Understanding Patterns in Marijuana Impaired Traffic Crashes: A Case Study on Louisiana

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ABSTRACT

The landscape of marijuana regulation is rapidly changing. While several countries worldwide have already legalized marijuana in some form, marijuana will become legal for recreational purposes for a quarter of the U.S. population soon. The potential increase in traffic fatalities because of impaired drivers remains a prominent debate among policymakers and in the media. One recent report showed that the fraction of fatal crashes in which at least one driver tested positive for marijuana has increased nationwide by an average of 10 percent from 2013 to 2016. In Louisiana, crashes involving marijuana have increased by 195% (from 2010 to 2016). This study collected seven years of marijuana involved crash data from Louisiana to identify the key association factors and their patterns. The research team identifies the hidden association patterns of key attributes from the complex crash dataset using the cluster correspondence analysis. The findings reveal some key clusters: female drivers at the intersection involved in multiple vehicle right angle crashes, multiple vehicle head-on crashes at two-lane roadways with no separation, multi-vehicle rear-end crashes at two-lane roadways with separation, careless single-vehicle crashes, single-vehicle crashes during dark with no streetlights, and open country interstate crashes. The findings of this study can be useful in the coordination of local and regional behavioral safety efforts to reduce the frequency and severity of marijuana-involved traffic crashes.

Keywords: marijuana, drug impairment, cluster correspondence analysis, traffic safety.

INTRODUCTION

Marijuana can be defined as the dehydrated stems, leaves, seeds, and flowers from a cannabis plant that possesses delta-9-tetrahydrocannabinol (THC), a psychoactive or mind-altering chemical, along with other related compounds. Under federal law, marijuana is considered a controlled substance, and the federal government groups marijuana in the most restrictive division of controlled substances. Many states have adopted new state laws that legalize marijuana use for medical purposes. Under state or territorial law, the distribution and possession of marijuana were legalized through legislation or voter initiatives by 24 states and the District of Columbia *(1).* In 1996, the Compassionate Use Act made California the first state to pass legislation for the medical use of marijuana that has led to an increasing number of states passing ballot initiatives, propositions, and even legislation in recent years. For example, the District of Columbia and 13 other states have passed some type of legal measure for the medical use of marijuana under state law from 2011 to June 2015. The medical marijuana legislation passed by these states varies, as well as the extent to which the states have implemented enforcement and regulatory systems (*1*). A recent nationwide report showed that from 2013 to 2016, the fraction of fatal crashes involving at least one driver testing positive for marijuana had increased by an average of 10 percent. In comparison to states that have legalized medical marijuana use since 2014, both Colorado and Washington showed increases of 92 percent and 28 percent, respectively (*2*). These statistics call for an in-depth study in determining the association between marijuana and traffic safety.

In 2015, a dispensing framework for medical marijuana was assembled in Louisiana. The structures aim to dispense medical cannabis to any patient by 2017 *(3).* Based on recent statistics, crashes related to marijuana use have increased by 195% (*4*). To determine the impact of driving under the influence of marijuana in Louisiana, additional research is crucial to identify the critical gaps in the existing literature. Crash data collected over seven years (2010-2016) identified crashes involving marijuana in Louisiana. Using cluster correspondence analysis to identify key association factors, the researchers search for appropriate measures to reduce marijuana involved crashes.

LITERATURE REVIEW

Besides alcohol, some commonly found drugs among drivers involved in crashes are marijuana, pot, cannabis, and benzodiazepines (BZDs). The driving risks associated with the effect of alcohol is well-known, but the effects of cannabis on driving risks are not thoroughly understood and remains an increasing concern. The Insurance Institute for Highway Safety (IIHS) performed a study that indicated a notable increase in the percentage of weekend riders checking for marijuana and other illegal drugs. Contrary to the rise in drug use, a decreasing number of riders were under the influence of alcohol in 2013-2014 opposed to 2007 (*5*). The IIHS reported an increase in the frequency of collision claims in Oregon, Colorado, and Washington associated with the arrival of retail marijuana sales (*6, 7*). In comparison to Nebraska, Utah, and Wyoming, the collision claim frequencies in Colorado were 12.5% higher, and in Washington, claim frequencies were 9.7% higher than in Montana and Idaho (*8*).

Marijuana Intoxication and Fatal Crashes

In the U.S., Colorado and Washington were the first states to pass legislation allowing the recreational use of marijuana. Marijuana use increased overall in both states as expected, but both states also experienced an unexpected increase in the rate of fatal crashes. Additionally, the number of arrests and crashes involving drivers testing positive for THC increased (*9*). In an assessment of the relative liability risk in fatal collisions involving riders under the influence of cannabis, the occurrence of such drivers in the driving population, and the associated proportions of fatal crashes, Laumon et al. (*10*) showed that 681 out of 10,748 riders in France involved in fatal crashes tested positive for cannabis. Of the total crashes, at least 2.5 percent was attributed to cannabis, while 28.6 percent were related to alcohol indicating that the effect of cannabis is much less than that of alcohol in fatal crashes. Beirness et al. *(11)* determined that the impairment of driving skills increased the crash risk as a result of both cannabis and benzodiazepines (BZDs) use.

Baldock et al. *(12)* emphasized the relative risk of crashes connected to driving after using cannabis. A case-control study was suggested to compare the ratio of cannabis in crash-involved drivers compared to non-crash-involved drivers. Salomonsen-Sautel et al. *(13)* examined differences in fatal motor vehicle crashes with drivers testing positive for marijuana or impaired by alcohol in Colorado and 34 non-medical marijuana countries (NMMS). The research revealed that since medical marijuana became commercially accessible and common, the trend has favored the percentage of riders who tested marijuana-positive in a fatal motor vehicle crash. From 2010-2014, Tefft et al. (*14*) quantified the involvement of marijuana in fatal crashes in the state of Washington. The data assessment reported that 10 percent of all riders engaged in fatal crashes tested positive for the presence of THC in their blood. Following the legalization of recreational marijuana use in Washington, the number of drivers in fatal crashes that were positive for THC increased for adults aged 21 years and older. Likewise, Steinmann et al. (*15*) investigated any correlation between crash fatalities of riders who tested positive for marijuana, high-risk behavior, and bad insurance status and legalization. The study concluded that THC-positive patients were less likely to use helmets or other protective measures, and the THC positivity among drivers' deaths increased by three-fold.

Marijuana Effects on Driving Skills

State Highway Safety Officers have stated that drugged driving is a major concern, and studies suggest that states must discuss effective policies to reduce impaired driving of marijuana or opioids (*16*). The research studied by Fergusson et al. (*17*) examined the link between riding under the impact of alcohol and marijuana and motor vehicles crash. The findings concluded that driving risks under marijuana influence could now be greater than riding risks under alcohol influence. To anticipate the impairment of drug-induced driving, Ramaekers et al. (*18*) concentrated on the efficiency of driving-related testing and illustrated a practical method for performance tests to calculate predictive validity. This study also linked performance impairments induced by THC and the guilt risks induced by THC. Van Elslande et al. (*19*) analyzed the failures that riders are exposed to when they have consumed cannabis. The use of cannabis was found to increase the driver's rate of generalized mistakes such as motor, sensorial, and cognitive functions.

Hartman and Huestis (*20*) showed that smoking cannabis increases the risk of motor vehicle crashes for reduced reflexes, lane weaving, impaired cognitive functions, and increased task complexity. Using immediate commentary with the driving simulator and self-reported interventions, Bergeron and Paquette (*21*) studied the association between reckless driving and self-reported under the influence of cannabis (DUIC). The study showed that people demonstrated more aggressive driving habits on the simulator when faced with real-life hazardous driving habits.

Marijuana and Alcohol

Agic et al. (*22*) investigated drivers reported to operate under the influence of alcohol (DUI) and DUIC and showed that last year's collision probability was 2-4 times that of drivers who reported impaired behavior on their own. Asbridge et al. (*23*) examined if the use of alcohol and cannabis increases the risk of collision among non-fatally wounded bicyclists. Studies determined that 14.5% reported using liquor and 15% of riders reported using marijuana before the crash. Research data proposed that both alcohol and cannabis increase the danger of a non-fatal injury-related crash among bicyclists. Romano et al. (*24*) used descriptive analyses and regression to determine the likelihood of being responsible in a fatal crash. The authors showed that the existence of cannabis increased collision liability for fatal crashes and emphasized that blame should not be merely on heavy-drinking riders. White (*25*) concluded that cannabis increases the risk of crashing; the increase is unlikely to be more than about 30%. Jewett et al. (*26*) examined self-reported incidences and variables associated with alcohol, marijuana, and prescription opioid use and impaired driving. Of the participants who used marijuana, 31.6% reported marijuana-impaired driving. Among all participants, 10.8% reported driving impaired by both alcohol and marijuana.

Marijuana Dependency and Impact on the Age

Le Strat et al. (*27*) analyzed the effect of the onset age of cannabis use on the risk of cannabis dependence and the likelihood of driving while under the influence of cannabis. In comparison to those who start using cannabis at the age of 21 years or older, participants who consumed cannabis before the age of 14 years were 3 times more likely to report having driven under the influence of cannabis and 4 times more likely to have a history of cannabis dependence. In contrast, Karush (*28*) determined that 76% of parents and 68% of teens considered driving under the influence of marijuana is risky, and 93% of parents and 88% of teens considered driving while being impaired by alcohol is dangerous.

Risk Factors for Driving After and During Marijuana Use

To predict the driving frequency after smoking marijuana (DASM) and smoking marijuana while driving (SMWD) using social learning theory, Aston et al. (*29*) analyzed the expectations of marijuana outcome and other driving-related cognitions. The study revealed a lower frequency of DASM and SMWD in relation to the anticipated driving-related peer norms and a lower frequency of DASM in relation to the anticipated danger of DASM. Banta- Green et al. (*30*) investigated the drivers engaged in crashes and/or detained on suspicion of DUI driving. The study concluded that THC-impaired driving is comparatively common and appears to be escalating.

Scherer et al. (*31*) showed that the promotion of the concept of being in a high-risk traffic safety community is a result of the increasing occurrence of crashes and connection of DUI with cannabis and other substance-using users. In addition, the use of poly drugs, psychiatric comorbidities, and cognitive impairment connected to substance addiction could lead to higher crash risk.

Monitoring DUI of Marijuana

To determine whether the government motor vehicle monitoring schemes can accurately check and track marijuana-influenced driving, Peterson et al. (*32*) evaluated Colorado's Department of Revenue Motor Vehicle Crash Data System, Electronic Accident Reporting System (EARS) to inquire about non-fatal crashes involving DUIC. To decrease crash risk, the study proposed standardized drug testing and mandatory reporting practices for riders linked to motor vehicle crashes. Lee et al. (*33*) analyzed the relationship between five types of marijuana law changes and marijuana-involved fatal crashes in the U.S. No significant changes in the number of marijuana-related crashes after the legalization of only medical marijuana were found. However, the number of marijuana-related crashes increased after other types of marijuana law changed. On the other hand, Sevigny (*34*) evaluated the impact of government medical cannabis legislation (MMLs) on drivers under the influence of cannabis involved in a fatal crash between 1993–2014. Findings conclude that MMLs had no impact on drivers testing positive for cannabis.

The literature review confirms a need for extensive studies focusing on identifying the key association factors of crashes involving marijuana. This study focuses on lessening the present research gap by applying a clustering technique to determine the trends of the contributing factors related to marijuana involved crashes.

CLUSTER CORRESPONDENCE ANALYSIS

Correspondence analysis (CA) is a data mining technique which purpose is to analyze simple two-way and multi-way tables that contain some measure of correspondence between the rows and columns in a complex dataset by performing dimension reduction. In recent years, several transportation safety analysis studies utilized CA to determine the patterns of the main contributing factors *(35-39).* Cluster correspondence analysis incorporates both dimension reduction and cluster analysis for categorical data by simultaneously assigning individuals to clusters and optimal scaling values to categories. In this way, the user achieves a single between variance maximization objective. This section presents a short overview of cluster correspondence analysis based on the work of Velden et al. *(40).*

Assume the user has data of n individuals for p categorical variables gathered in a super indicator matrix $\mathbf{Z}$ with the dimensionality of $n \times Q$, where $Q = \sum_{j=1}^{p} q_j$. The user can consider the cluster membership as a categorical variable that the user can code using an indicator matrix $\boldsymbol{Z}_K$. This will help in developing a table to cross-tabulate cluster memberships with the categorical variables such as $\boldsymbol{F} = \boldsymbol{Z}'_K\boldsymbol{Z}$, where $\boldsymbol{Z}_K$ is the $n \times K$ indicator matrix indicating cluster membership. Applying CA framework to this matrix yields optimal scaling values for rows (as clusters) and columns (as categories). The clusters are optimally separated with respect to the distributions over the categorical variables. Similarly, the categories with differing distributions over the clusters are optimally separated. The optimal cluster allocation $\boldsymbol{Z}_K$ can be expressed as *(40):*

$$max\emptyset_{clusca}(\boldsymbol{Z}_K, \boldsymbol{B}^*) = \frac{1}{p} trace\boldsymbol{B}^{*\prime}\boldsymbol{D}_z^{-1/2}\boldsymbol{Z}'\boldsymbol{M}\boldsymbol{Z}_K\boldsymbol{D}_Z^{-1}\boldsymbol{Z}'_K\boldsymbol{M}\boldsymbol{Z}\boldsymbol{D}_z^{-1/2}\boldsymbol{B}^* \tag{1}$$

where: $\boldsymbol{Z}_K$ is an indicator matrix. For fixed $\boldsymbol{B}^*$, this optimization problem can be re-expressed into a K-means clustering issue. Maximizing $\emptyset(\boldsymbol{Z}_K, \boldsymbol{B}^*)$ with respect to $\boldsymbol{Z}_K$ helps in solving the following K-means objective *(40):*

$$min\emptyset'_{clusca}(\boldsymbol{Z}_K, \boldsymbol{G}) = \left\|\sqrt{\frac{n}{p}}\boldsymbol{M}\boldsymbol{Z}\boldsymbol{D}_z^{\frac{-1}{2}}\boldsymbol{B}^* - \boldsymbol{Z}_K\boldsymbol{G}\right\|^2, \tag{2}$$

where:

G= the matrix with cluster means

B= column coordinate matrix of rank k, where k is the dimensionality of the approximation.

$\boldsymbol{M} = \boldsymbol{I}_n - \mathbf{1}_n\mathbf{1}'_n/n.$

$\boldsymbol{D}_z$ = Diagonal matrix can be defined such that $\boldsymbol{D}_z\mathbf{1}_Q = \boldsymbol{Z}'\mathbf{1}_n$

METHODOLOGY

Data Preparation

As mentioned earlier, medical marijuana was legalized in Louisiana in 2015 (see Figure 1). The dataset of the current study includes police-reported crashes in Louisiana from 2010 to 2016. The current dataset does not provide marijuana-related filtering options. However, the crash dataset contains a crash narrative report in text format for each crash. The researchers used a text searching algorithm to determine the crashes associated with the keywords: 'marijuana,' 'cannabis,' and 'benzodiazepine'. Primarily 1134 crashes were identified. These reports are manually examined to remove irrelevant reports. The final dataset contains 808 marijuana crash events. Table 1 lists marijuana-related crash severities by year. From 2010 to 2016, marijuana-related crash severities increased by 195%. Figure 3 illustrates the flowchart of the study design.

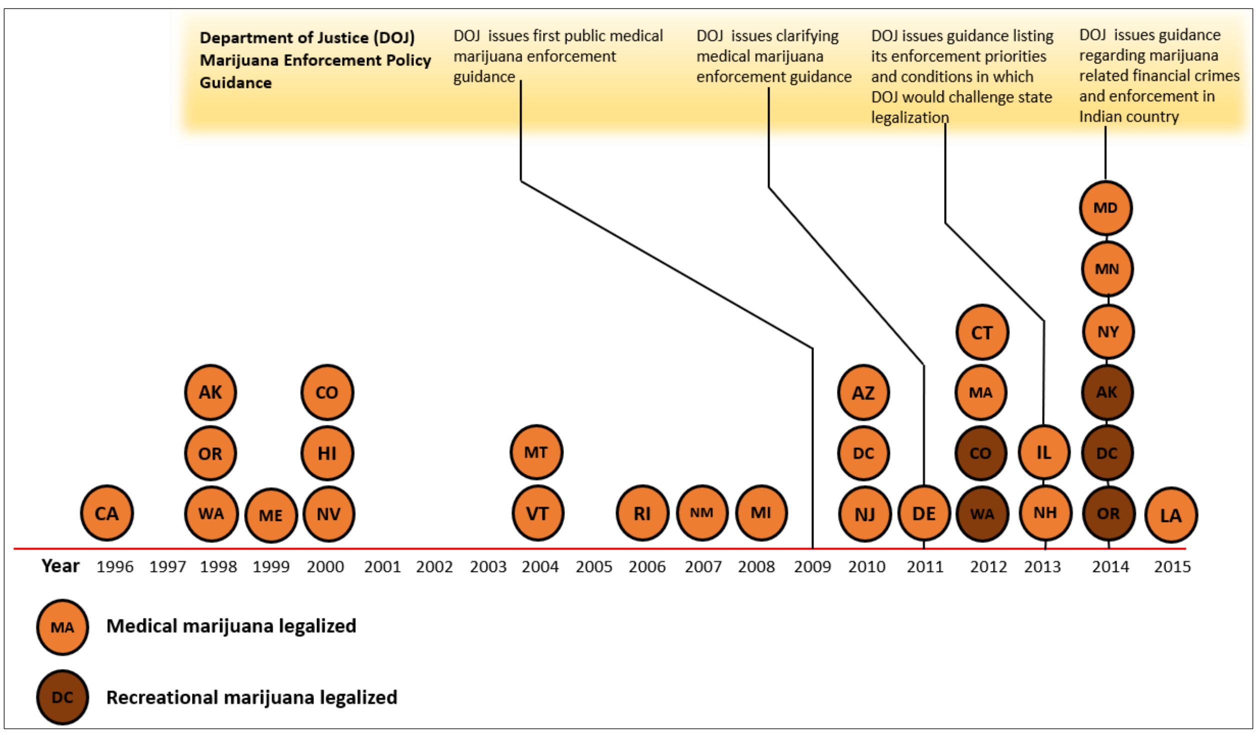

Figure 1 Marijuana legalization by states.

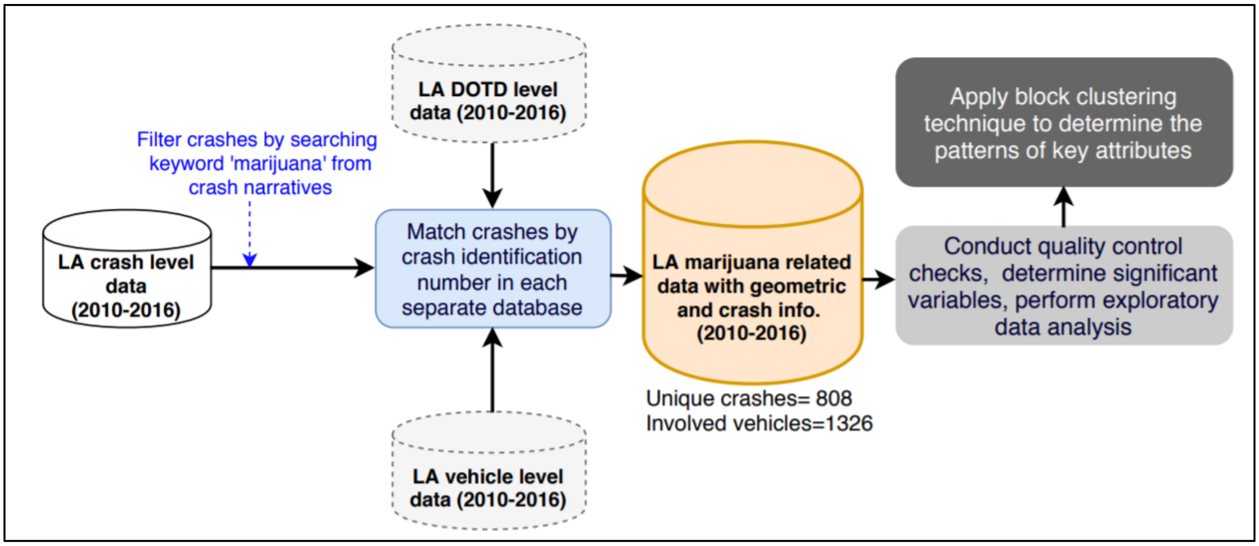

Figure 2 Data integration flowchart.

Table 1 Marijuana-related Crash Severities by Year

Year	Fatal (K)	Incapacitating Injury (A)	Non-incapacitating Injury (B)	Minor Injury (C)	No Injury (O)	Total
2010	1	6	13	11	33	64
2011	0	3	8	13	40	64
2012	1	6	17	21	50	95
2013	2	4	17	26	47	96
2014	1	9	13	38	70	131
2015	1	8	35	41	84	169
2016	1	6	28	54	100	189
Grand Total	7	42	131	204	424	808

RESULTS AND DISCUSSIONS

Figure 3 illustrates the biplots of all attributes. The centroids of the clusters (C1, C2, C4, C5, and C6) are shown in parabolic shapes (light brown background with blue outlines. This visualization is helpful in understanding the overall locations of all attributes. Figure 4 and Figure 5 illustrate the top 20 largest standardized residuals per cluster in cluster 1-3 and 4-6, respectively. This study applied a two-dimensional, six-cluster solution. The solution depicting clusters and attributes is displayed in Figure 3. One can project individual subject points into this biplot map and thus visualize the variability within and between clusters. In CA, the origin indicates the average profile, and all other points depict deviations from this average profile. The biplot display depicts two clusters are near to the origin (Cluster 2 and Cluster 3), two clusters (Cluster 1, 4) are within the ranges of the origin. The rest clusters (Cluster 5, and Cluster 6) have large distances from the origin. To assess the quality of cluster solutions, several internal cluster validity measures exist. This study used Calinski-Harabasz value (also known as valence ratio criterion) that applies k-means clustering to perform clustering for different k values. These k-means runs are randomly initialized and therefore have to be run a number of times to ensure an optimal clustering. The value of this study is identified as 20.966, and the objective criterion value is 95.258.

Table 2 Size, Sum of Squares, and Dimensions of the Clusters

Cluster	Size (percentage)	Sum of Squares	Dimension 1	Dimension 2
Cluster 1	307 (23.2%)	27.4472	-0.7919	-0.4002
Cluster 2	296 (22.3%)	26.8047	-0.0668	-0.4070
Cluster 3	232 (17.5%)	34.8508	-0.6451	0.3324
Cluster 4	212 (16.0%)	39.3088	0.6730	-0.0372
Cluster 5	178 (13.4%)	26.9384	1.5319	-0.1636
Cluster 6	101 (7.6%)	56.7526	-0.0279	2.0126

The occurrence and outcome of crashes have long been recognized as complex events which involve interactions between many contributing factors such as roadway, driver, traffic characteristics, and environment. The injury severity of driver is a combined effect of numerous factors, including the driver involved, vehicle type, environmental conditions, roadway characteristics, and crash characteristics. On the other hand, marijuana use has proven to be one of the potential factors which influence the driver's condition that result in a fatal or non-fatal crash. However, it is difficult to assess the independent contribution of a large number of variables. Preliminary data exploration was first conducted to determine the important factors that may contribute to crash occurrence. Table 3 describes the statistics of the selected sixteen variables. Each variable is identified in italic, bold font with their corresponding attributes listed below. The frequency of each attribute is also included in the table to easily determine the most prominent attribute. Variables such as driver injury, driver violation, driver age, gender, traffic control, vehicle type, highway type, collision type, and more are evaluated. The frequency percentage of each attribute identifies the characteristics that may lead to marijuana involved crashes. Based on the data collected, the most frequent collision type involves rear-end crashes, and most crashes occur at business locations. Males have a higher crash frequency compared to female drivers. Moreover, a high percentage of crashes occur in daylight conditions, between 25 to 44 years old, in the city streets, and without any driver's distraction.

Table 3 Descriptive Statistics

Attributes	Percentage	Attributes	Percentage
Dr Inj (Driver Injury)		***Traff Cont (Traffic Control)***	
K	0.15	No Control	24.13
A	2.11	White Dashed Line	21.95
B	9.43	Yellow No Passing Line	12.44
C	19.00	Red Signal On	10.33
O	69.31	Stop Sign	9.58
Violation (Driver Violation)		Yellow Dashed Line	6.64
No Violations	36.65	Other	14.93
Careless	26.92	***Hwy Typ (Highway Type)***	
Driver Condition	12.22	City Street	34.24
Other	24.21	State Hwy	26.40
Distraction (Driver Distraction)		Parish Road	17.72
Not Distracted	60.11	U.S. Hwy	12.75
Other Inside	3.54	Interstate	7.99
Cell Phone	2.41	Other	0.90
Other Outside	2.41	***Lighting***	

Unknown	31.52	Daylight	50.23
Gender (Driver Gender)		Dark Cont Street Light	29.86
M	64.03	Dark - No Street Lights	11.09
F	28.13	Dark Street Light at Int	6.03
U	7.84	Dawn/Dusk	2.41
Dr Age (Driver Age)		Other	0.38
14-24	35.52	***Loc (Locality)***	
25-44	42.23	Business	58.22
45-64	17.95	Open Country	4.37
> 64	4.30	Manufacturing Or Industrial	1.51
Veh Typ (Vehicle Type)		Other	4.52
Passenger Car	52.56	Residential	
Lt. Truck (P.U., Etc.)	21.12	***Coll Typ (Collision Type)***	
Suv	18.33	Rear End	29.26
Other	7.99	Single Vehicle	23.91
Pri Contri (Primary Contributing Factor)		Right Angle	12.59
Violations	66.06	Sideswipe	12.14
Condition of Driver	21.49	Left Turn	6.41
Movement Prior To Crash	10.26	Head-On	4.00
Other	2.19	Right Turn	1.81
Road Typ (Road Type)		Other	9.88
Two-Way with No Separation	66.97	***Int (Intersection)***	
Two-Way with Separation	21.79	N	61.61
One-Way Road	6.56	Y	38.39
Two-Way with Barrier	3.85	***Num Veh (Number of Vehicles)***	
Other	0.83	Multi	73.45
DOW (Day of Week)		Single	26.55
FSS	52.41		
MTWT	47.59		

Figure 3 to Figure 5 illustrate the trends and association of key attributes. To comprehend the interpretation of the clusters, it is useful to identify the attributes that deviate the most from the independent condition. The six plots in Figure 4 and Figure 5 show the 20 attributes in each cluster with the highest standardized residuals (positive or negative). A positive (negative) residual means that the attribute has an above (below) average frequency within the cluster. The following explanation considers attributes with positive residual means.

Cluster 1

This cluster has nine attributes with positive residual means: red signal on, intersection, right angle, business location, traffic control as other, no violation, females, multi-vehicle, and state highway. This cluster indicates the association between multi-vehicle right-angle crashes in business locations with no violation. These findings are in line with what Lee and Li discussed in their study (*41*). They suggested that median width and surface width should be increased, and curvature should be reduced to reduce multi-vehicle crashes with different collision types.

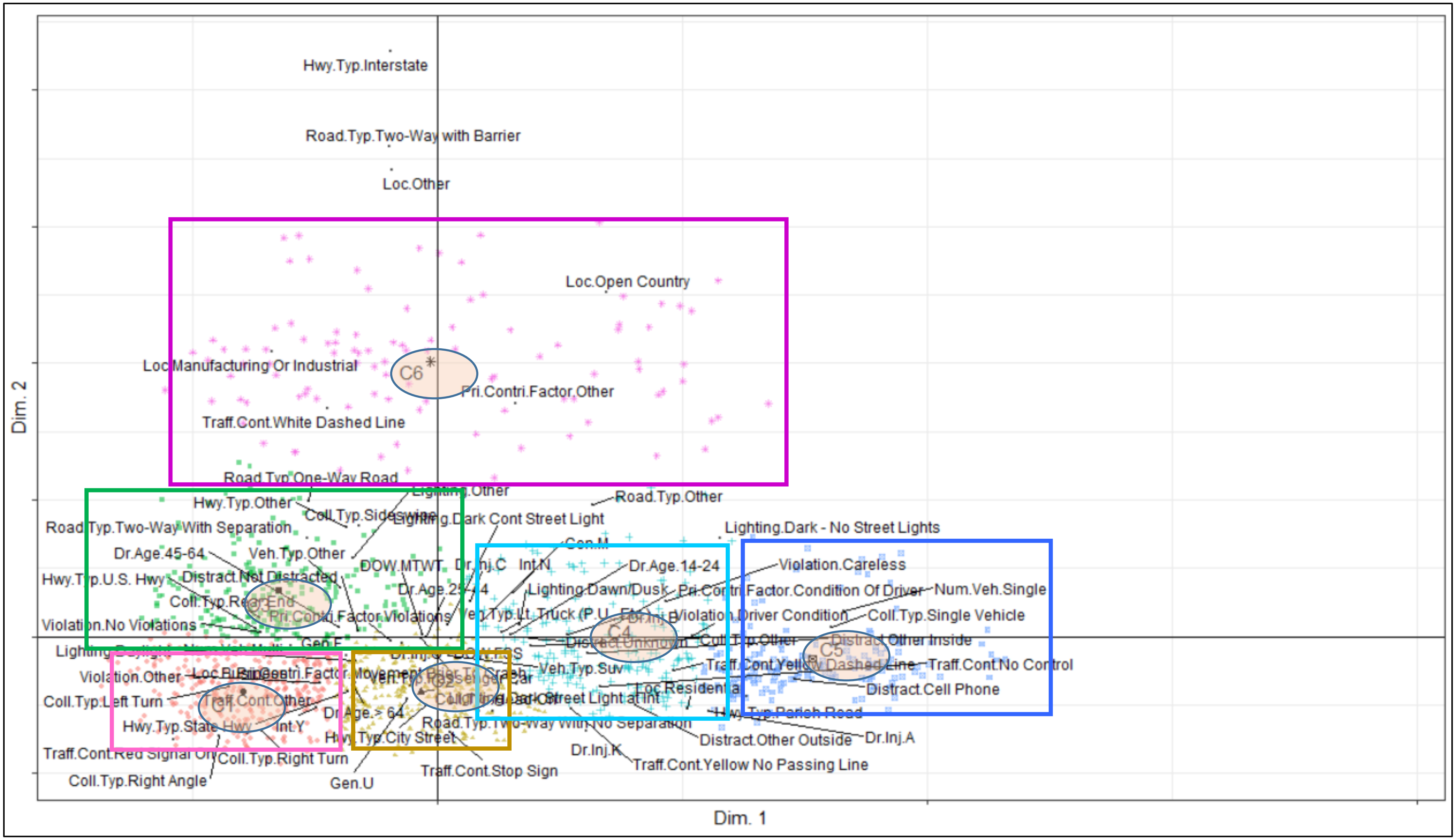

Figure 3 Biplot of all attributes.

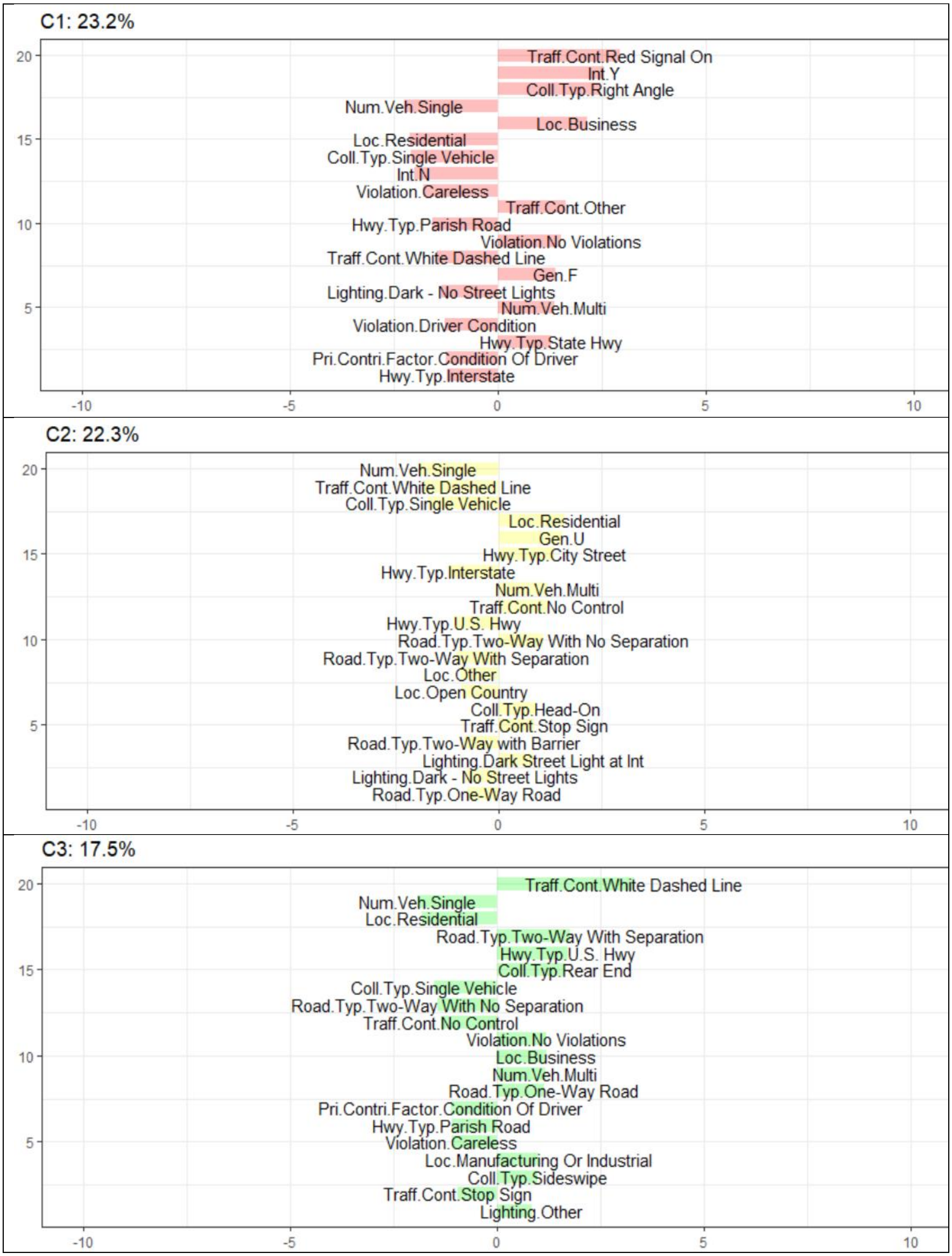

Figure 4 Top 20's of the largest standardized residuals per cluster (cluster 1-3).

Cluster 2

The attributes with positive residual means are residential, unspecified gender, city street, multi-vehicle involvement, no control, two-way with no separation, head-on, stop sign, dark street light at the intersection. This cluster indicates the loss of control in multi-vehicle crashes on residential two-way no separation roadways in dark street-light condition. The findings are in line with a study by Farmer (*42*) suggesting the use of electronic stability control (ESC) systems that can reduce the crash risk (especially single-vehicle crashes) significantly.

Cluster 3

This cluster has ten attributes with positive residual means: white dashed line, two-way with separation, U. S highway, rear end, no violations, business, multi-vehicle involvement, one-way road, manufacturing or industrial localities, sideswipe, and others as lighting condition. This cluster highlights on rear-end multi-vehicle crashes in U. S highways and is not associated with any driver violations.

Cluster 4

The attributes with positive residual means in Cluster 4 are single-vehicle, violation as driver condition, careless operation, others as collision type, segment, others as road type, dark condition with a continuous streetlight, and residential. This cluster shows an association between single-vehicle crashes with careless drivers involved in crashes at residential locations in dark condition. The findings in this cluster are consistent with Chipman and Jin (*43*). They found that the interaction between the streets/highways lighting condition and the drivers' carelessness, drowsiness, and loss of attention can be addressed by improving the lighting conditions of the roadways.

Cluster 5

The twelve attributes with positive residual means are single-vehicle, parish road, residential, dark with no streetlights, careless operation, cell phone as a distraction, yellow dashed line, no control, driver condition, and two-way roadway with no separation. This cluster shows single-vehicle crashes and their association with driver's distraction like using a cellphone, as well as drivers' carelessness, parish highway type, two-way with no separation road type and no traffic control. The findings are in line with the findings of Ranney (*44*). This study suggested that much is needed to reduce drivers' distractions as the standard behavioral countermeasures such as laws, enforcement, and sanctions are not enough since it is a complicated societal problem which is related to lifestyle patterns and choices.

Cluster 6

This cluster has twelve attributes with positive residual means: interstate, other locality, two-way with barrier, white dashed line, open country, two-way with separation, sideswipe, dark with no street lights, others as a primary contributing factor, manufacturing or industrial locality, one-way road, and roadway segment. It indicates sideswipe crashes on open country two-way with barrier and separation roadways with the white dashed line as traffic control tools. Chipman and Jin (*43*) also showed similar findings and suggested treatments to address crashes in dark/no light conditions.

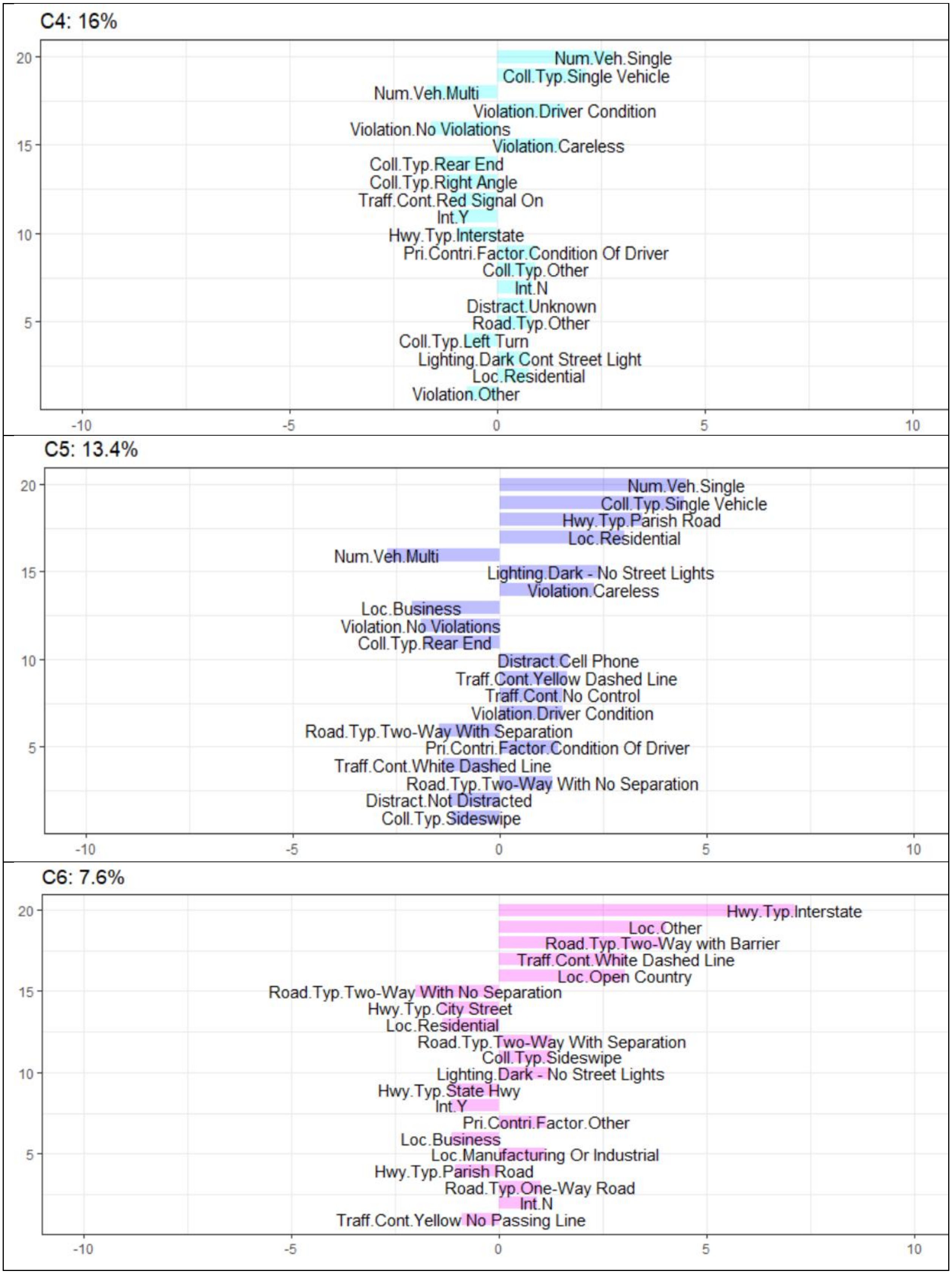

Figure 5 Top 20's of the largest standardized residuals per cluster (cluster 4-6).

CONCLUSIONS

Although the influence of alcohol on driving performance is well documented, the impact of marijuana on driving skills have not been thoroughly researched. Swerving in the lane, slower reaction time, impaired decision making, impaired driving performance, and risk-taking are just some of the side effects drivers suffer under the influence of marijuana. However, other studies have not found any adverse effects on sudden lane change, sign detection, or response to sudden hazards (*45*). Both experimental and observational studies have established the effects of consuming alcohol while driving. However, learning about the effects of consuming marijuana is controversial because the range of effects of cannabis on people differs more than alcohol. The differences are a result of consumption techniques, individual tolerance differences, and concentrations (*46*). The reactions of cannabis consumption are difficult to acquire, but its effect on driving is considered as less severe than alcohol. To identify the 'marijuana involved' crashes, this study applied text mining algorithms to seven years of crash data in Louisiana. Using cluster correspondence analysis, this study determined the patterns of associated factors. Six different clusters of attribute groups were identified using the analytical method. Some of the key clusters are: single-vehicle crashes during dark with no streetlights, multi-vehicle rear-end crashes at two-lane roadways with separation, multiple vehicle head-on crashes at two-lane roadways with no separation, female drivers at the intersection involved in multiple-vehicle right-angle crashes, careless single-vehicle crashes, and open country interstate crashes.

The current study does have limitations. The current marijuana-related data is restricted to crashes reported to the police that were filtered as marijuana involved based on the type of violation. To improve the current model performance and enhance the comprehensive investigation by adding variables of interest, further research would be beneficial. The limitations of the current study provide guidance for potential research in this scope. Another caveat that is frequently encountered is data reliability, particularly when the crash data is acquired from police reports.

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AUTHOR CONTRIBUTION STATEMENT

The authors confirm the contribution to the paper as follows: study conception and design: Subasish Das; data collection: Subasish Das; analysis and interpretation of results: Subasish Das; draft manuscript preparation: Subasish Das, Ly-Na Tran, and Bita Maraghehpour. All authors reviewed the results and approved the final version of the manuscript.

REFERENCES

1. The U. S. Government Accountability Office. State Marijuana Legalization: DOJ Should Documents its Approach to Monitoring the Effects of Legalization. Washington, DC, 2015.
2. Hansen, B., K. Miller, and C. Weber. Early Evidence on Recreational Marijuana Legalization and Traffic Fatalities. https://faculty.washington.edu/ceweber/HMW_marijuana_traffic.pdf Accessed: July 2019.
3. Highway Safety Research Group. Louisiana Crash Data Reports. http://datareports.lsu.edu/ Accessed: July 2019.

4. Louisiana Board of Pharmacy. Revised Guidance Document re Cannabidiol (CBD) Oil. http://www.pharmacy.la.gov/assets/docs/GuidanceDocuments/CBD-Oil_RevisedGuidance_2019-0219.pdf Accessed; July 2019.
5. Insurance Institute for Highway Safety. More Drivers Use Marijuana, But Link to Crashes Is Murky. Status Report, Vol. 50, No. 4, 2015.
6. Insurance Institute for Highway Safety. High Claims: Legalizing Recreational Marijuana Is Linked to Increased Crashes. Status Report, Vol. 52, No. 4, 2017.
7. Insurance Institute for Highway Safety. Studies Link Legalized Use of Recreational Marijuana with Increase in Crashes. Status Report, Vol. 52, No. 5, 2017.
8. Highway Loss Data Institute. Recreational Marijuana and Collision Claim Frequencies. Highway Loss Data Institute, 2018.
9. Governors Highway Safety Association. Traffic Safety Impacts of Marijuana Legalization, 2018, p. 4p.
10. Laumon, B., B. Gadegbeku, M. B. Biecheler, and J. L. Martin. Cannabis Intoxication and Fatal Road Crashes in France: Population Based Case-Control Study. BMJ, Vol. 331, No. 7529, 2005, p. pp 1371-1373.
11. Beirness, D. J., H. M. Simpson, and A. F. Williams. Role of Cannabis and Benzodiazepines in Motor Vehicle Crashes. Presented at the Transportation Research Circular, 2006.
12. Baldock, M. University of Adelaide, and Australia Department of Infrastructure and Transport. Review of the Literature on Cannabis and Crash Risk. University of Adelaide, 2007.
13. Salomonsen-Sautel, S., S. J. Min, J. T. Sakai, C. Thurstone, and C. Hopfer. Trends in Fatal Motor Vehicle Crashes before and after Marijuana Commercialization in Colorado. Drug and Alcohol Dependence, Vol. 140, 2014, p. pp 137-144.
14. Tefft, B. C., L. S. Arnold, J. G. Grabowski, and AAA Foundation for Traffic Safety. Prevalence of Marijuana Involvement in Fatal Crashes: Washington, 2010 – 2014, 2016, p. 26p.
15. Steinemann, S., D. Galanis, T. Nguyen, and W. Biffl. Motor Vehicle Crash Fatalities and Undercompensated Care Associated with Legalization of Marijuana. Journal of Trauma and Acute Care Surgery, Vol. 85, No. 3, 2018, p. pp 566-571.
16. Hedlund, J., and Governors Highway Safety Association. Drug-Impaired Driving: Marijuana and Opioids Raise Critical Issues for States, 2018, p. 40p.
17. Fergusson, D. M., L. J. Horwood, and J. M. Boden. Is Driving under the Influence of Cannabis Becoming a Greater Risk to Driver Safety than Drink Driving? Findings from a Longitudinal Study. Accident Analysis & Prevention, Vol. 40, No. 4, 2008, p. pp 1345-1350.
18. Ramaekers, J. G., M. R. Moeller, E. L. Theunissen, G. F. Kauert, and CRC Press. Validity of Three Experimental Performance Tests for Predicting Risk of Cannabis Induced Road Crashes, 2011, p. pp 45-1 – 45-8.
19. van Elslande, P., J. Y. Fournier, and M. Jaffard. Influence of Cannabis on Fatal Traffic Crashes: Detailed Analysis. Transportation Research Record: Journal of the Transportation Research Board, No. 2281, 2012, p. pp 43–50.
20. Hartman, R. L., and M. A. Huestis. Cannabis Effects on Driving Skills. Clinical Chemistry, Vol. 59, No. 3, 2013, p. pp 478-492.
21. Bergeron, J., and M. Paquette. Relationships between Frequency of Driving under the Influence of Cannabis, Self-Reported Reckless Driving and Risk-Taking Behavior Observed in A Driving Simulator. Journal of Safety Research, Vol. 49, 2014, p. pp 19-24.

22. Agic, B., G. Stoduto, G. Sayer, A. Ialomiteanu, C. M. Wickens, R. E. Mann, B. Le Foll, and B. Brands. Characteristics of People Who Report Both Driving after Drinking and Driving after Cannabis Use, 2013.
23. Asbridge, M., R. Mann, M. D. Cusimano, J. M. Tallon, C. Pauley, and J. Rehm. Cycling-Related Crash Risk and the Role of Cannabis and Alcohol: A Case-Crossover Study. Preventive Medicine, Vol. 66, 2014, p. pp 80-86.
24. Romano, E., R. B. Voas, and B. Camp. Cannabis and Crash Responsibility While Driving below the Alcohol per Se Legal Limit. Accident Analysis & Prevention, Vol. 108, 2017, p. pp 37-43.
25. White, M. Cannabis and Road Crashes: A Close Look at the Best Epidemiological Evidence, School of Psychology, University of Adelaide, South Australia, 2017.
26. Jewett, A., A. B. Peterson, and E. K. Sauber-Schatz. Exploring Substance Use and Impaired Driving among Adults Aged 21 Years and Older in the United States, 2015. Traffic Injury Prevention, Vol. 19, No. 7, 2018, p. pp 693-700.
27. Le Strat, Y., C. Dubertret, and B. Le Foll. Impact of Age at Onset of Cannabis Use on Cannabis Dependence and Driving under the Influence in the United States. Accident Analysis & Prevention, Vol. 76, 2015, p. pp 1-5.
28. Karush, S. Some Teens, Parents Think Mixing Pot and Driving Is OK. Status Report, Vol. 52, No. 8, 2017, p. n.p.
29. Aston, E. R., J. E. Merrill, D. M. McCarthy, and J. Metrik. Risk Factors for Driving After and During Marijuana Use. Journal of Studies on Alcohol and Drugs, Vol. 77, No. 2, 2016, p. pp 309-316.
30. Banta-Green, C., A. Rowhani-Rahbar, B. E. Ebel, L. M. Andris, Q. Qiu, and AAA Foundation for Traffic Safety. Cannabis Use among Drivers Suspected of Driving Under the Influence or Involved in Collisions: Analyses of Washington State Patrol Data, 2016, p. 35p.
31. Scherer, J. N., R. Silvestrin, F. Ornell, V. Roglio, T. R. V. Sousa, L. Von Diemen, F. H. P. Kessler, and F. Pechansky. Prevalence of Driving under the Influence of Psychoactive Substances and Road Traffic Crashes among Brazilian Crack-Using Drivers. Drug and Alcohol Dependence, Vol. 168, 2016, p. pp 255-262.
32. Peterson, A. B., E. K. Sauber-Schatz, and K. A. Mack. Ability to Monitor Driving Under the Influence of Marijuana among Non-Fatal Motor-Vehicle Crashes: An Evaluation of the Colorado Electronic Accident Reporting System. Journal of Safety Research, Vol. 65, 2018, p. pp 161-167.
33. Lee, J., A. Abdel-Aty, and J. Park. Investigation of Associations between Marijuana Law Changes and Marijuana-Involved Fatal Traffic Crashes: A State-Level Analysis. Journal of Transport & Health, Vol. 10, 2018, p. pp 194-202.
34. Sevigny, E. L. The Effects of Medical Marijuana Laws on Cannabis-Involved Driving. Accident Analysis & Prevention, Vol. 118, 2018, p. pp 57-65.
35. Das, S., and X. Sun. Association Knowledge for Fatal Run-off-Road Crashes by Multiple Correspondence Analysis. IATSS Research, Vol. 39, No. 2, 2016, pp. 146–155.
36. Das, S., and X. Sun. Factor Association with Multiple Correspondence Analysis in Vehicle–Pedestrian Crashes. Transportation Research Record: Journal of the Transportation Research Board, Vol. 2519, No. 1, 2015, pp. 95–103.
37. Das, S., R. Avelar, K. Dixon, and X. Sun. Investigation on the Wrong Way Driving Crash Patterns Using Multiple Correspondence Analysis. Accident Analysis & Prevention, Vol. 111, 2018, pp. 43–55.

38. Jalayer, M., M. Pour-Rouholamin, and H. Zhou. Wrong-Way Driving Crashes: A Multiple Correspondence Approach to Identify Contributing Factors. Traffic Injury Prevention, Vol. 19, No. 1, 2018, pp. 35–41.
39. Das, S., K. Jha, K. Fitzpatrick, M. Brewer, and T. H. Shimu. Pattern Identification from Older Bicyclist Fatal Crashes. Transportation Research Record: Journal of the Transportation Research Board, 2019.
40. van de Velden, M., A. I. D' Enza, and F. Palumbo. Cluster correspondence analysis. Psychometrika, 82(1), 2017, 158-185.
41. Lee, C., and X. Li. Analysis of injury severity of drivers involved in single-and two-vehicle crashes on highways in Ontario. *Accident Analysis & Prevention*, *71*, 2014, 286-295.
42. Farmer, C. M. Effect of electronic stability control on automobile crash risk. *Traffic injury prevention*, *5*(4), 2004, 317-325.
43. Chipman, M., and Y. L. Jin. Drowsy drivers: The effect of light and circadian rhythm on crash occurrence. *Safety Science*, *47*(10), 2009, 1364-1370.
44. Ranney, T. A. Driver distraction: A review of the current state-of-knowledge (No. HS-810 787), 2008.
45. Sewell, R., J. Poling, and M. Sofuoglu. The Effect of Cannabis Compared with Alcohol on Driving. The American Journal on Addictions. Vol 18 (3), 2009, 185-193.
46. NIDA. Effects of Marijuana – With and Without Alcohol – on Driving Performance.National Institute on Drug Abuse. June 23, 2015. https://www.drugabuse.gov/news-events/newsreleases/2015/06/effects-marijuana-without-alcohol-driving-performance. Accessed: July 2019.