**(1.62, 4.16)**	**7.27E-05**	1.48	(0.93, 2.36)	0.09
Age	1.15	(0.35, 3.73)	0.81	1.50	(0.54, 4.16)	0.43
Marriage status	2.08	(0.47, 9.15)	0.33	1.05	(0.29, 3.76)	0.94
Education level	4.67	(0.72, 30.1)	0.11	1.97	(0.37, 10.3)	0.42
Unit	1.12	(0.25, 5.05)	0.88	0.63	(0.17, 2.31)	0.49

Significant effects are highlighted in bold.

3.1. Factors that Contribute to the Occurrence of near-Crashes

Table 3 shows the rate ratio estimates and their 95% confidence intervals. The occurrence of a hard brake had a significant effect on swerves. The greater number of hard brakes resulted in an increased occurrence of swerves by 1.69 (LL = 1.45, UL = 1.99). The occurrence of a swerve had a significant effect on hard brakes. The increased number of swerves led to an increase of hard brakes by 2.51 (LL = 1.86, UL = 3.43). The length of the drive had a significant effect on swerves. The longer the drive, the occurrence of a swerve increased by 2.59 (LL = 1.62, UL = 4.16). Demographic, work factors, and sleep behavior factors were not significant.

3.3. Near-Crash Occurrence by Functional Classification

The nurses' commutes were homogenous; all commutes started at an urban hospital and continued on a highway that ended in the suburban municipalities. Almost all of the observed near-crashes occurred on principal arterials ($n = 293$; swerves = 88, hard brakes = 205). Figure 2 depicts the normalized and total occurrences of hard brakes and swerves by the functional classification of the roadway where the near-crashes occurred. A shown in this Figure, the vast majority of the hard brake events occurred on principal arterials. Major collectors and principal arterials had similar normalized occurrence as did minor arterial and interstate at a lower occurrence. Few hard brakes occurred on residential (7) and commercial roadways (1). Only one hard-brake event during rural road driving was observed. Since only a small amount of time was spent driving on rural roads, this resulted in a normalized rate that is an outlier. Therefore, rural road near crashes were not included in Figure 2. Despite the majority of swerves occurring on principal arterials, the greatest proportion of swerves occurred on minor arterials and major collectors, followed by interstate and principal arterials.

3.4. Near-Crashes and Commute Duration

Figure 3 shows cumulative distributions for the occurrence of near-crashes by time into the drive. This figure illustrates that a substantial portion of near-crashes occurred in the first 15 minutes of driving. For swerves, 68 of the total 169 swerves (40.2%) occurred within the first 15 minutes of the drive, and 148 occurred in the first 30 minutes. Only four swerves occurred after one hour of driving. For hard brakes, 141 of the 302 (48.1%) occurred within the first 15 minutes of the drive and a total of 261 (89.1%) after 30 minutes. Only six hard brakes occurred after one hour of driving. It is important to note that given the commute-based nature of the data collection, few drives ($n = 311$) exceeded 30 minutes and even fewer exceeded 60 minutes ($n = 41$, median drive length of 25.7 minutes).

4. Discussion

The findings here reinforce the well-established dangers of driving after prolonged shift work and suggest that drowsy driving among nurses may be more prevalent than previously reported. While Scott et al. (2007) reported that 79% of nurses experienced drowsy driving once per month, we found that 89.4%

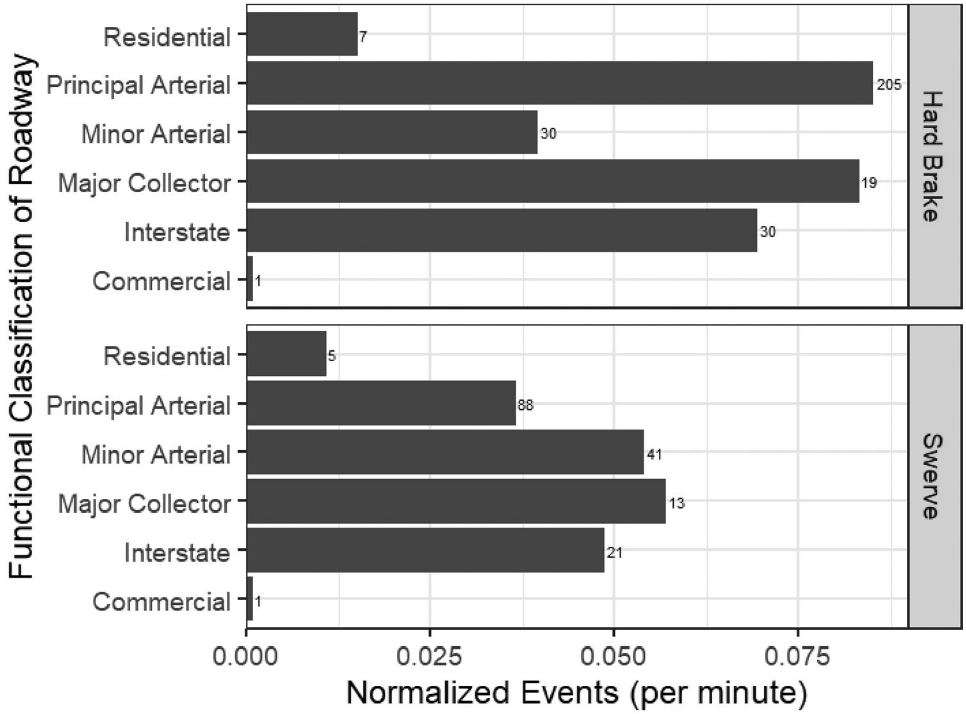

Figure 2. Hard brake and swerve occurrence normalized by minute, with totals to the right, and identified by functional classification. Note, a single hard brake on a rural road was removed because it was an outlier.

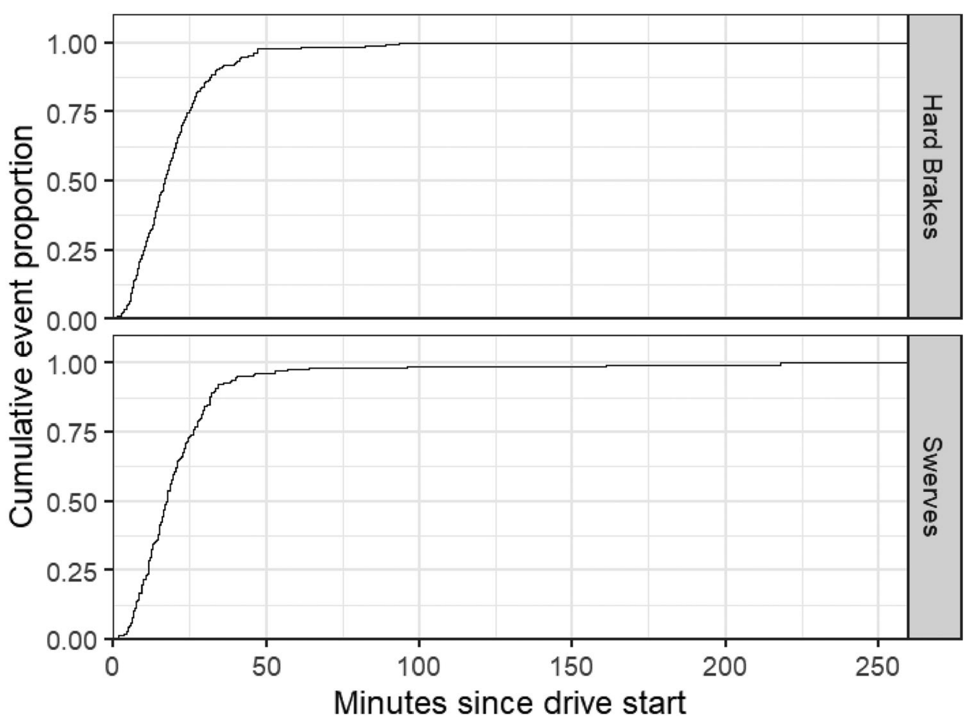

Figure 3. Cumulative hard brake and swerve events with driving duration.

(19/22) experienced at least one near-crash over the four months of data collection. Furthermore, the 1.12 near-crashes per hour of driving observed here is substantially higher than the 0.34 near-crashes per hour observed in Lee et al. (2016). There are several factors that may contribute to this difference. First, Lee et al. (2016) terminated drives when participants were unable to maintain adequate control of the vehicle, whereas in this study participants continued to drive after near-crashes. Second, the protocol in Lee et al. (2016) included providing participants transportation from the hospital facility to the test facility after their shift. Prior work suggests many nurses experience peak drowsiness in the period immediately following the shift (Dorrian et al., 2008; Mulhall et al., 2019; Smith et al., 2020). This interpretation is further supported by the high volume of near-crashes observed in the first 15 minutes of driving (Figure 3) compared to the lack of near-crashes before 45 minutes of driving in Lee et al. (Figure 1 on p. 178). While there is some risk that the near-crashes observed in this study were false positives, it is important to note that the frequency is well within observed rates from driving simulation studies that have observed as many as four near-crashes per drive (Åkerstedt et al., 2005). It is also important to note that while many near-crashes were observed in this study, no crashes were observed. This was expected in a naturalistic study, given the fact that crashes are a rare occurrence; for example, the SHRP2 study (Dingus et al., 2006) observed only 82 crashes across approximately 2,000,000 miles of driving data (0.000041 crashes/mile). However, we captured only 10,903 miles, meaning we would expect to see less than one crash. Thus, while the rates here should be cautiously interpreted, there is sufficient support to suggest an urgent need for countermeasures to prevent crashes and near-crashes among shift work nurses.

The novel analyses here linking work, sleep, and drive factors to objectively measured near-crashes may serve as a guide for drowsy driving countermeasures. Regression analyses identified the presence of a prior near-crash during the drive as a significant contributor to both types of near-crashes. In addition, drive length significantly impacted the occurrence of swerves. At a high level, these factors highlight the need for countermeasures that consider the work (e.g., through shift reductions), the nurse (e.g., through training or technology to improve ease of sleep), and the drive (e.g., through in-vehicle countermeasures that alert nurses prior to near-crashes), which supports prior recommendations from the healthcare and transportation safety communities (Higgins et al., 2017). At a more granular level, the findings suggest that, among the factors explored here, the occurrence of a prior near-crash during a commute is the strongest predictor of near-crashes. While this finding can be expected given the well-established progressive nature of drowsiness (Brown, 1994), it also suggests that in the absence of countermeasures that can ensure sufficient sleep, in-vehicle countermeasures will likely have the largest effect on near-crash—and crash—occurrence on post shift commutes.

Our finding that many near-crashes occurred in the first 15 minutes of the commute on major collectors and principal arterials are also novel. While prior work has shown that many drowsy driving incidents occur on rural, monotonous, roadways (Horne & Reyner, 1995; Thiffault & Bergeron, 2003), our findings suggest that highway driving is also a concern. This observation extends our prior interview analysis, which suggested that many nurses feel their drowsiest at the start of their commute and during free flow traffic (Smith et al., 2020). This finding further underscore the need for in-vehicle drowsy driving countermeasures given that taking a break on major collectors and principal arterials may not be possible due to infrequent highway exits and dense traffic.

4.1. Limitations and Future Work

Despite the novel findings of the study, there are several limiting factors. First, the single sample method from one hospital system may limit the extension of these findings to other hospital systems with alternative shift schedules and regulations. Second, the majority of the nurses in this study commuted from an urban hospital location to a suburban home. Thus, the findings here may not be applicable to other hospital locations, especially rural hospitals, where the rates of drowsy driving can be expected to be much higher. In addition, the data collection method, which specifically focused on data collection during work days, limits the analysis on the effects of prolonged sleep deprivation or near-crashes occurring on non-commute drives. Another limitation is the threshold-based identification of near-crashes, which may have introduced false positives into the dataset. Finally, the use of GPS data to connect to functional classification may be limited by errors in GPS readings, especially on roadways including multiple layers. Despite these limitations, the consistency in the results reported in this work and prior similar studies suggest that the findings possess relatively high validity. Future work should investigate various lifestyle factors of shift-workers that have been shown to influence drowsiness such as preference for working during the night, circadian conditioning, smoking and activity levels (Alward, 1988; Johnston et al., 2019; Van Amelsvoort et al., 2006).

5. Conclusions

The goals of this study were to measure the frequency of near-crashes among night-shift nurses and to assess factors that significantly impact the occurrence of near-crashes during the post-shift commute. The results indicate that, while no crashes were observed, near-crashes occur at an alarming rate among shift work nurses during the post-work commute, which presents danger to themselves and other road users. The findings suggest that the occurrence of near crashes is significantly impacted by drive duration, and prior near-crashes during the post work commute. Another important finding is the high frequency of occurrence of near-crashes in the first 15 minutes of the drive Another important finding is the high frequency of occurrence of near-crashes in the first 15 minutes of the drive. Finally, the results demonstrate the effectiveness of our low-cost, naturalistic data collection approach, which may be used in the future work to evaluate interventions or assess crash risk in other occupational populations at risk of drowsy driving crashes (e.g., oil and gas extraction or home healthcare workers). Despite several limitations, to our knowledge this is the first study quantifying the occurrence of near-crashes among night-shift nurses in a naturalistic setting. Collectively the findings highlight the urgent need for countermeasures that address occupational fatigue and drowsiness, as well as effective, non-intrusive, and accepted in-vehicle interventions.

Conflict of Interest

The authors declare no conflicts of interest.

Acknowledgements

The authors would like to acknowledge Dr. Shannan Hamlin, Lenis Sosa, Christine Ouko, and Lorelie Lazaro for their assistance with this project.

Funding

Support for this research was provided in part by a Road to Zero Safe Systems Innovation grant from the National Safety Council.

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Appendix A. Abbreviated Daily Questionnaire Item List

1. How many consecutive shifts have you worked? (enter 1 if this is your first consecutive shift)
2. How many total shifts have you worked this week?
3. I went to bed at (what time? e.g. 19:00, all times are in military time)
4. I fell asleep at (what time? e.g. 19:00, all times are in military time)
5. I woke up at (what time? e.g. 19:00, all times are in military time)
6. I fell asleep [multiple choices; easily, after some time with difficulty]
7. I woke up during my sleep (how many times)
8. How rested were you when you woke up? [measured on a scale of 1-10]