Journal of Safety Research 84 (2023) 167–181

Contents lists available at ScienceDirect

Journal of Safety Research

journal homepage: www.elsevier.com/locate/jsr

Understanding the drowsy driving crash patterns from correspondence regression analysis

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ARTICLE INFO

Article history:
Received 13 October 2021
Received in revised form 26 July 2022
Accepted 21 October 2022
Available online 2 November 2022

Keywords:
Drowsy driving
Fatigue
Correspondence regression
Sleepy drivers
Driver behavior

ABSTRACT

Abstract: Drowsy driving-related crashes have been a key concern in transportation safety. In Louisiana, 14% (1,758 out of 12,512) of police-reported drowsy driving-related crashes during 2015–2019 resulted in injury (fatal, severe, or moderate). Amid the calls for action against drowsy driving by national agencies, it is of paramount importance to explore the key reportable attributes of drowsy driving behaviors and their potential association with crash severity. *Method:* This study used 5-years (2015–2019) of crash data and utilized the correspondence regression analysis method to identify the key collective associations of attributes in drowsy driving-related crashes and interpretable patterns based on injury levels. *Results:* Several drowsy driving-related crash patterns were identified through crash clusters – afternoon fatigue crashes by middle-aged female drivers on urban multilane curves, crossover crashes by young drivers on low-speed roadways, crashes by male drivers during dark rainy conditions, pickup truck crashes in manufacturing/industrial areas, late-night crashes in business and residential districts, and heavy truck crashes on elevated curves. Several attributes – scattered residential areas indicating rural areas, multiple passengers, and older drivers (aged more than 65 years) – showed a strong association with fatal and severe injury crashes. *Practical Applications:* The findings of this study are expected to help researchers, planners, and policymakers in understanding and developing strategic mitigation measures to prevent drowsy driving.

1. Introduction

Drowsy driving is a growing risky behavior that is greatly affecting transportation safety (Yong et al., 2016). In transportation safety analysis, the term 'drowsy' is interchangeably used with 'fatigued' and 'sleepy.' In police crash reports, this driving condition is identified if the driver experiences a temporary loss of consciousness, is found to be drowsy or asleep, or is operating at a reduced physical or mental capacity due to weariness. The 'ill' condition of the driver is also often connected with drowsy driving. The 'drowsy' category in the crash report usually presents a distinct identifiable driving condition. Drowsy drivers could exhibit a range of expressions – from facial relaxation and restless movement to a lack of apparent activity for moderate to complete drowsiness (Klauer et al., 2006).

Drowsy driving is mostly related to drivers' sleep deprivation. The recent trend suggests that a lack of quality sleep has become a global problem, especially in developed countries (Phillips, 2020). A myriad of issues related to lifestyle factors, including but not limited to work pressure and technological enhancement, are aligned with sleep deprivation (National Highway Traffic Safety Administration [NHTSA], 2020). By impairing cognitive function, a lack of sleep could cause poor attention and working memory (Alhola & Polo-Kantola, 2007) and is likely to have a serious impact on drivers' driving awareness and defensive driving skills. Being awake for 21 hours could mimic the cognitive condition of blood alcohol concentration (BAC) of the legal limit (0.08%; Fischer, 2016), and the impairment due to wakefulness after 24 hours is equivalent to a BAC of 0.1% (Dawson & Reid, 1997). The deteriorated capability of decision-making of drowsy drivers could translate to isolated irrecoverable movements, which poses a serious crash risk to the drivers themselves and to other road users. Additionally, drug-related fatigue or driving after taking sleep medication can also cause drowsy driving-related traffic crashes (Brown, Spurgin, Milavetz, Gaffney, & Johnson, 2015; Verster, Mooren, Bervoets, & Roth, 2018).

Self-reported sleep duration decreased from 1985 into the 2000s in the United States as Ford, Cunningham, and Croft

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https://doi.org/10.1016/j.jsr.2022.10.017
0022-4375/

(2015) found an increase in the percentage of adults who reported sleeping 6 hours or less in a 24-hour period in each year from 2004 to 2012 compared to 1985 in the National Health Interview Survey (NHIS) data. Another study with NHIS data by Sheehan, Frochen, Walsemann, and Ailshire (2019) estimated that prevalence of short sleep duration was relatively stable from 2004 to 2012, followed by an increasing trend toward short sleep (6 hours or less) beginning in 2013 and continuing through 2017. The National Transportation Safety Board (NTSB) identified drowsy driving as a contributing factor in 20% of the major investigations of transportation crashes that occurred between 2001 to 2012 (NTSB, 2018). The census of fatal crashes by NHTSA indicates that fatal crashes associated with driver conditions of drowsy/asleep/fatigued/ill/blackout comprised of 1,240 fatal crashes (National Center for Statistics and Analysis, n.d.). In Louisiana, 14% (1,758 out of 12,512) of police-reported drowsy driving crashes resulted in a confirmed (fatal, severe, or moderate) injury during 2015–2019. Despite the considerably large frequency of crashes, drowsy driving crash factors have not been sufficiently studied.

As one of the consequential societal impacts of fatigue due to prolonged wakefulness, the growing risk of drowsy driving will most likely continue to affect traffic safety in the coming years. Only two states in the United States – Arkansas and New Jersey – have undertaken a legislative approach to prevent drowsy driving. However, complicacies in establishing enforceable parameters using a legislative approach against drowsy driving (National Conference of State Legislatures, 2018) have been recognized, which could be attributed to a lack of understanding of critical factors associated with drowsy driving and its severity outcomes. Prior to combating the issue of drowsy driving, investigation of distinctive associative factors of drowsy driving is necessary and could also largely benefit the application of potential strategic countermeasures.

2. Prior studies and objectives of the current study

To date, a number of approaches have been undertaken to understand the drowsy driving issues. A total of 701 severe, moderate, and minor crashes that occurred during the second Strategic Highway Research Program (SHRP2) Naturalistic Driving Study (NDS) were identified to have involved drowsy driving based on videos using the PERCLOS (the percentage of eyelid closure over the pupil over time) measure in the preceding minutes leading to crashes (Owens et al., 2016). With Fisher's exact tests, the study deduced that drowsiness varied significantly by lighting conditions. However, variation by age, sex, and crash severity was estimated to not be statistically significant.

In the earlier 100 car NDS study, the odds ratio for risk of driving while drowsy was four to six times that of normal, baseline driving, engaging in complex secondary tasks was three times, and engaging in moderate secondary tasks was two times that of an alert driver (Klauer et al., 2006). An analysis of the survey questionnaire in the study found a strong correlation between engagement in secondary tasks and driving while drowsy.

The NHTSA's National Motor Vehicle Crash Causation Survey (NMVCCS) data (July 2005 to December 2007), a crash sample comprising 7,234 drivers involved in 4,571 crashes, was used with the aim of quantifying the crash risk in terms of sleep length (Tefft, 2016). The study identified drivers who had slept for less than 4 hours, 4–5 hours, 5–6 hours, and 6–7 hours in the past 24 hours, and found they had an estimated 11.5, 4.3, 1.9, and 1.3 times the crash rate, respectively, of drivers who had slept for 7 hours or more in the past 24 hours. Additionally, drivers who slept less than their regular amount also had higher crash rates associated with each of the sleep lengths.

Aiming to locate the most vulnerable highway segments for drowsy driving in Utah, a 3-year (2002–2004) drowsy driving crash analysis was conducted (Schultz & Young, 2007). This study also conducted a review of existing countermeasures and identified that drowsy driving freeway signage reduced crashes by 63%. A public opinion survey was also conducted that supplemented these findings.

Using the crash records from Guangdong Province, China during 2005–2014, Li, Yamamoto, and Zhang (2018) identified that about 13% and 11% of serious injury and minor injury crashes, respectively, were misclassified as non-fatigue-related crashes. The study findings concluded that for single-vehicle crashes, driver groups aged more than 31 years can be underreported in fatigue-related crashes resulted in serious injuries, whereas drivers with categorized occupations of clerks and normal workers have been found to be underreported in fatigue-related minor injury crashes. Powell et al. (2007) hypothesized near-miss drowsy driving crashes to be associated with actual drowsy driving crashes. From over 35,000 interviews they estimated that participants who reported at least one near-miss sleepy crash event were 1.13 times as likely to have reported at least one actual crash as participants reporting no near-miss sleepy crashes. Participants who reported four or more sleep-related near-miss crashes had twice the risk of involvement in a sleep-related crashes than those who had no-near miss events. A similar study by was undertaken in Australia in which characteristics for the fatigue/sleep-related events (either a near miss or crash) of 1,000 drivers were investigated. Proxy definitions adopted by national and several state agencies using criteria associated with time of the day, roadway speed limit, crash outcome, and reporting officer consideration, were found to be underestimating fatigue/sleep-related crashes, especially in urban areas and low speed roads (Armstrong, Filtness, Watling, Barraclough, & Haworth, 2013).

A South Korean study on freeway crashes involving drowsy driving with 2006–2012 crash data applied a multinomial logit model to associate crash factors with crash injury severity (Kim & Oh, 2021). The findings revealed that nighttime, work zone, concrete barrier shoulder or no shoulder, van, work zone, male drivers, and old drivers (60 + years) were among the significant factors of fatal crashes. The authors argued that speeding and disproportionately high ownership of vehicles by older drivers are among some considerable issues that influenced the results. Zhang, Yau, Zhang, and Li (2016) investigated crashes occurred 21 cities in Guangdong province in 2011 and identified that driving at night without street-lights contributes to fatigue-related crashes and severe casualties. However, male drivers, trucks, driving during midnight to dawn, and morning rush hours are identified as risk factors of fatigue-related crashes but do not necessarily result in severe casualties.

Research studies have been conducted to detect the key demographics engaged in drowsy driving. In the latest national survey conducted by the American Automobile Association (AAA) in 2019, 24% of the standard probability sample of 3,511 respondents across the United States who were drivers aged 16 and older reported extreme drowsiness while driving during the last 30 days (AAA, 2020). There are examples in which survey questionnaire studies have been directed to identify specific areas of drowsy/fatigued driving (driving behaviors and attitudes, Vanlaar, Simpson, Mayhew, & Robertson, 2008; sleep habits, Sunwoo et al., 2017; lifestyle, Gnardellis, Tzamalouka, Papadakaki, & Chliaoutakis, 2008) and specific demographics (teen drivers, Hutchens, Senserrick, Jamieson, Romer, & Winston, 2008; truck drivers, Leechawengwongs, Leechawengwongs, Sukying, & Udomsubpayakul, 2006; shift-workers, Kuo et al., 2019; drivers with sleep apnea syndrome, Komada, Shiomi, Mishima, & Inoue, 2010; drivers in a particular state, McCartt, Ribner, Pack, &

Hammer, 1996, etc.). An earlier literature review study compiled various issues of driver fatigue associated with traffic crashes from research in 2001 and prior years (RoSPA, 2001).

In addition to the above studies, large research efforts have been dedicated to the identification of drowsy driving. A substantial amount of literature involves the practical detection of drowsiness while driving using behavioral, vehicular, and physiological parameters with advanced machine learning methods (Ramzan et al., 2019). A wide range of driving simulator studies showed findings from drowsy driving – typically including increasing lane deviations, high variability in operating speed, slow reaction times, and so forth. For further reading, the review study by Soares et al. (2020) can be referred to.

A plethora of studies exist that quantified the risk and explored associated characteristics that often target specific demographics. Due to an increase in driving workload and fatigue in recent years, the crash risk of drowsy driving has increased, but little research has been conducted on the impact of this risky behavior utilizing available crash data. As crashes are a direct impact of drowsy driving, studies exploring associative crash characteristics could uncover drowsy driving crash patterns. In the midst of a decade-long call for action for preventing drowsy driving through data-driven analysis (Higgins et al., 2017; NCSDR/NHTSA, 1998), the focus of this study is to reduce the drowsy driving research gap through an analysis of recent (2015–2019) crash data obtained from the Louisiana Department of Transportation and Development (DOTD). The researchers applied an advanced data mining method, correspondence regression analysis, to identify the drowsy driving crash pattern and crucial injury severity factors. The findings of this study are expected to help researchers, planners, and policymakers in understanding and developing countermeasures to prevent drowsy driving.

3. Methodology

3.1. Data preparation

To explore drowsy driving characteristics and their potential associations with crash severity, the researchers used the crash dataset of 2015–2019, which was extracted from the crash databases collected from the Louisiana Department of Transportation and Development (DOTD). The raw data were assembled in MS Access files for each year and consisted of several data tables, three of which were necessary for the drowsy driving dataset compilation – roadway data, crash data, and vehicle data. The vehicle data were filtered for two driver condition criteria as coded by the officers who investigated crash incidents that presented the drivers at fault for having a temporary loss of consciousness, being drowsy or asleep, or operating in a reduced physical or mental capacity due to weariness (Louisiana State Highway Commission, 2019). Fig. 1 presents a flowchart illustrating the data preparation process.

The raw dataset was merged from these three tables using the above-mentioned filtering criteria and several matching criteria of crash ID, control section, and logmile (roadway section identifier). Before applying the analysis algorithm, the dataset required quality control by understanding the data distribution and the presence of missing values through data profiling. Since the previous crash studies on drowsy driving are limited, the researchers selected a number of variables to be presumably connected to drowsy driving based on engineering judgment and knowledge from previous crash studies related to driver inattention. The final dataset had a total of 12,512 drowsy driving crashes.

3.2. Data description

The distributions of crash characteristics in the final dataset are presented in Tables 1–3. Most crashes occurred between 6 a.m. to 12p.m. among the four crash hour intervals of the day. Crashes around the weekend (i.e., during Friday, Saturday, Sunday) had higher rates (crashes per day) compared to the rest of the week. About a quarter of all drowsy driving crashes occurred during

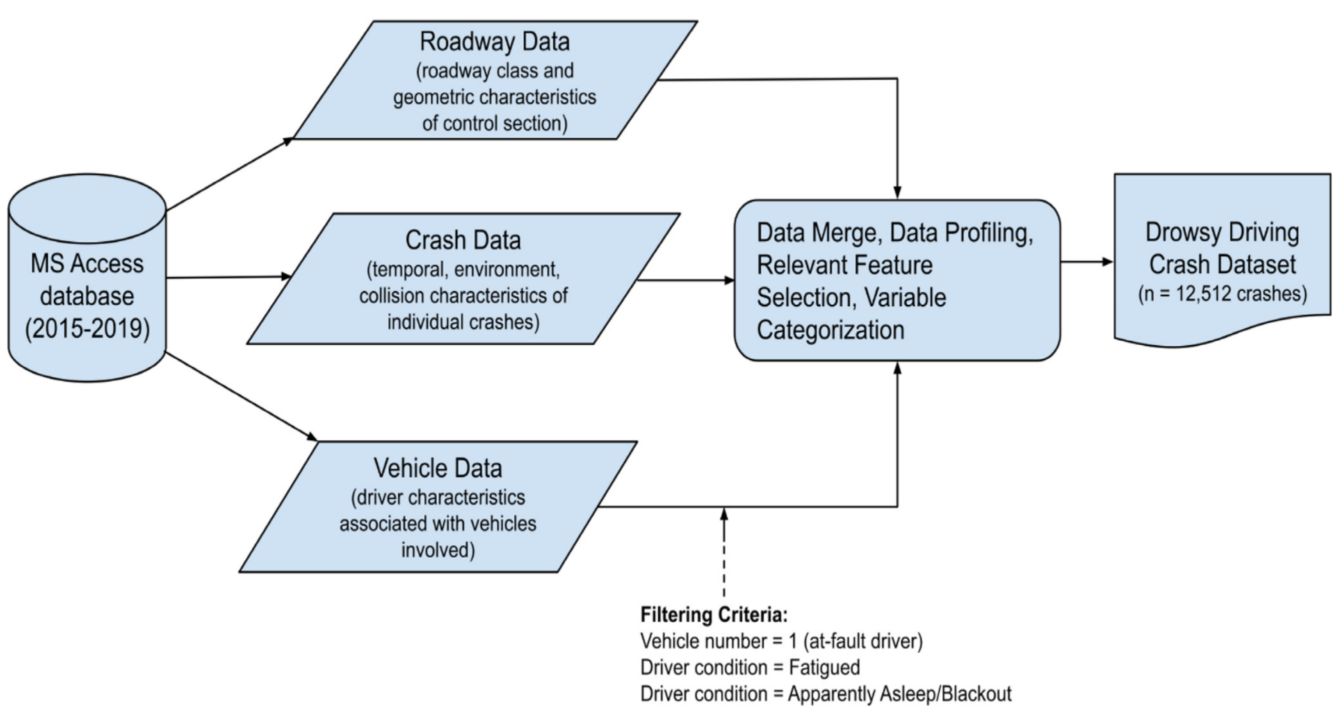

Fig. 1. Preparation of Drowsy Driving Crash Dataset.

Table 1
Distribution of drowsy driving crashes by temporal and environment characteristics for severity classes.

Variables and Categories	Code	All Drowsy Crashes (%)	Fatal and Incapacitating Injury, KA (%)	Non-Incapacitating Injury, B (%)	Complaint/Possible Injury, C (%)	No Injury/Property Damage Only, O (%)
Crash Hour	*CrHr*					
12 a.m. to 6 a.m.	12 am-6 am	3044 (24.33)	39 (19.31)	350 (22.49)	898 (20.95)	1757 (27.16)
6 a.m. to 12 p.m.	6 am-12 pm	4187 (33.46)	68 (33.66)	537 (34.51)	1366 (31.87)	2216 (34.26)
12 p.m. to 6 p.m.	12 pm-6 pm	3092 (24.71)	55 (27.23)	418 (26.86)	1243 (29)	1376 (21.27)
6 p.m. to 12 a.m.	6 pm-12 am	2189 (17.5)	40 (19.8)	251 (16.13)	779 (18.18)	1119 (17.3)
Day of the Week	*DoW*					
Monday to Thursday	Mo-Th	6698 (53.53)	119 (58.91)	853 (54.82)	2309 (53.87)	3417 (52.83)
Friday to Sunday	Fr-Su	5814 (46.47)	83 (41.09)	703 (45.18)	1977 (46.13)	3051 (47.17)
Season	*Season*					
Fall	Fall	3245 (25.94)	61 (30.2)	384 (24.68)	1164 (27.16)	1636 (25.29)
Winter	Wntr	2910 (23.26)	47 (23.27)	356 (22.88)	992 (23.15)	1515 (23.42)
Spring	Sprng	3254 (26.01)	47 (23.27)	420 (26.99)	1105 (25.78)	1682 (26)
Summer	Smr	3103 (24.8)	47 (23.27)	396 (25.45)	1025 (23.92)	1635 (25.28)
Lighting Condition	*LgtCond*					
Daylight	Dalgt	6596 (52.72)	112 (55.45)	872 (56.04)	2425 (56.58)	3187 (49.27)
Dark	Dark	3052 (24.39)	52 (25.74)	369 (23.71)	943 (22)	1688 (26.1)
Dark but lighted	DarkLgtd	1849 (14.78)	18 (8.91)	190 (12.21)	599 (13.98)	1042 (16.11)
Dusk or Dawn	Dusk-Dawn	521 (4.16)	11 (5.45)	65 (4.18)	175 (4.08)	270 (4.17)
Other	Other	494 (3.95)	9 (4.46)	60 (3.86)	144 (3.36)	281 (4.34)
Surface Condition	*SurfCond*					
Dry	Dry	11,122 (88.89)	178 (88.12)	1398 (89.85)	3841 (89.62)	5705 (88.2)
Non-Dry	NonDry	1390 (11.11)	24 (11.88)	158 (10.15)	445 (10.38)	763 (11.8)
Weather	*Weather*					
Normal	Normal	9456 (75.58)	163 (80.69)	1201 (77.19)	3211 (74.92)	4881 (75.46)
Cloudy	Cloudy	2086 (16.67)	22 (10.89)	236 (15.17)	758 (17.69)	1070 (16.54)
Rainy	Rainy	739 (5.91)	12 (5.94)	90 (5.78)	249 (5.81)	388 (6)
Fog-Smoke-Other	Fog-Smk-Other	231 (1.85)	5 (2.48)	29 (1.86)	68 (1.59)	129 (1.99)

unlighted dark conditions. The distribution of crashes by highway class shows about 35% of crashes occurred on state-controlled two-lane highways and more than 25% of crashes occurred on local roadways managed by parishes and municipalities. These high proportions could be strongly related to the proportion of roadway classes in the roadway network. Straight-level and curve-level segments had a higher proportion of crashes. 'Open country' locations had a higher proportion of crashes compared to any locations with residential or commercial establishments. Roadway segments with speed limits of 50 to 55 miles per hour (mph) possessed the majority of crashes. More than 10% of the crashes had out-of-state drivers at fault. Although non-use of restraint was not prevalent, the percentage was comparatively high in fatal (K) and incapacitating (A) injury crashes. Passenger cars, SUVs, and vans also had the highest proportions of crashes due to their high ownerships. Single-vehicle crashes and crossover (i.e., head-on and opposite direction sideswipe) crashes were the predominant manners of collisions.

3.3. Analysis method: Correspondence regression analysis

To model a multinomial variable in terms of several categorical explanatory variables, the confounding concept of correspondence regression was explained by Gilula and Haberman (1988). A brief overview of the theory is provided below. Readers can consult Gilula and Haberman (1988) for additional details. Several recent studies applied correspondence analysis for dimensional reduction and subsequently clustering or regression. For example, Das, Ashraf, Dutta, and Tran (2020) applied correspondence regression analysis method to identify patterns of crashes with pedestrians under influence in addition to individual influences of attributes associated with severity of such crashes. In recent years, similar clustering methods (cluster correspondence analysis method) that jointly reduces dimensions and finds clusters in two-dimensional approximations are widely being utilized to detect distinguishable patterns in high-dimensional datasets. M. A. Rahman, Das, and Sun (2022) recently applied cluster correspondence analysis in rainy weather crash data and found that clusters in such crashes identified are highly distinguishable based on roadway functional classes and their associated geometric and exposure characteristics rather than driver-based characteristics. Some examples of other crash studies include pattern recognition of light delivery vehicle crash characteristics (Das, Dutta, & Rahman, 2021), identifying patterns of key factors in sun glare-related traffic crashes (Das, Sun, Dadashova, Rahman, & Sun, 2021), understanding moped and seated motor scooter involved fatal crashes (Das et al., 2022), and so forth.

To analyze the effects of a polytomous/multinomial outcome variable, Y, correspondence regression can be conjectured as the correspondence analysis of the crosstabulation of Y in the function of another categorical variable, X, where X can be constituted by a combination of various categorical variables. Following a frequency table produced by the response variable (Y) with explanatory variables (X), corresponding regression produces a three-way table by using every possible combination of the conditional variables (Z) along with the frequency table of Y and X. The next step is to calculate the Pearson residuals $P = \frac{O-E}{\sqrt{E}}$ of this table, where E is calculated considering the conditional independence of Y and X given Z.

The three-way correspondence analysis, as described by van der Heijden et al. (1989), is equivalent to the final matrix of Y and X. For inferential validation of the effects, bootstrapping by the Monte

Table 2
Distribution of drowsy driving crashes by highway characteristics for severity classes.

Variables and Categories	Code	All Drowsy Crashes (%)	Fatal and Incapacitating Injury, KA (%)	Non-Incapacitating Injury, B (%)	Complaint/Possible Injury, C (%)	No Injury/Property Damage Only, O (%)
Highway Class	*HwyCls*					
Rural two-lane	Rural-2L	2524 (20.17)	48 (23.76)	369 (23.71)	964 (22.49)	1143 (17.67)
Rural multilane undivided	Rural-ML-U	46 (0.37)	2 (0.99)	4 (0.26)	21 (0.49)	19 (0.29)
Rural multilane divided	Rural-ML-D	290 (2.32)	5 (2.48)	36 (2.31)	99 (2.31)	150 (2.32)
Rural interstate	Rural-I	875 (6.99)	13 (6.44)	92 (5.91)	252 (5.88)	518 (8.01)
Urban two-lane	Urban-2L	1840 (14.71)	26 (12.87)	255 (16.39)	586 (13.67)	973 (15.04)
Urban multilane undivided	Urban-ML-U	941 (7.52)	18 (8.91)	125 (8.03)	376 (8.77)	422 (6.52)
Urban multilane divided	Urban-ML-D	1036 (8.28)	19 (9.41)	103 (6.62)	405 (9.45)	509 (7.87)
Urban interstate and freeway	Urban-I-F	1449 (11.58)	16 (7.92)	132 (8.48)	456 (10.64)	845 (13.06)
Local Undivided	Local-U	2591 (20.71)	42 (20.79)	334 (21.47)	804 (18.76)	1411 (21.82)
Local divided	Local-D	651 (5.2)	10 (4.95)	76 (4.88)	228 (5.32)	337 (5.21)
Local one-way	Local-1W	211 (1.69)	2 (0.99)	26 (1.67)	81 (1.89)	102 (1.58)
Other	Other	58 (0.46)	1 (0.5)	4 (0.26)	14 (0.33)	39 (0.6)
Intersection	*Int*					
Yes	Yes	2761 (22.07)	38 (18.81)	324 (20.82)	1011 (23.59)	1388 (21.46)
No	No	9751 (77.93)	164 (81.19)	1232 (79.18)	3275 (76.41)	5080 (78.54)
Alignment	*Alnmt*					
Straight-Level	StrLvl	9883 (78.99)	149 (73.76)	1199 (77.06)	3393 (79.16)	5142 (79.5)
Straight-Level-Elevated	StrLvlElv	456 (3.64)	10 (4.95)	37 (2.38)	153 (3.57)	256 (3.96)
Curve-Level	CrvLvl	1461 (11.68)	27 (13.37)	215 (13.82)	486 (11.34)	733 (11.33)
Curve-Level-Elevated	CrvLvlElv	175 (1.4)	4 (1.98)	28 (1.8)	49 (1.14)	94 (1.45)
On Grade-Straight	OGrStr	235 (1.88)	2 (0.99)	33 (2.12)	84 (1.96)	116 (1.79)
On Grade-Curve	OGrCrv	138 (1.1)	4 (1.98)	19 (1.22)	57 (1.33)	58 (0.9)
Hillcrest-Straight	HillStr	77 (0.62)	2 (0.99)	10 (0.64)	29 (0.68)	36 (0.56)
Hillcrest-Curve	HillCrv	25 (0.2)	3 (1.49)	3 (0.19)	10 (0.23)	9 (0.14)
Other	Other	62 (0.5)	1 (0.5)	12 (0.77)	25 (0.58)	24 (0.37)
Location Type	*LocTyp*					
Manufacturing or Industrial	Mfg-Ind	312 (2.49)	6 (2.97)	40 (2.57)	99 (2.31)	167 (2.58)
Business Continuous	BizCont	2030 (16.22)	27 (13.37)	217 (13.95)	721 (16.82)	1065 (16.47)
Business, Mixed Residential	BizMixedResi	2447 (19.56)	36 (17.82)	319 (20.5)	878 (20.49)	1214 (18.77)
Residential District	ResiDist	1783 (14.25)	22 (10.89)	204 (13.11)	604 (14.09)	953 (14.73)
Residential Scattered	ResiSctd	2381 (19.03)	52 (25.74)	355 (22.81)	821 (19.16)	1153 (17.83)
School or Playground	Sch-Play	68 (0.54)	3 (1.49)	5 (0.32)	22 (0.51)	38 (0.59)
Open Country	OpenCtry	3188 (25.48)	50 (24.75)	380 (24.42)	1040 (24.27)	1718 (26.56)
Other	Other	303 (2.42)	6 (2.97)	36 (2.31)	101 (2.36)	160 (2.47)
Speed Limit	*SpLim*					
25 miles per hour or less	<=25mph	1310 (10.47)	11 (5.45)	133 (8.55)	417 (9.73)	749 (11.58)
30 to 35 miles per hour	30-35mph	2006 (16.03)	35 (17.33)	256 (16.45)	742 (17.31)	973 (15.04)
40 to 45 miles per hour	40-45mph	2637 (21.08)	38 (18.81)	344 (22.11)	903 (21.07)	1352 (20.9)
50 to 55 miles per hour	50-55mph	3771 (30.14)	72 (35.64)	530 (34.06)	1358 (31.68)	1811 (28)
60 miles per hour or greater	>=60mph	2436 (19.47)	38 (18.81)	242 (15.55)	755 (17.62)	1401 (21.66)
Unknown	Unk	352 (2.81)	8 (3.96)	51 (3.28)	111 (2.59)	182 (2.81)

Carlo simulation was incorporated in the corresponding regression analysis. By replicating the contingency table generated with multinomial sampling, new values were derived for the scores/coordinates in both *Y* and *X* as well as for the eigenvalues, which are often termed "principal inertias." On the basis of the replicated/simulated values, confidence intervals of the individual associations between *X* and the response *Y* can be computed. In this study, the final corresponding regression model was identified based on a sufficient 1000 Monte Carlo simulation run of the models from combinations of the important individual association, excluding the variables of all insignificant attributes at a 95% confidence interval. The "corregp" package (Plevoets, 2018) in R software (R Development Core Team, 2022) was used to perform the corresponding regression analysis.

4. Results and discussions

The results of the correspondence regression analysis are presented through eigenvalues. The distribution of the 'eigenvalues' provides measures of 'explanatory power' of each latent axis. Equivalent to latent variables, these underlying axes are often termed 'principal axes.' The results of eigenvalues are presented in three ways: first, the actual eigenvalues; second, percentages

Table 3
Distribution of drowsy driving crashes by driver and vehicle characteristics and collision type for severity classes.

Variables and Categories	Code	All Drowsy Crashes (%)	Fatal and Incapacitating Injury, KA (%)	Non-Incapacitating Injury, B (%)	Complaint/Possible Injury, C (%)	No Injury/Property Damage Only, O (%)
Driver Gender	*DrGndr*					
Female	F	3221 (25.74)	55 (27.23)	439 (28.21)	1276 (29.77)	1451 (22.43)
Male	M	9236 (73.82)	147 (72.77)	1114 (71.59)	2997 (69.93)	4978 (76.96)
Driver Age	*DrAge*					
15 years to 19 years	15-19y	1282 (10.25)	16 (7.92)	129 (8.29)	409 (9.54)	728 (11.26)
20 years to 25 years	20-25y	2906 (23.23)	29 (14.36)	294 (18.89)	903 (21.07)	1680 (25.97)
26 years to 35 years	26-35y	3181 (25.42)	43 (21.29)	371 (23.84)	1061 (24.76)	1706 (26.38)
36 years to 45 years	36-45y	1889 (15.1)	35 (17.33)	269 (17.29)	639 (14.91)	946 (14.63)
46 years to 55 years	46-55y	1290 (10.31)	30 (14.85)	169 (10.86)	462 (10.78)	629 (9.72)
56 years to 65 years	56-65y	1065 (8.51)	22 (10.89)	159 (10.22)	417 (9.73)	467 (7.22)
Older than 65 years	>65y	852 (6.81)	26 (12.87)	162 (10.41)	381 (8.89)	283 (4.38)
Unknown	Unk	47 (0.38)	1 (0.5)	3 (0.19)	14 (0.33)	29 (0.45)
Driver License State	*DrLicSt*					
Louisiana	LA	10,765 (86.04)	173 (85.64)	1343 (86.31)	3747 (87.42)	5502 (85.06)
Out of State	Oos	1400 (11.19)	22 (10.89)	169 (10.86)	441 (10.29)	768 (11.87)
Unknown	Unk	347 (2.77)	7 (3.47)	44 (2.83)	98 (2.29)	198 (3.06)
Number of Passengers	*Psgr*					
None	0	6460 (51.63)	88 (43.56)	805 (51.74)	2131 (49.72)	3436 (53.12)
One	1	3537 (28.27)	56 (27.72)	379 (24.36)	1168 (27.25)	1934 (29.9)
More than One	>1	2515 (20.1)	58 (28.71)	372 (23.91)	987 (23.03)	1098 (16.98)
Restraint Use	*RstrntUse*					
Yes	Yes	11,589 (92.62)	139 (68.81)	1276 (82.01)	3931 (91.72)	6243 (96.52)
No	No	923 (7.38)	63 (31.19)	280 (17.99)	355 (8.28)	225 (3.48)
Vehicle Type	*VehTyp*					
Passenger Car	Car	5582 (44.61)	70 (34.65)	666 (42.8)	1926 (44.94)	2920 (45.15)
Pickup Truck	PU	3842 (30.71)	73 (36.14)	482 (30.98)	1221 (28.49)	2066 (31.94)
SUV	SUV	2233 (17.85)	42 (20.79)	291 (18.7)	831 (19.39)	1069 (16.53)
Van	Van	335 (2.68)	5 (2.48)	41 (2.63)	125 (2.92)	164 (2.54)
Heavy Truck	Truck	340 (2.72)	8 (3.96)	50 (3.21)	119 (2.78)	163 (2.52)
Other	Other	180 (1.44)	4 (1.98)	26 (1.67)	64 (1.49)	86 (1.33)
Collision Type	*CollTyp*					
Single Vehicle	SV	6737 (53.84)	118 (58.42)	1011 (64.97)	2223 (51.87)	3385 (52.33)
Right Angle	Rt-Ang	324 (2.59)	8 (3.96)	58 (3.73)	138 (3.22)	120 (1.86)
Turning	Turn	132 (1.05)	0 (0)	18 (1.16)	57 (1.33)	57 (0.88)
Crossover	Xovr	3255 (26.02)	37 (18.32)	314 (20.18)	1173 (27.37)	1731 (26.76)
Sideswipe - same direction	SS-SD	597 (4.77)	8 (3.96)	35 (2.25)	135 (3.15)	419 (6.48)
Other	Other	1467 (11.72)	31 (15.35)	120 (7.71)	560 (13.07)	756 (11.69)

showing the relative values; and third, cumulative percentages showing the cumulative relative values. The sum of the actual eigenvalues is equal to the Chi-squared value, which indicates that the latent axes decompose the observed association between the response variable and explanatory variables into different sets. The summary statistics – Phi-squared and Chi-squared values – manifest the dependence between the response variable (i.e., the severity of drowsy driving crashes) and the explanatory variables (e.g., lighting conditions, roadway alignment). The Phi-squared value (2.96) is equal to the Chi-squared value (37,075.92) divided by the total number of observations (N = 12,512). The percentage of eigenvalues suggests that the majority of the variance (67.1%) in the correspondence analysis can be explained by the two latent axes.

The major assumption behind the correspondence regression model is that the response variable and the explanatory variables can be modeled on the basis of latent axes which explain the observed dependencies. Therefore, quantitative influence of attributes associated with latent axes after dimensional reduction provides important contexts to the final regression model. Correspondence regression has been performed with bootstrapping (Monte Carlo simulations); therefore, confidence intervals for the eigenvalues can be computed. The explanatory power by each axis can be presented with 95% confidence intervals of the percentage eigen values, and the cumulative percentages are presented together with a lower confidence bound and an upper confidence bound (Table 4). For example, the 95% confidence interval for the first relative eigenvalue is [0.314; 0.363], and the confidence interval for the second relative eigenvalue is [0.318, 0.346].

Table 4
The explanatory power by each latent axis.

Measures	Latent Axis 1	Latent Axis 2	Total
Percentage			
Value	0.341	0.330	0.671
Lower	0.314	0.318	
Upper	0.363	0.346	
Cumulative Percentage			
Value	0.341	0.671	1
Lower	0.139	0.139	
Upper	1.201	1.204	

The relationship between latent axes and individual categories can be presented through two measures. The contributions of the points to the principal or latent axes, which are also called the 'absolute contributions,' measure the inertia corresponding to a certain latent axis – the extent to which each category represents a latent axis. Conversely, the contributions of the axes to the points, which are also called 'squared correlations,' express how well each latent axis reflects a certain category. Simply put, the sum of the absolute contributions is 100% for each latent axis, whereas the sum of the squared correlations is 100% for each category. The squared correlations presented in Table 5 indicate that fatal and severe injury (KA), as well as moderate injury (B) crashes, have high total correlation values in comparison to complaint/possible

Table 5
Contributions of the axes to the points or squared correlations for response variables.

Severity	Latent Axis 1	Latent Axis 2	Total
KA	0.99900	0.00098	0.99998
B	0.00663	0.91963	0.92626
C	0.00785	0.00007	0.00792
O	0.01404	0.40250	0.41654

injury (C) and no injury (O) crashes. The values by axis also indicate that axis 1 substantially explains KA injury crashes (99.9%), where axis 2 largely explains B crashes (91.9%) and partially O crashes (40.3%). Overall, crashes with two top injury levels, KAB (K, A, and B), can be explained by the two latent axes.

Table 6 shows the percentage contributions of the points to axes or absolute correlations. For example, 'Restraint Use: No' had the highest contributions on both axis 1 and axis 2. These values between categories within variables can be used to compare their contributions to a certain latent axis. The final model of corresponding regression was run only for significant variables.

4.1. Collective association by biplots

The biplot offers an illustration of the collective association of crash attributes in a two-dimensional coordinate space of the two latent axes. All of the attributes are presented in the biplot of Axis 1 and Axis 2. Some of the attributes away from the clusters can be considered outliers. Associative attributes identified from the biplots in correspondence analysis can be presented in distinguishable crash clusters (Baireddy, Zhou, & Jalayer, 2018; Das, Avelar, Dixon, & Sun, 2018; Das & Sun, 2016; Hossain, Rahman, Sun, & Mitran, 2021). These clusters often represent interpretable crash patterns of crash scenarios. Fig. 2 presents a truncated biplot of two latent axes from the corresponding regression analysis results for the convenience of illustrating the associations.

4.1.1. Cluster 1: {CollTyp:SV, DrGndr:F, CrHr:12 pm-6 pm, Alnmt:CrvLvl, SpLim:50-55mph, HwyCls:Urban-ML-U, DrAge:36-45y}

This cluster presents female drivers aged between 36 to 45 years who had single-vehicle crashes from 12p.m. to 6p.m. on curved urban multilane highways with a speed limit of 50 to 55 miles per hour. In this scenario, drivers veering off on curves on

Table 6
Percentage contributions of the points to axes for explanatory variables.

Variable Category	Latent Axis 1	Latent Axis 2	*Variable* Category	Latent Axis 1	Latent Axis 2
Crash Hour			*Location Type*		
12 a.m. to 6 a.m.	0.01584	0.09701	Manufacturing or Industrial	0.00152	0.00000
6 a.m. to 12 p.m.	0.00001	0.00024	Business Continuous	0.00732	0.04336
12 p.m. to 6 p.m.	0.00336	0.13449	Business, Mixed Residential	0.00295	0.01581
6 p.m. to 12 a.m.	0.00569	0.00807	Residential District	0.01251	0.02081
Lighting Condition			Residential Scattered	0.03577	0.14479
Daylight	0.00173	0.09274	School or Playground	0.02895	0.01270
Dark	0.00149	0.02399	Open Country	0.00024	0.01916
Dark but lighted	0.03592	0.11388	Other	0.00220	0.00103
Dusk or Dawn	0.00668	0.00001	*Driver Gender*		
Other	0.00120	0.00612	Female	0.00088	0.13759
Weather			Male	0.00013	0.04132
Normal	0.00554	0.00456	*Driver Age*		
Cloudy	0.03248	0.01371	15 years to 19 years	0.00742	0.09320
Rainy	0.00001	0.00082	20 years to 25 years	0.05145	0.23680
Fog-Smoke-Other	0.00367	0.00083	26 years to 35 years	0.01049	0.02798
Highway Class			36 years to 45 years	0.00457	0.05143
Rural two-lane	0.00857	0.19503	46 years to 55 years	0.03292	0.01467
Rural multilane undivided	0.01831	0.00027	56 years to 65 years	0.00951	0.11430
Rural multilane divided	0.00018	0.00000	Older than 65 years	0.07983	0.58294
Rural interstate	0.00044	0.06689	Unknown	0.00086	0.01832
Urban two-lane	0.00450	0.01296	*Speed Limit*		
Urban multilane undivided	0.00388	0.03254	25 miles per hour or less	0.03759	0.09750
Urban multilane divided	0.00326	0.02020	30 to 35 miles per hour	0.00159	0.01329
Urban interstate and freeway	0.01629	0.19707	40 to 45 miles per hour	0.00449	0.00703
Local Undivided	0.00000	0.00055	50 to 55 miles per hour	0.01455	0.13282
Local divided	0.00016	0.00225	60 miles per hour or greater	0.00005	0.20430
Local one-way	0.00491	0.00043	Unknown	0.00737	0.00881
Other	0.00011	0.02732	*Restraint Use*		
Alignment			Yes	0.09466	0.25351
Straight-Level	0.00545	0.00855	No	1.18853	3.18302
Straight-Level-Elevated	0.00951	0.07176	*Vehicle Type*		
Curve-Level	0.00321	0.05779	Passenger Car	0.03637	0.01468
Curve-Level-Elevated	0.00363	0.00974	Pickup Truck	0.01639	0.00264
On Grade-Straight	0.00752	0.00566	SUV	0.00759	0.02887
On Grade-Curve	0.01138	0.01075	Van	0.00026	0.00035
Hillcrest-Straight	0.00378	0.00141	Heavy Truck	0.00887	0.01977
Hillcrest-Curve	0.13998	0.00259	Other	0.00315	0.00899
Other	0.00003	0.03443	*Collision Type*		
Number of Passengers			Single Vehicle	0.00392	0.32189
None	0.02117	0.00447	Right Angle	0.01016	0.14651
One	0.00001	0.11622	Turning	0.01840	0.00681
More than One	0.05634	0.26152	Crossover	0.03335	0.18459
			Sideswipe - same direction	0.00100	0.39968
			Other	0.02292	0.14226

Note: All percentage absolute correlations are rounded to the fifth decimal.

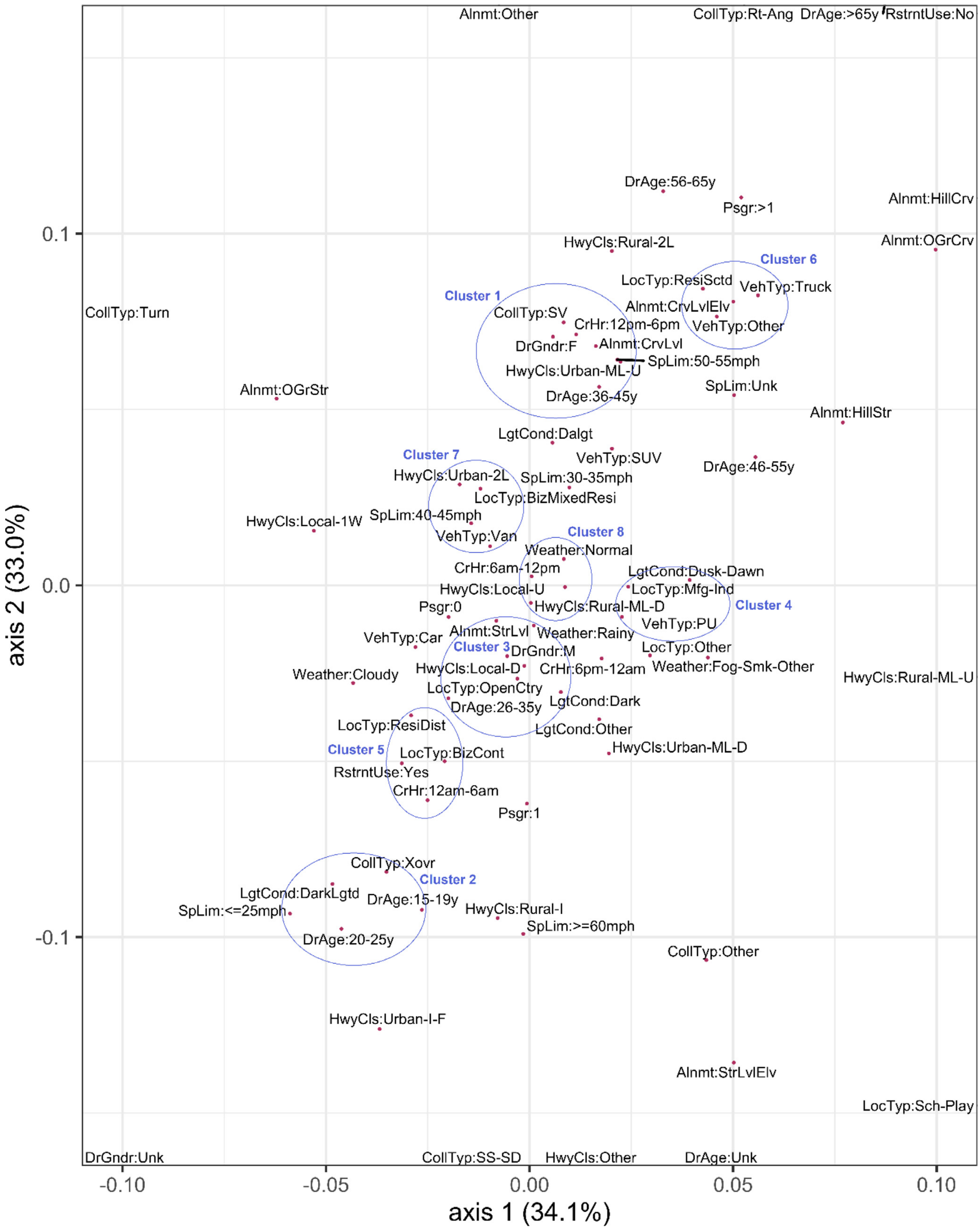

Fig. 2. A truncated biplot of axis 1 and axis 2.

urban multilane undivided roads during the afternoon roads could be accrued with fatigue resulting from a drop in energy levels. The finding of middle age female drivers' afternoon work fatigue translating into urban multilane curve crashes is interesting as work fatigue has been prevalently linked to male drivers (Filtness, Armstrong, Watson, & Smith, 2017a; Williamson & Boufous, 2007).

4.1.2. Cluster 2: {DrAge:15-19y, DrAge:20-25y, LgtCond:Darklgtd, SpLim:<=25mph, CollTyp:Xovr}

This cluster presents crossover crashes with young drivers on low-speed roadways during dark but lighted conditions. Two of the relevant findings are that both darkness and young drivers can be significantly overrepresented in these crashes compared to non-sleep-related crashes (Filtness, Armstrong, Watson, & Smith, 2017b). Additionally, the dark but lighted condition mostly exists in the urban environment, and research indicates that the road environment has very little impact on the sleepiness of young male drivers (Ahlström, Anund, Fors, & Åkerstedt, 2018).

4.1.3. Cluster 3: {HwyCls:Local-D, LocTyp:OpenCtry, DrGndr:M, Alnmt:StrLvl, Weather:Rainy, LgtCond:Dark}

This cluster contains attributes such as local divided highways, open country location, male drivers, straight-level alignment, rainy weather, and dark condition. The local highways, managed by parishes or municipalities, typically possess lower traffic volume than state-controlled highways. This cluster represents an association of male drivers being at fault in dark and rainy conditions due to drowsiness on local highways despite these highways possessing features of straight-alignment and divided separation between opposing traffic. It has been argued that the glare of oncoming lights during darkness and the rain on the windshield can cause temporary loss of visibility and increase fatigue (Texas Department of Insurance, 2020).

4.1.4. Cluster 4: {LgtCond:Dusk-Dawn, LocTyp:Mfg-Ind, VehTyp:PU}

This cluster presents drowsy driving crashes by pickup truck drivers in manufacturing or industrial areas that occur during dusk or dawn. Manufacturing employees are one of the most critical demographics who suffer from work-related fatigue (NSC, 2018). The lighting conditions imply that these crashes are most likely related to the entrance and egress of manufacturing and industrial establishments at daybreak and nightfall by the pickup drivers who work in these areas. Regulatory interventions such as industry-level enforcement of hours-of-service policies for sufficient sleep for manufacturing employees can improve this condition (NSC, 2018; Transportation Research Board, 2016).

4.1.5. Cluster 5: {LocTyp:ResiDist, LocTyp:BizCont, RstrntUse:Yes, CrHr:12am-6am}

This cluster presents drowsy driving crashes that occur in areas of residential districts and continuous business establishments from late night towards morning (i.e., 12 a.m. to 6 a.m.), which is also associated with drivers' restraint use. Although these continuous establishments are typically characterized by a low speed limit, this cluster suggests that the drivers driving through these establishments could be at fault in crashes due to late-night drowsiness regardless of the speed limit.

4.1.6. Cluster 6: {LocTyp:ResiSctd, Alnmt:CrvLvlElv, VehTyp:Truck, VehTyp:Other}

This cluster presents drowsy driving crashes with trucks and other vehicles at fault in scattered residential areas with curve-level-elevated alignment. Curve-level-elevated alignment is expected to pose less chance of recovery from any isolated movement due to drivers' drowsiness. This cluster suggests it should be more associated with truck drivers in scattered residential establishments, which are most likely located in rural areas. Retroreflective traffic control devices such as raised pavement markers and delineators are expected to guide truck drivers in properly maneuvering their trucks even at nighttime (Carlson et al., 2015). However, rumble strips with retroreflective markings (often termed rumble stripes) are perhaps the most inexpensive roadway countermeasure that could provide both auditory and visual warning for drowsy truck drivers to avoid a lane departure on curves. Drowsy driver detection systems have long been recommended, especially for commercial truck drivers, and are already in application (Transportation Research Board, 2016). Other vehicular technologies such as lane departure warning or lane-keeping assistance in trucks should also assist drivers in avoiding crashes on curve roadways. It is also important to investigate the factors behind drowsiness for truck drivers. Conditions such as obstructive sleep apnea (OSA) and poor sleep quality have been reported to be prevalent among truck drivers (Garbarino et al., 2016; Guglielmi, Magnavita, & Garbarino, 2018; Huhta, Hirvonen, & Partinen, 2021). Psychostimulant medications are expected to increase their occupational performance (de Oliveira et al., 2020; Dini, Bragazzi, Montecucco, Rahmani, & Durando, 2019; Williamson, 2007). However, fatigue could reappear as an after-effect of such psychostimulant drugs or medication (de la Torre et al., 2004; Williamson, 2007).

4.1.7. Cluster 7: {HwyCls:Urban-2L, SpLim:40-45mph, LocTyp:BizMixedResi, VehTyp:Van}

This cluster presents drowsy driving crashes with van drivers at fault on urban two-lane highways with 40 to 45 miles per hour speed limits with a surrounding area of mixed business and residential development. Drowsy driving crashes can often be associated with traffic generated from numerous cross streets and driveways in these developments.

4.1.8. Cluster 8: {CrHr:6am-12 pm, Weather:Normal, HwyCls:Local-U, HwyCls:Rural-ML-D}

This cluster represents drowsy driving crashes that occur on local undivided roads and rural multilane roads from the early morning to noon in normal weather. This crash cluster could be linked to commuters who are night-shift workers, as this demographic has been mostly linked to a high risk of crashes due to morning drowsiness (Caponecchia & Williamson, 2018; Lee et al., 2016; Liang et al., 2019).

Apart from crossover crashes, none of the collision types showed a specific association with multiple attributes. Additionally, the proximity of some attributes in the biplot implies common logical crash scenarios. For example, rural interstates and a speed limit of 60 miles per hour or greater are a very common combination of crash attributes. The same can be stated for passenger cars and no passengers, which are a combination in the majority of crashes, regardless of drowsy driving, due to high ownership of passenger cars.

4.2. Individual associations from association graphs

Statistically significant associations between attributes and latent axes in the correspondence regression are presented by association graphs. Association graphs are directional acyclic graphs, in which the response variable and explanatory variables are illustrated as boxes with the latent axes illustrated as circles in the middle. Arrows from a specific latent axis towards a specific attribute indicate that the attribute on that latent axis is significantly different from 0 within the 95% confidence interval. Logically, if the score of that category on that latent axis is not significantly different from 0, no arrow is presented. For simplicity, a breakdown of association graphs from corresponding regression analysis has been presented in multiple figures (Figs. 3 to 6) illustrating the highway characteristics, temporal and environment characteristics, driver and vehicle characteristics, and collision type, respectively. Positive and negative associations are presented with green and maroon colors, respectively.

In the following figures presenting association graphs, the 'Latent Axis 1′ is associated with all four severity levels (KA, B, C,

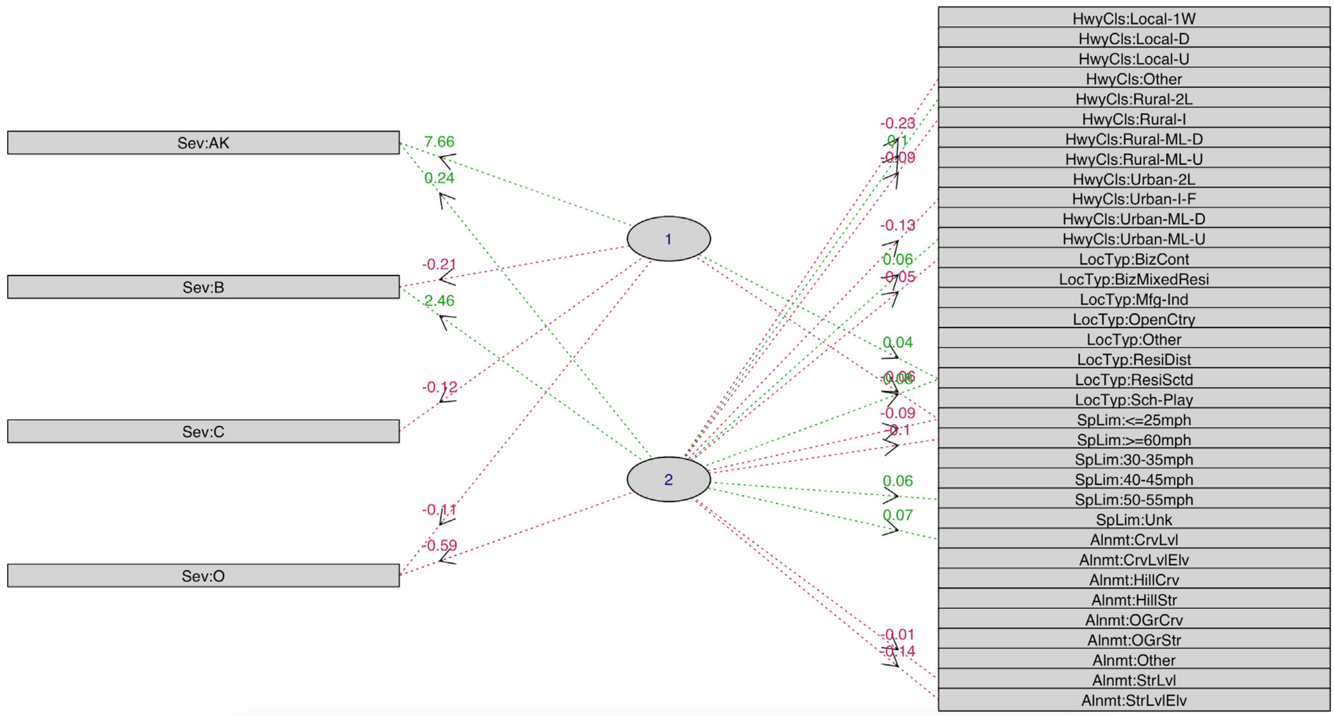

Fig. 3. Association graph for highway characteristics.

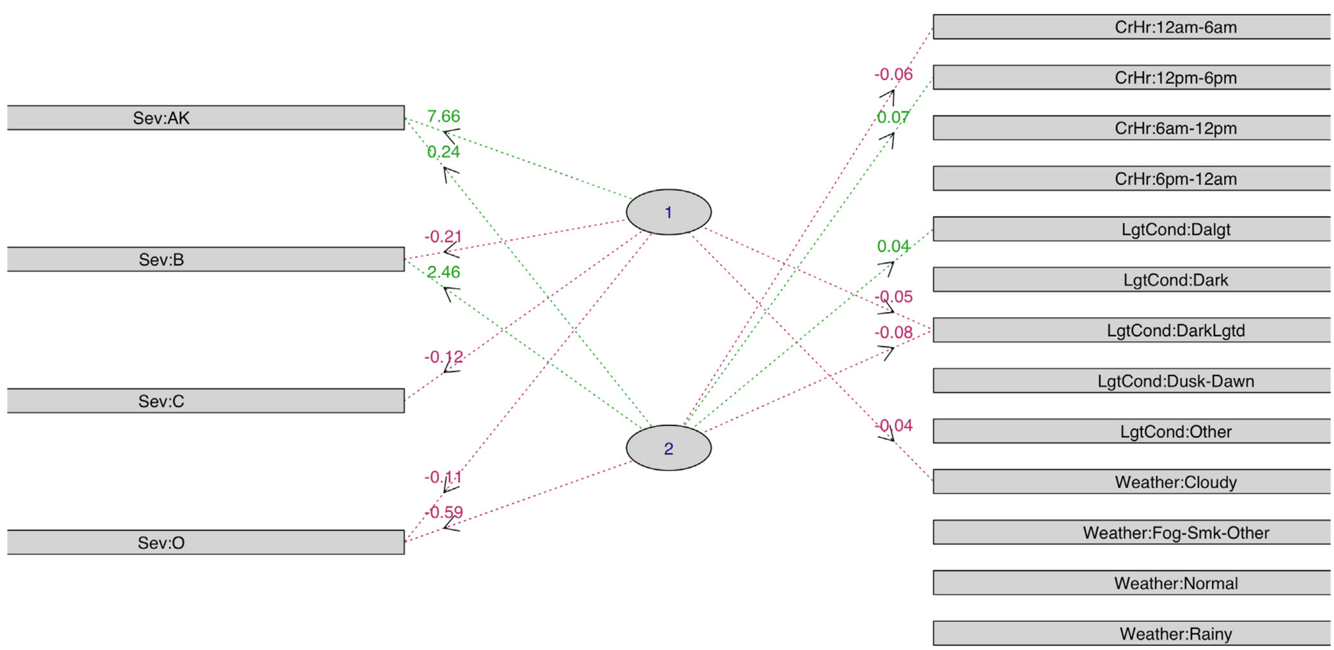

Fig. 4. Association graph for temporal and environment characteristics.

and O), and 'Latent Axis 2′ is associated with KA, B, and O severity levels. For the Latent Axis 1, the KA injury severity has positive eigenvalues, and B, C, and O have negative eigenvalues, whereas for the Latent Axis 2, KA and B have positive eigenvalues, and C and O have negative eigenvalues. The positive values indicate that the Latent Axis 1 is associated with KA injuries, and Latent Axis 2 is more strongly associated with moderate/non-incapacitating (B) injury than fatal and severe injury crashes. Therefore, the interpretations of explanatory attributes essentially constitute associations with either KA or B injury crashes based on their eigenvalues linked to the latent axes.

In Fig. 3, which presents the graph for highway characteristics, Axis 1 is positively associated with scattered residential areas. Axis 2 is positively associated with rural two-lane highways, urban multilane undivided highways, scattered residential areas, a speed limit of 50–55 miles per hour, and curve-level alignment. The results indicate that scattered residential areas are more likely to be associated with both KA and B injury severity due to driver drowsiness. A low-speed limit (i.e., 25 miles per hour or less) is less likely to be associated with both KA and B injury crashes. Additionally, rural interstates, urban interstates and freeways, other highways, continuous business/commercial development, a speed

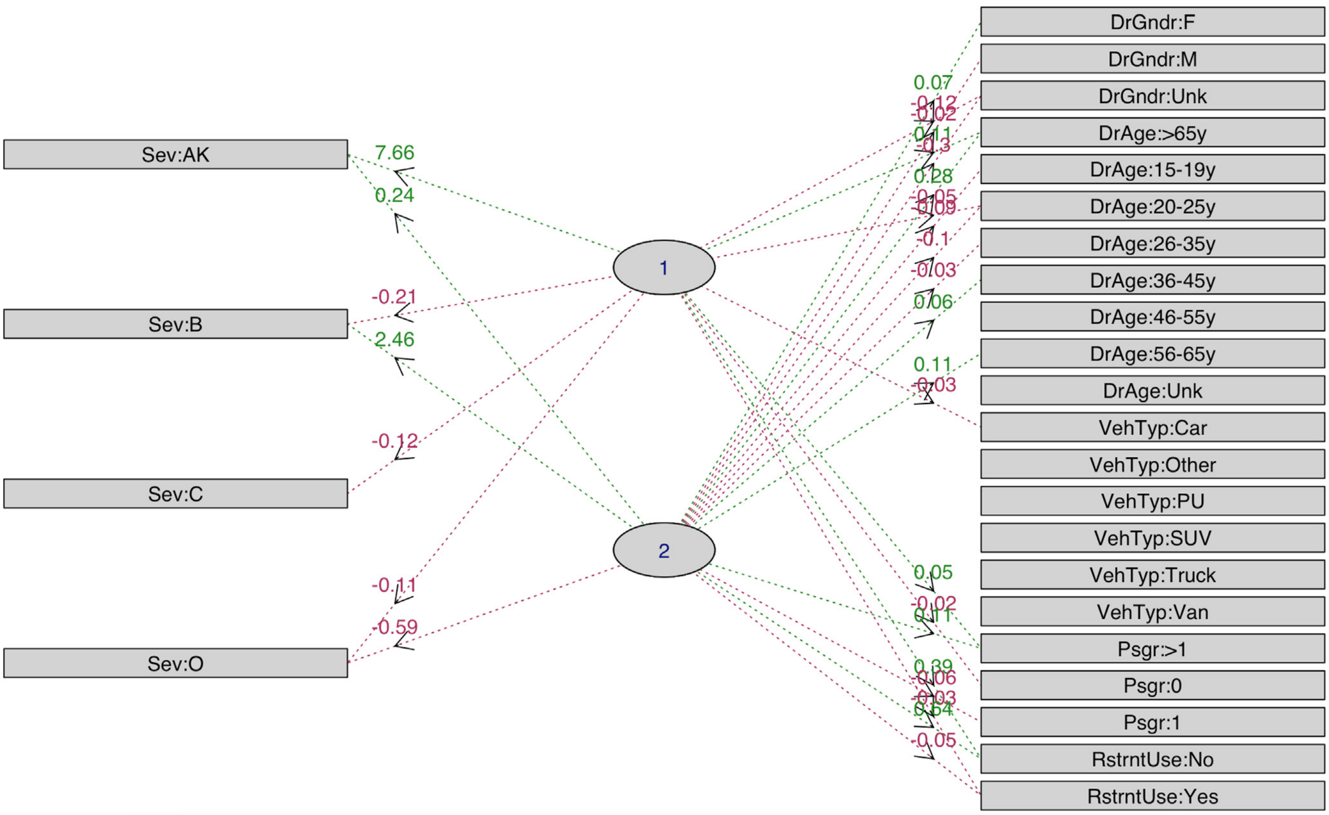

Fig. 5. Association graph for driver and vehicle characteristics.

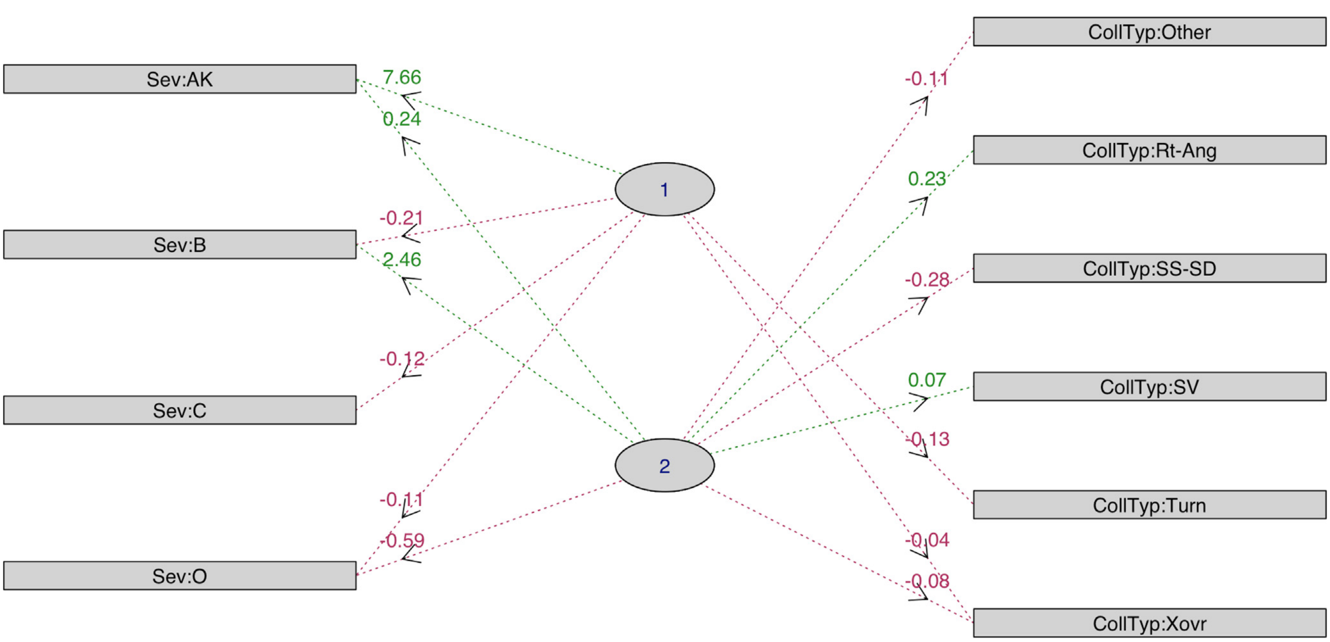

Fig. 6. Association graph for the manner of collision.

limit of 60 miles per hour or more, straight-level alignment, and straight-level-elevated alignment are less likely to be associated with B injury severity. The rest of the attributes presenting highway characteristics are not significantly associated with any injury severity types.

As opposed to a potentially high risk of injury on curved roads due to roadway departure, roadways with straight alignment understandably pose less risk for fatal, severe, or moderate injuries in the event of crashes – although the crash likelihood on straight alignment could be increasingly influenced by long monotonous trips (Farahmand & Boroujerdian, 2018). In contrast with rural two-lanes, rural interstates, and scattered residential areas, the negative association of continuous commercial developments and urban interstates and freeways with injuries can be explained by low operating speed, and more active roadway environments countering drivers' drowsiness levels.

The negative associations of the 'dark but lighted' condition with both latent axes imply that the presence of street lighting may be influential in curbing severity in cases of drowsy driving crashes (Fig. 4). Interestingly, cloudy weather is negatively associated with KA injury crashes. The negative association of crashes from late night towards morning with B injury crashes (mainly latent axis 2) is also an interesting finding that could most likely be explained by drivers' restraint usage during that time, as presented by cluster 5 in the biplot. Two attributes – 12 p.m. to 6 p.m. and daylight – were positively associated with moderate (B) injury crashes and are more likely to be linked to afternoon fatigue crashes.

The association graph of driver and vehicle (Fig. 5) suggests that female drowsy drivers are more likely to be involved in moderate injury crashes, whereas male drivers are less likely to have moderate injury crashes. Positive associations with both latent axes of older drivers (greater than 65 years) suggest that they are significantly more likely to be involved in both KA and B injury crashes. Driver age groups of 36 to 45 years and 56 to 65 years are significantly associated with moderate injury crashes. Passenger cars are less likely to be associated with KA injury crashes, and other vehicle types do not show any significant associations.

The results imply that the absence of passengers and single passengers are less likely to be associated with KA and B crashes, respectively. Although drowsy drivers without passengers are expected to have higher odds of having been in a crash (Hutchens et al., 2008), multiple passengers possibly increase the probability of injury severity, as indicated by the significant associations of both KA or B injury crashes from the positive eigenvalues. Understandably, restraint non-use is positively associated with both KA and B crashes, whereas restraint use is negatively associated with these two severity types.

As indicated in Fig. 6, single-vehicle and right-angle collision types due to drowsy driving are more likely to be associated with moderate injury crashes. Eigenvalue measures also indicate that turning-related and crossover crashes are less likely to be associated with KA injury types, whereas the sideswipe same direction crashes and other crashes are less likely to be associated with B injury types.

5. Conclusions

Due to the rapidly increasing fatigue due to prolonged wakefulness in recent years, the call for action to address the long-withstanding problem of drowsy driving is more important now than at any previous time. Sleep deprivation, drug-associated fatigue, and driving after taking sleep-inducing medication are the primary factors of driving-related drowsiness. For multidisciplinary preventative actions to lower drowsy and fatigue-related crashes, an improved understanding of drowsy driving crash patterns rendering the interconnections of a wide array of crash attributes encompassing driver, vehicle, roadway, and temporal characteristics is required. Large-scale crash data facilitates the investigation of the attributes contributing to more severe crashes for potential prioritization of drowsy driving crash countermeasures.

Previously, survey studies and simulation studies extensively studied different aspects of drowsy driving, mostly by analyzing self-reported and measurable attributes. Using statewide crash data, this study analyzed a multitude of crash attributes of drowsy driving. Challenges remain in detecting drowsiness in drivers at fault in crashes as they require a judgment of reporting officers and confession from the drivers; subsequently, these crashes are often presumed to be underreported. Considering that the scale of underreporting is not known, the five-year drowsy driving crash data of Louisiana constituted a representative sample. The advanced method of corresponding regression analysis incorporates dimensional reduction to overcome limitations of the categorical datasets and provides interpretable insight into drowsy driving crashes presenting underlying associations of multiple attributes as well as individual associations of those attributes with crash severity.

The findings from clusters in the two-dimensional biplot revealed that associative attributes of the different driver, vehicle, and roadway conditions interconnect, varying mostly by location types and highway classes. The collective associations of these attributes depict unique crash scenarios that cannot be detected through conventional statistical models. Several drowsy driving crash patterns were identified, such as afternoon fatigue crashes by middle-aged female drivers on urban multilane curves, crossover crashes by young drivers on low-speed roadways, crashes by male drivers on local roadways surrounded by open country areas during dark rainy conditions, pickup truck crashes in manufacturing/industrial areas during dusk and dawn, late-night crashes in business and residential districts, heavy truck crashes on elevated curves, and so forth. The collective associations (i.e., roadway type, location type, crash time, etc.) identified in this study could further be assessed aiming to develop operational definitions that could fundamentally assist enforcement agencies to strategize better identification and potential minimization of underreporting of drowsy driving crashes. For example, one of the identified clusters includes drowsy driving crashes by pickup truck drivers in manufacturing or industrial areas that occur during dusk or dawn. And it is known that identification of drowsy driving is different as drowsiness is not traceable like the impaired driving crashes. The identified clusters and patterns of risk factors can be used as surrogate measures to develop pattern based operational definition of drowsy driving. In Australia, roadway and temporal characteristics that have been repeatedly found by research studies to be associated with fatigue/sleepiness related crashes were utilized to develop proxy measures by state and national transportation agencies (Armstrong et al., 2013). Regulatory policy-making could also benefit from further investigations for thorough evaluations of the associative attributes identified in this study.

Through dimensional reduction, the two latent axes in the correspondence regression were also able to explain individual associations with the two most severe injury types in drowsy driving crashes – 'fatal and severe injury' and 'moderate injury.' Several attributes – scattered residential areas (indicating rural areas), multiple passengers, and older drivers (aged more than 65 years) – showed a strong association with fatal and severe injury crashes. The attributes that showed significant individual associations with moderate crashes are rural two-lane and urban multilane highways, scattered residential areas, speed limits of 50–55 miles per hour, curve-level alignments, crash hours between 12p.m. to 6p.m., daylight conditions, female drivers, driver age groups of 36 to 45 years and greater than 55 years, multiple passengers, and non-use of safety restraints.

Although the emphasis on drowsy driving has conventionally been on urban areas and young drivers, analysis results from statewide data in this study suggest that rural areas and older drivers are also important areas. Based on the collective associations of important attributes, this study also suggested several countermeasures. Conventional countermeasures often proposed are rumble strips and cable median barriers to prevent roadway departure and encroaching to the opposite direction from isolated movement due to driver drowsiness. Advisory systems exclusively meant for drowsy driving, including advance warning signage in association with rest areas to avoid fatigue during long trips on the interstates, have been estimated to be successful in terms of safety benefits (M.

Rahman & Kang, 2020). A drowsy driving detection system, along with existing in-vehicle technologies such as lane-keeping assistance, could play an important role as prevention measures. The patterns identified in this study can be considered as case study scenarios to determine the appropriate detection system or operational design of the detection system. For example, temporal and age-related patterns (risk groups identified in this study) can be associated with location services to determine thresholds for vehicle operational design requirement for detection system.

Middle-aged drivers with afternoon fatigue, young drivers in low-speed areas, and drivers with severe crashes are the specific demographic-related issues associated with severe drowsy driving crashes that need to be addressed. It appears that public campaigns against drowsy driving for young drivers may require expansion toward older driver groups as well, as the fatigue from prolonged wakefulness due to issues not limited to lifestyle changes is expanding to a wider demographic and is being translated into crashes. Informative social media outreach is another avenue that could be extensively explored for campaigning against drowsy driving. It is known that there is a need for a national drowsy driving campaign similar to other campaigns such as *Click It or Ticket, Drive Sober or Get Pulled Over, and U Text, U Drive, U Lose*. As there is no measurable test for sleepiness and relevant state laws and regulations like other driving impairments, it is often difficult to initiate large-scale campaigns. However, many states and agencies initiate drowsy driving related campaigns: Florida's *You Snooze, You Lose*, the Huffington Post's *#TakeABreaktoStayAwake* campaign, National Sleep Foundation's *Sleep Awareness Week* and *Drowsy Driving Prevention Week (DDPW)*. Findings from the current study can be beneficial for safety campaigns so that interventions can be targeted toward high-risk factors and populations.

It is important to note that drowsiness is a transient impairment unlike alcohol impairment. As there is no one universally accepted definition or strategy to determine if a motorist is too tired to drive, it is difficult to make legislative and policy level recommendations. States promote many strategies such as nighttime driving restrictions for teens, later school start program, and drowsy driving training. NHTSA recently started its first-ever *Drowsy Driving Research and Program Plan* to enhance the science and program initiatives. The multi-year plan aims to address six major focus areas: problem identification, public awareness education, policy development, identification of high-risk populations, vehicle technology, and infrastructure (NHTSA, 2016).

This study has several limitations. The limitations of data quantity due to difficulties in accurate drowsy driving data collection by reporting officers clearly exists (Li et al., 2018). Future studies directed toward a specific focus on this limitation can extensively investigate possible causes for bias in reporting drowsy driving-related crashes. The Model Minimum Uniform Crash Criteria (MMUCC) guidelines suggest collecting data elements that can separately describe driving under the influence of intoxicants (alcohol or drugs) and drowsy driving (NHTSA, 2017). A comparison of drowsy driving with and without the influence of intoxicants could help alleviate the research gap of drowsy or fatigued driving exclusively caused by prolonged wakefulness. With regards to the selection of variables in this study, the researchers initially used only the ones that were deemed useful based on expert judgment, previous studies, and availability in the crash database. In the future, whether unobserved heterogeneity can be minimized within the framework of correspondence regression analysis needs to be examined.

Conflict of Interest

All the authors have no conflict of interest with the funding entity and any organization mentioned in this article in the past three years that may have influenced the conduct of this research and the findings.

Acknowledgments

The authors would like to thank the Louisiana Department of Transportation and Development (DOTD) for providing the data. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. The authors like to thank two anonymous reviewers for their valuable suggestions. The current version is much improved due to their well-thought suggestions and feedbacks.

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