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Single-Vehicle Run-Off Road Crashes Because of Cellphone Distraction: Finding Patterns with Rule Mining

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Abstract
A wide array of literature strongly indicates a higher likelihood of roadway departure because of cellphone use; however, patterns of associative attributes in single-vehicle run-off-road (SVROR) crashes because of cellphone distraction remained unexplored. Using the association rule mining (ARM) method, this study aimed to identify the variable categories that concurrently occur in such crashes, visualize the structures representing those concurrent associations, and discuss the crash patterns associated with different severity types. The SVROR crashes with cellphone use by the driver at fault were highlighted to be strongly connected to non-usage of safety restraints, weekends, both lighted and unlighted dark conditions, two-lane highways without physical separation, roadway curves, and so forth. Alongside several attributes, non-usage of restraints was strongly associated with fatal and both incapacitating and non-incapacitating injury crashes. The findings of this study can benefit the determination of suitable countermeasures to prevent cellphone-related SVROR crashes.

Keywords
run-off road, cell-phone use, distraction, roadway desparture, association rule mining

Distracted driving was identified as a growing traffic safety concern worldwide decades ago (*1–3*). The enormous rise in smart devices such as smart cellphones, tablets, and smartwatches in the last decade resulted in the noticeably higher engagement of drivers in secondary activities during the primary activity of driving (*4–7*). However, cellphone usage has emerged as a major source of distraction because of its versatile applications, ranging from cellphone conversations and texting, to browsing webpages, social media, navigational applications, and so forth (*8*). A wide array of research has already established that different forms of cellphone use are among the distracted driving behaviors that typically require drivers to deal with a high level of visual and cognitive demand, which all negatively affect normal reaction times in addressing a hazardous event (*9*, *10*), and therefore lead to higher risks of a crash or of near-crash situations (*11*, *12*). The latest data on driver electronic device use provided in Traffic Safety Facts shows an increase in cellphone manipulation from 1.3% in 2011 to 2.8% in 2020, implying the associated growing risk (*13*).

Single-vehicle run-off-road (SVROR) crashes are intricate in nature as they present a broad variety of circumstances triggered by environmental conditions (poor visibility because of inclement weather), roadway conditions (wet pavement surface, potholes/ruts in the roadway, etc.), vehicle conditions (brake failure, engine failure, etc.), and/or driver conditions (distraction, intoxication, drowsiness, etc.) (*14–16*). Among driver conditions, distraction has long been cited in roadway departure crashes, with the majority of those crashes resulting in SVROR events (*2*). Using common perception and circumstantial evidence from case studies, earlier studies identified cellphone use as a common issue, with drivers drifting out of their travel lane and off the edge of the roadway, and as a key reason for inadvertent roadside encroachments (*16–19*).

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Amid the rise of roadway departure crashes in recent years, addressing roadway departure through the application of strategic interventions remains one of the critical transportation safety goals in Louisiana. Distracted driving crashes, including crashes involving cellphone distraction, have remained consistently high and therefore are a key focus area in the Louisiana strategic highway safety plan (*20*). A smartphone application known as "Everdrive" tracked distraction along with other driving behaviors with the permission of its users and found that in Louisiana 43% of drives contained at least one distracted driving event, which is more than in any other state (*21*). Exploration of crash data in Louisiana also suggests that SVROR crashes in tandem with driver distraction are also consistently high, with a 13% increase from 2011 to 2020 (*22*). For an exclusive understanding of cellphone-related SVROR crashes, this study identified the key factors that might coexist in such crashes using the association rules mining (ARM) approach.

The paper has been organized as follows. The literature review section details the implications of SVROR crash risks identified in previous studies, the background of ARM in transportation safety analysis, and study objectives based on research gaps. The methodology section explains the data preparation, data description, and the key measures of the ARM method adopted for the analysis. The results and discussion section lists and visualizes the key rules of cellphone-related SVROR crashes, and also presents results specific to crash severity. The conclusions section summarizes the findings and discusses some countermeasure implications.

Literature Review

Cellphone Distraction and SVROR Crashes

Cellphone-affected distracted driving crashes in the U.S. are still high (*13*); however, the substantial underreporting of these crashes has been implicated in previous studies (*20*, *23–25*) as distracted drivers are often seriously injured or deceased, or are suspected to not be forthcoming about reporting cellphone use (*26*). Insufficient reporting of cellphone distraction fails to show its significance in run-off road (ROR) crashes (*27*) and could lead to biased results and misinterpretations (*28*, *29*). Roadway departure or ROR crash studies often exclude cellphone use as one of the contributory factors, possibly because of its substantial underreporting. Different studies have documented a wide range of effects on crash risk from cellphone usage while driving. There are at least two systematic review papers on cellphone-related driving studies (*30*, *31*). The trends in the literature show that there is a substantial lack of studies that exclusively analyze or highlight cellphone distraction-related SVROR crashes despite a direct possible linkage between roadway departure and cellphone use implicated by previous studies.

SVROR Risk by Cellphone Distraction

Previous study approaches revealed the quantified risks in experimental or non-experimental terms in their approaches to connecting roadway departure to cellphone usage. Survey research studies suggested that drivers using a cellphone while driving generally could have difficulty maintaining lanes (*32*). Frequent cellphone users also engage in faster driving, changing lanes more frequently, harder braking maneuvers, and faster acceleration (*33*), indicating driving patterns that could lead to a high likelihood of roadway departures. Results in driving simulation studies quantified the impact of cognitive demands because of cellphone use in relation to lateral control measures, which has generally shown a higher variability in drivers' lane maintenance that indicates a higher probability of roadway departure (*34–36*), especially in unpredictable driving conditions (*37*).

Naturalistic driving studies (NDS) also identified the prevalence of cellphone use within the secondary task distraction category, which resulted in roadway departure events (*12*, *38*). SVROR crashes are highly associated with maintaining lane position during driving. Speech comprehension tasks did not affect performance in keeping the vehicle in the designated lane, but they reduced comprehension tasks (*39*). Some studies reported that distracted drivers are associated with less lane deviation while conversing (*40*, *41*) but increased deviation while texting on their cellphones (*42*, *43*) in comparison with non-distracted drivers. Engaging in secondary tasks while driving is associated with deleterious effects on driving by increasing risk (*42*). On the contrary, some studies reported negligible and insignificant differences in lane-keeping while driving between the baseline and the distracted driving conditions (*39*, *44–46*). Several NDS from Strategic Highway Research Program Two (SHRP-2) also examined cellphone-related distractions while driving. These studies found that drivers were not always able to maintain their lateral position on the designated traffic way when distracted by a phone (*30*, *47*, *48*). A compilation of prior studies on experimental studies (simulator, naturalistic study, on-road, test track, etc.) also implied that dialing a cellphone could have a large effect on maintaining lateral position in relation to the combined estimates of standard deviations of lateral position, lane exceedance, and their effects on sample size (*49*). Table 1 assembles key findings from several selected studies that have implications associated with SVROR risk or likelihood because of cellphone use.

Table 1. Key Findings from Previous Studies

Reference	Data	Key findings
Liu and Ye (*28*)	The National Motor Vehicle Crash Causation Survey (NMVCCS) data of 2005-2007	Cellphone use could be associated with a high risk of SVROR crashes, though the association is not statistically significant.
Kim et al. (*29*)	California Crash Data of 2003-2004	A mixed logit analysis concluded that cellphone usage was somewhat related to injury severity in single-vehicle crashes.
Owens et al. (*12*)	NDS data from SHRP-2 (the second Strategic Highway Research Program)	Crash involvement due to cellphone use while driving has an odds ratio of 1.83 in relation to driving without cellphone use.
Rahman et al. (*14*)	Louisiana crash data (2005-2017)	Cellphone use while driving could be 1.527 times more likely to result in a roadway departure crash than a non-departure crash.
Lipovac et al. (*30*)	60 papers on mobile phone use from 1994 to 2013	Detrimental effects have been identified because of mobile phone use while driving.
Oviedo-Trespalacios et al. (*31*)	Eleven literature review/meta-analyses papers and 62 recent research articles from 2005 to 2015	Several forms of cellphone use could contribute to increase in lane deviations according to multiple studies.
Cao and Liu (*39*)	Simulated driving environment developed with Animator3D simulation in Micro Saint® Sharp	The results showed that the standard deviation of lane position (SDLP) was increased when the driving speed was faster. Mental workload was significantly higher in the dual-task condition compared with the single-task conditions.
Garrison and Williams (*40*)	Driving simulator and eye tracking	Performance measures indicated that distraction negatively impacted vehicle control.
Reimer et al. (*41*)	36 young adult drivers' eye movements, driving behavior, and task completion time	Standard deviation of lane position was the highest when not dialing a phone, followed by when dialing the flip phone, and was the lowest when dialing the iPhone.
McKeever et al. (*42*)	28 healthy individuals (12 female)	Comparison of task durations indicated that both texting tasks (i.e. typing and sending) took significantly longer to complete than the radio tuning task while driving.
Rudin-Brown et al. (*43*)	Twenty-four participants (25–50 years) drove in simulated highway and tunnel road environments while reading and writing text messages using their own mobile phones.	Driver distraction in tunnels is associated with generally similar driving decrements as freeway driving; however, the potential consequences of these decrements in tunnels remain significantly more serious.
Collet et al. (*44*)	Epidemiological studies that give an overview of cellphone use	The decision to answer or initiate a cellphone call while driving depends on complex interaction among several variables, including driving conditions and driver's own characteristics.
Irwin et al. (*45*)	Twenty-eight healthy individuals (13 female) participated in a crossover design study involving 3 experimental trials	Driving tasks involving texting and eating were associated with significant impairment in driving performance measures compared to baseline driving.
Young et al. (*46*)	Twenty-four participants (25–50 years) sent and received text messages on either a touch screen or numeric keypad phone while driving a simulated freeway environment.	Receiving and particularly sending text messages led to decrements in speed monitoring, decreased the amount of time spent looking at the forward roadway by up to 29%, and increased subjective workload.
Jeong and Liu (*47*)	Eye movements, lane-keeping performance, and subjective workload of 24 participants	Drivers performing non-driving-related tasks using visual stimuli or manual responses on curved roads fixated less frequently and with shorter durations on the road and showed poorer lane-keeping performance compared to other modalities.
Rumschlag et al. (*48*)	Fifty participants	Text task duration was significantly correlated with the number of lane excursions, and texting skill level and driver age were significantly correlated with the percent of subjects exhibiting lane excursions.

Note: SVROR = single-vehicle run-off-road; NDS = naturalistic driving studies.

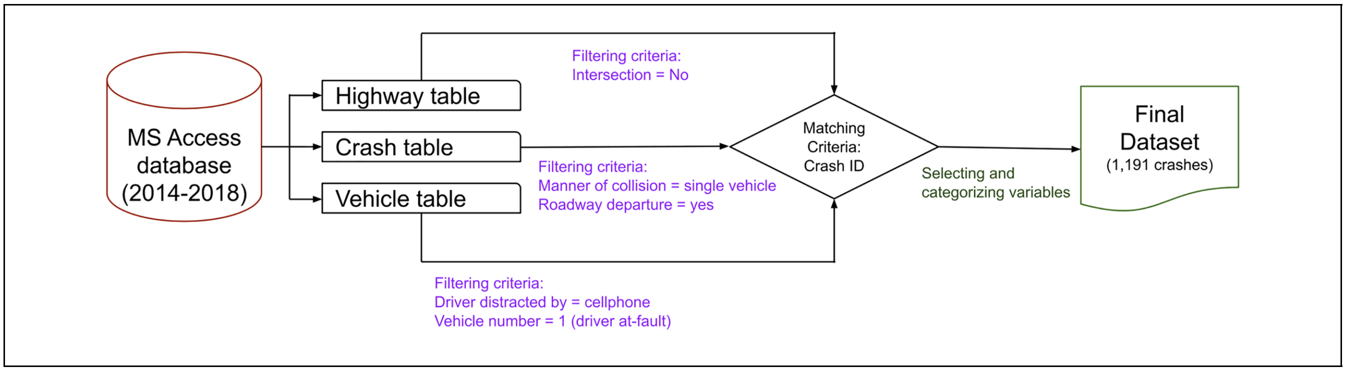

Figure 1. The framework for dataset preparation.

Association Rule Mining Approach

Association rule mining (ARM), a rule-based data mining method, has become popular in transportation safety research for exploring the collective association of multiple crash characteristics (*23*, *50–56*). ARM has also been identified as a potential decision-making tool for road safety agencies (*50*, *57*). As cellphone-related SVROR crashes will most likely include characteristics associated with drivers, vehicles, and roadways, analysis using ARM of a substantial sample of SVROR crashes with cellphone distraction could unveil the associations of crash variable categories that could simultaneously be present in such crashes. This study applied ARM to inspect the coexisting crash characteristics of SVROR crashes because of cellphone distraction and the coexisting factors associated with the severity of such crashes.

Study Objectives

Although a broad array of the literature implicates a high risk of lane deviation because of cellphone application, no previous studies have undertaken a comprehensive approach to identify and quantify the associative impacts of the factors in cellphone-related SVROR crashes. The specific objectives of this study were: (1) identify the variable categories that concurrently occur with single-vehicle crashes related to cellphone distracted driving; (2) visualize the structures representing concurrent associations of those variable categories; (3) identify the important characteristics exclusive to specific injury severity; and (4) discuss the patterns of associations of variable categories to implicate the connections toward possible recommendations.

Methodology

Data

Data Preparation. This study used five years (2014 to 2018) of traffic crash data collected from the Louisiana Department of Transportation and Development (DOTD). The Louisiana DOTD prepares annual comprehensive crash databases in Microsoft (MS) Access file format by compiling the crash data extracted from individual crash reports. The crash databases comprised several tables including highway, crash, and vehicle tables.

To find SVROR crashes because of drivers' cellphone use, the databases were filtered for three criteria: *manner of collision = single-vehicle, roadway departure = yes, and driver distracted by = cellphone*. The crashes were also filtered for drivers who were reported to be responsible for the crashes and who were using cellphones according to the code presented in the crash report. The variables were selected based on their availability, and the research team's presumable judgment for possible associations. The data for selected variables were extracted using structured query language (SQL) from Louisiana DOTD annual dataset of MS Access files. The annual datasets were merged and then categorized for each selected variable. The dataset preparation framework has been presented in Figure 1.

Data Description. Table 2 displays relative frequencies of crash attributes by presenting the percentage of categories within variables analyzed in this study. Crashes during dark conditions (both lighted and unlighted conditions) were more frequent than crashes in daylight. No passenger presence was expected to be frequent in cellphone-related SVROR crashes. Interestingly, the difference in frequencies between weekday and weekend crashes was very small. Day of the week was imputed as Friday 6 pm to Sunday 6 pm (weekend) and the rest of the week (weekday). Younger age groups—20 to 24 years and 25 to 34 years—were frequently involved in SVROR crashes associated with cellphone usage; it is important to note that drivers aged 17 years or less are not allowed to use cellphones while driving except in emergencies. Drivers' cognitive ability could be further diminished if cellphone use is compounded with alcohol intoxication

Table 2. Frequency and Distribution of Cellphone-Related SVROR Crash Characteristics

Variable	Category	Frequency	Percentage	Variable	Category	Frequency	Percentage
driver_age_group	15–19 y	170	14.27	lighting_condition	daylight	505	42.40
	20–24 y	241	20.24		dark_no_street_light	457	38.37
	25–34 y	359	30.14		dark_street_light	199	16.71
	35–44 y	214	17.97		dusk_dawn	27	2.27
	45–54 y	119	9.99		other	3	0.25
	55–64 y	64	5.37	weather_condition	clear	881	73.97
	65–74 y	17	1.43		cloudy	203	17.04
	⩾75 y	4	0.34		rain	87	7.30
	unknown	3	0.25		snow_sleet_hail	3	0.25
driver_gender	female	770	64.65		other	13	1.09
	male	417	35.01		unknown	4	0.34
	unknown	4	0.34	road_type	two-way_road_with_a_physical_separation	172	14.44
alcohol	BAC:0	1024	85.98		two-way_road_with_a_physical_barrier	75	6.30
	BAC:0-0.02	2	0.17		two-way_road_with_no_physical_separation	894	75.06
	BAC:0.02-0.08	26	2.18		one-way_road	48	4.03
	BAC:0.08-0.15	63	5.29		other	2	0.17
	BAC: ⩾0.15	76	6.38	alignment	straight-level	759	63.73
passenger_presence	more_than_one	30	2.52		straight-on-grade	18	1.51
	none	1054	88.50		straight-level-elevated	24	2.02
	one	107	8.98		straight-hillcrest	12	1.01
restraint_usage	properly_used	963	80.86		straight-dip-hump	2	0.17
	improperly_used	20	1.68		curve-level	307	25.78
	not_used	133	11.17		curve-on-grade	28	2.35
	unknown	75	6.30		curve-level-elevated	35	2.94
vehicle_type	car	533	44.75		curve-hillcrest	4	0.34
	van_suv	225	18.89		other	2	0.17
	light_truck	406	34.09	distance_from_intersection	500ft_or_less	331	27.79
	motorcycle	2	0.17		greater_than_500ft	836	70.19
	other	25	2.10		unknown	24	2.02
day_of_the_week	weekday	673	56.51	severity_type	fatal_and_incapacitating_injury	18	1.51
	weekend	518	43.49		non-incapacitating_injury	480	40.30
					no_injury	693	58.19

Note: SVROR = single-vehicle run-off-road; BAC = blood alcohol concentration.

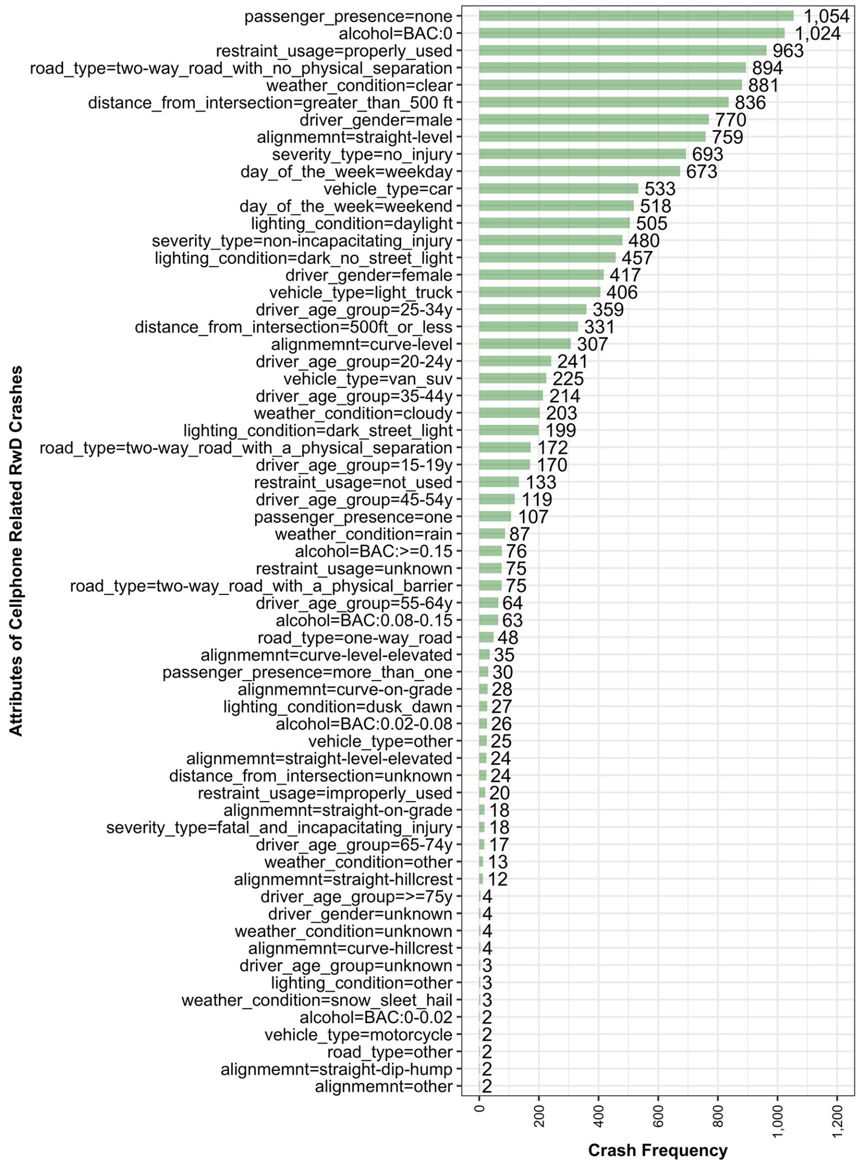

Figure 2. Frequency of crash characteristics in descending order.
Note: RwD = roadway departure; BAC = blood alcohol concentration.

(expressed by blood alcohol concentration, BAC, and measured by grams of alcohol in 100 milliliters of blood), but these crashes are less frequent. Drivers used restraints properly in the majority of the crashes, although the improper or non-use of protection systems (that is, seatbelt or helmet) could also be underreported in crashes. The majority of the crashes occurred on two-way roads without any barrier, where the probability of roadside encroachment is higher because of a lack of midblock separation or barrier. Male drivers are more involved in cellphone-related SVROR crashes than female drivers, which could also be because of the longer travel times of male drivers. The high frequency of crashes with passenger cars (44.75%) could be because of their large ownership compared to other vehicles. Less severe (no injury and non-incapacitating injury, 58.19% and 40.30% respectively) crashes are highly prevalent, but it needs to be considered that cellphone usage during fatal and severe crashes could still be underreported, especially in the absence of passengers.

Figure 2 presents all of the attributes in the final dataset, presenting cellphone-related SVROR crash characteristics in descending order by frequency. The chart shows that most of the crash characteristics are associated with the most prevalent conditions, such as *weather_condition = clear, roadway_alignment = straight_level, lighting_condition = daylight, day_of_the_week = weekday*, and so forth.

To avoid using highly correlated variables in the association rules, an analysis of the Goodman and Kruskal tau was performed. The Goodman and Kruskal tau measure is an asymmetric association measure between two categorical variables, based on the extent to which variation in one variable can be explained by the other (*58*). The highest correlative association was only 0.13, found between vehicle type and driver gender. The correlations between other variables were low, indicating that the exclusion of any pre-selected variables is not required because of multicollinearity.

Association Rule Mining

As a nonparametric method, the ARM does not require any parametric assumptions. While statistical modeling typically assumes independence among dependent variable choices or attributes, the ARM does not require any predictor variable to identify associations among independent attributes. There are different data mining and dimension reduction techniques such as correspondence analysis and k-means clustering. Multiple correspondence analysis, a notable non-parametric method and a categorical form of principal component analysis, allows for the reduction of the number of original variables through their linear combinations usually in the form of two-dimensional plots. However, because of a loss of information in the process of dimensionality reduction, this method may result in associations of attributes where a two-dimensional depiction may not be sufficient. The ARM algorithm can overcome such restrictions and let users identify the associations through pre-specified measures. In addition, conventional regression analysis is not able to identify the sub-group effect in the data. The ARM can quantify interesting sub-group effects in the data with specific performance measures such as support, confidence, and lift. A brief theoretical description of ARM performance measures is described below.

Theoretical Background. Let $I = \{i_1, i_2, i_3, \ldots, i_n\}$ represent n crash attributes called items and $T = \{t_1, t_2, t_3, \ldots, t_m\}$ represent a set of databases with information about m number of crashes (observations) in the dataset. Each crash in T comprises a subset of items (a set of crash attributes).

Rule: A rule could take the form $A \rightarrow B$, where $A, B \subseteq I$ and $A \cap B = \varnothing$, where A is the antecedent (presented on the left-hand side) and B is the consequent (presented on the right-hand side). A rule contains one or more items in the antecedent and is often restricted to a single item in the consequent. The rules are quantified by three interest measures—support, confidence, and lift. Association rules usually have user-specified minimum support and minimum confidence.

Support: Support of any rule, $S(A \rightarrow B)$, can be estimated by the proportion of observations, which contain both the antecedent A and the consequent B.

Confidence: Confidence in the rule can be defined by $C(A \rightarrow B) = S(A \cup B)/S(A)$, where the support $S(A)$ of an itemset A is defined by the proportion of the observations that contain the itemset. Therefore, an association rule will satisfy two conditions: $S(A \rightarrow B) \geqslant \sigma$ and $C(A \rightarrow B) \geqslant \delta$, where σ and δ are minimum support and minimum confidence, respectively.

Lift: Lift of the rule $A \rightarrow B$ can be defined as $L(A \rightarrow B) = S(A \cup B)/(S(A) \times S(B))$ and is often interpreted as the deviation of the support of the whole rule from the support expected under independence provided by the support of both sides of the rule. A higher lift value ($L \gg 1$) of a rule indicates a stronger association.

ARM Algorithm Types. Several algorithms are available for exploring association rules—notably apriori, eclat, and FP-growth. This study used the apriori algorithm for ARM, which performs a breadth-first search in the dataset. Details of the apriori algorithm can be found in Agarwal and Srikant (*59*). Apriori algorithms perform better than eclat and FP-growth algorithms in datasets with higher itemset density (*60*).

Pruning of Association Rules. For a condensed representation of interesting associations, repeated and uninteresting rules were filtered out using two criteria. First, 2-itemset rules (i.e. a rule with one antecedent and one consequent) with interchanged antecedents and consequents with lower lift values were removed. Second, rules with the same consequent that have more items in the antecedent but lower lifts are known as super rules to the rules with smaller antecedents and higher lifts. These super rules were also removed as they do not provide any new knowledge.

Results and Discussion

Association rules were generated by running an apriori algorithm using the "arules" package (*61*) in R statistical software (*62*). The selections of minimum support and minimum confidence are optimized using an iterative approach (*23*, *52*), as $\sigma = 0.05$ and $\delta = 0.2$, respectively. Some studies used rules with lift values of $L > 1$; however, by setting up a lift condition of a higher value of $L > 1.2$, a total of 1,014 strongly associated rules were identified after pruning. Table 3 presents the top 30 rules ordered in relation to descending values of lift. Previously, results have been presented in relation to

Table 3. Top 30 Strongly Associated Rules in Descending Order by Lift Value

No.	Rule (Antecedent → Consequent)	Support (S) (%)	Confidence (C) (%)	Lift (L)
1	driver_gender = male, passenger_presence = none, severity_type = non-incapacitating_injury → restraint_usage = not_used	5	23.8	2.132
2	driver_gender = male, severity_type = non-incapacitating_injury → restraint_usage = not_used	5.5	22.9	2.052
3	lighting_condition = dark_street_light, alignment = straight-level → distance_from_intersection = 500ft_or_less	6.1	54.9	1.975
4	weather_condition = clear, road_type = two-way_road_with_no_physical_separation, severity_type = non-incapacitating_injury → restraint_usage = not_used	5.2	21.3	1.908
5	lighting_condition = dark_street_light, road_type = two-way_road_with_no_physical_separation → distance_from_intersection = 500ft_or_less	5	52.6	1.894
6	lighting_condition = dark_street_light, severity_type = no_injury → distance_from_intersection = 500ft_or_less	5.4	52.5	1.888
7	passenger_presence = none, restraint_usage = not_used, road_type = two-way_road_with_no_physical_separation → severity_type = non-incapacitating_injury	5.4	74.4	1.847
8	weather_condition = clear, distance_from_intersection = 500ft_or_less → lighting_condition = dark_street_light	6.2	30.7	1.838
9	passenger_presence = none, weather_condition = clear, severity_type = non-incapacitating_injury → restraint_usage = not_used	5.5	20.4	1.825
10	passenger_presence = none, day_of_the_week = weekend, lighting_condition = dark_no_street_light, road_type = two-way_road_with_no_physical_separation, distance_from_intersection = greater_than_500ft → alignment = curve-level	5	46.9	1.819
11	driver_gender = male, lighting_condition = dark_street_light → distance_from_intersection = 500ft_or_less	5.2	50.4	1.814
12	driver_gender = male, lighting_condition = dark_no_street_light, road_type = two-way_road_with_no_physical_separation, alignment = straight-level, distance_from_intersection = greater_than_500ft → vehicle_type = light_truck	5.7	61.8	1.813
13	road_type = two-way_road_with_no_physical_separation, severity_type = non-incapacitating_injury → restraint_usage = not_used	6.3	20.2	1.805
14	weather_condition = clear, severity_type = non-incapacitating_injury → restraint_usage = not_used	6.2	20.1	1.796
15	driver_gender = female, passenger_presence = none, restraint_usage = properly_used, lighting_condition = dark_no_street_light, severity_type = no_injury → vehicle_type = car	5.2	79.5	1.776
16	day_of_the_week = weekend, road_type = two-way_road_with_no_physical_separation, alignment = curve-level, distance_from_intersection = greater_than_500ft → lighting_condition = dark_no_street_light	5.7	68	1.772
17	driver_gender = female, passenger_presence = none, lighting_condition = dark_no_street_light, severity_type = no_injury → vehicle_type = car	5.5	79.3	1.771

(continued)

Table 3. (continued)

No.	Rule (Antecedent → Consequent)	Support (S) (%)	Confidence (C) (%)	Lift (L)
18	passenger_presence = none, lighting_condition = dark_street_light → distance_from_intersection = 500ft_or_less	7.2	49.1	1.768
19	driver_gender = male, lighting_condition = dark_no_street_light, road_type = two-way_road_with_no_physical_separation, distance_from_intersection = greater_than_500ft, severity_type = no_injury → vehicle_type = light_truck	6.1	59.8	1.755
20	lighting_condition = dark_street_light → distance_from_intersection = 500ft_or_less	8.1	48.7	1.754
21	driver_gender = female, alcohol = BAC:0, lighting_condition = dark_no_street_light, severity_type = no_injury → vehicle_type = car	5.2	78.5	1.754
22	passenger_presence = none, restraint_usage = not_used → severity_type = non-incapacitating_injury	6.6	70.5	1.75
23	day_of_the_week = weekend, weather_condition = clear, road_type = two-way_road_with_no_physical_separation, alignment = curve-level → lighting_condition = dark_no_street_light	5.3	66.3	1.728
24	restraint_usage = properly_used, day_of_the_week = weekend, lighting_condition = dark_no_street_light, road_type = two-way_road_with_no_physical_separation → alignment = curve-level	5.9	44.3	1.719
25	driver_gender = male, lighting_condition = dark_no_street_light, weather_condition = clear, distance_from_intersection = greater_than_500ft, severity_type = no_injury → vehicle_type = light_truck	5.2	58.5	1.716
26	driver_gender = female, lighting_condition = dark_no_street_light, severity_type = no_injury → vehicle_type = car	5.8	76.7	1.713
27	day_of_the_week = weekend, alignment = curve-level, distance_from_intersection = greater_than_500ft → lighting_condition = dark_no_street_light	5.9	65.4	1.705
28	alcohol = BAC:0, restraint_usage = not_used → severity_type = non-incapacitating_injury	6.2	68.5	1.7
29	restraint_usage = not_used → severity_type = non-incapacitating_injury	7.6	68.4	1.698
30	day_of_the_week = weekend, road_type = two-way_road_with_no_physical_separation, alignment = curve-level → lighting_condition = dark_no_street_light	7.1	65.1	1.697

Note: BAC = blood alcohol concentration.

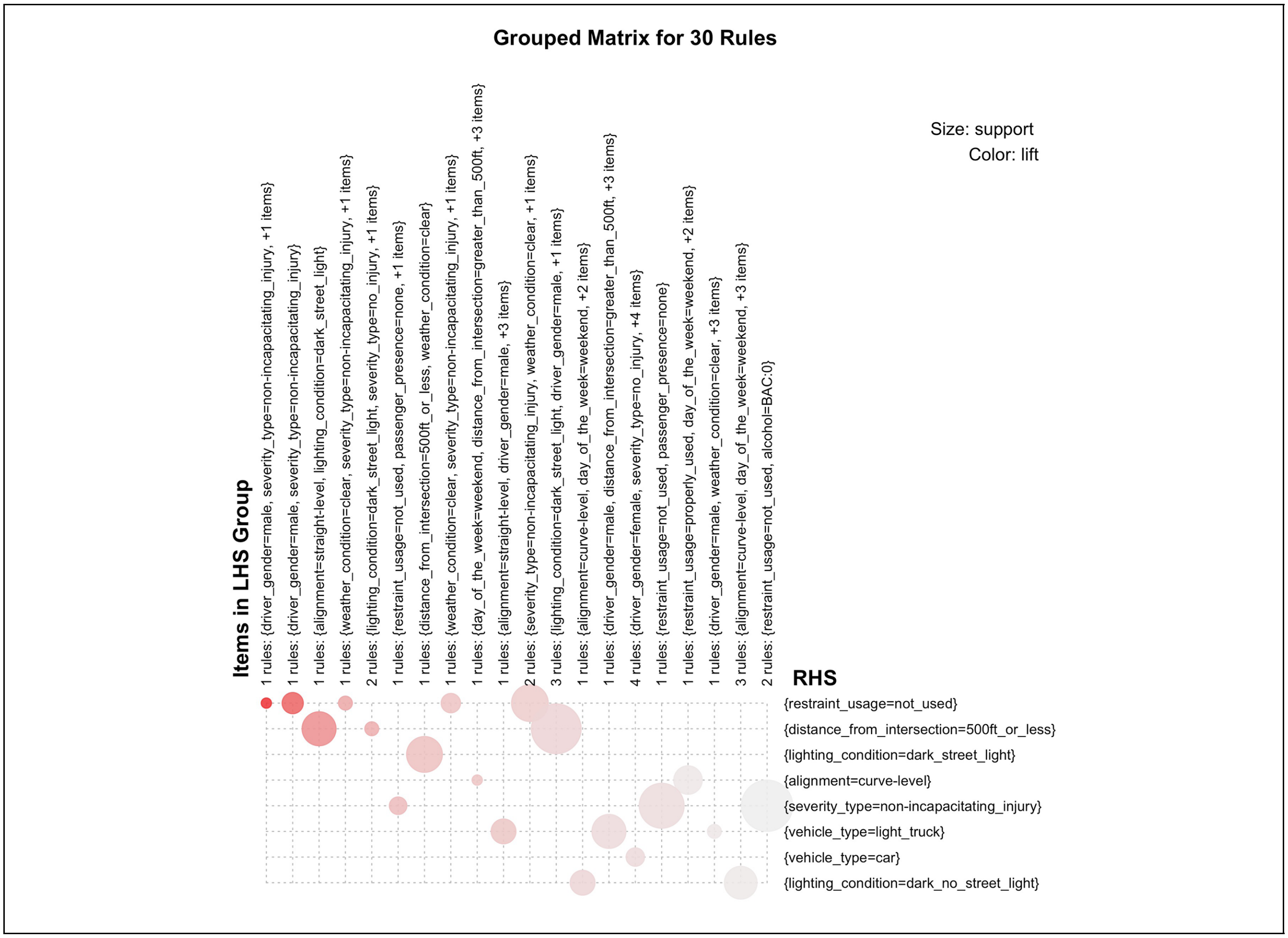

Figure 3. Top 30 rules visualized in grouped matrix method.
Note: LHS = left hand side (or, antecedent); RHS = right hand side (or, consequent); BAC = blood alcohol concentration.

higher support alongside higher lift values indicating more frequently present associations (*51*). For the sake of conciseness, the researchers selected only the top 30 rules ordered by lift, aiming to showcase rules with stronger associations.

Visualization of the Top 30 Rules

The rules identified can be visualized in several ways, and the two types of visualizations used for the top 30 high-lift rules presented were generated using the "arulesViz" package (*63*) for R software. In the grouped matrix method displayed in Figure 3, rules are presented in a matrix format with antecedents and consequents in rows and columns, respectively. Elements of the matrix (that is, rules) are presented by circles, of which bigger circles indicate higher support and circles with a deeper color indicate a higher value of lift.

The plot by graph method illustrated the network of variable categories connecting all antecedents and consequents through circles and arrows. While the antecedents are often summarized in the matrix method, the network in the graph method provides vivid details of the connections among all crash characteristics by representing each rule as a circle. The direction of arrows indicates whether the variable category is the left (outward for antecedents) or right (inward for consequents) side of a rule. Figure 4 displays all of the top 30 high-lift rules in a network using the graph method in the "arulesViz" package. Similar to Figure 3, nodes of a bigger circle size and deeper color indicate higher support and higher lift, respectively. The network provides an explicit visualization beneficial for understanding both the qualitative and quantitative interconnections that narrate the results in the following subsections.

Patterns of Associative Crash Characteristics

From the repetitive presence of associative characteristics, the SVROR crashes with cellphone use by the driver

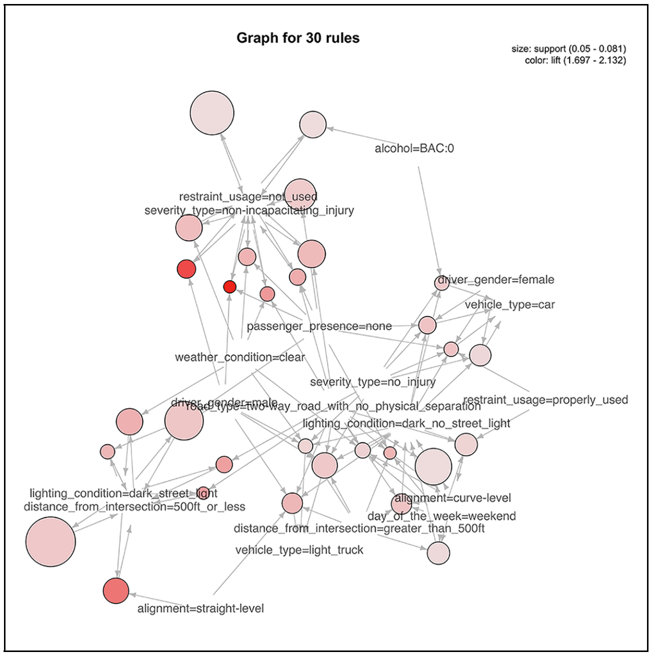

Figure 4. Visualization of top 30 rules by graph method.
Note: BAC = blood alcohol concentration.

at fault can be highlighted to be strongly connected to driving behaviors such as non-use of restraints (seatbelt, helmet, etc.), specific days (such as weekends), both lighted and unlighted dark conditions, road characteristics (such as two-lane highways without physical separation), curved roadway alignment, both close to and away from intersections, and so forth. The key takeaways from the patterns that provide possible linkages for the perceived coexistence of features in cellphone-related SVROR crashes based on the understanding of the top 30 strongly associated rules and their visualizations are as follows:

- The combination of nighttime driving and cellphone use appears to be strongly influential for SVROR crashes. Poor visibility because of unlighted (that is, absence of streetlights) dark conditions poses a serious risk, especially away from intersections (rules 10, 12, 16, 19, 25, 27) on two-way roads with no physical separation (rules 10, 12, 19, 23, 24, 30). Even with the presence of streetlights at intersections (rules 3, 5, 6, 8, 11, 20), crashes occurred within 500 ft of intersections.
- Driving during the weekend is linked to cellphone-related SVROR crashes. These weekend crashes can further be associated with curve roads, dark conditions in the absence of streetlights, and two-way roads with no physical separation (rules 10, 16, 23, 24, 30).
- Negotiating a horizontal curve while using a cellphone is a strong factor that triggers roadway departures on two-way roads with no physical separation on both left and right sides. ‘Curve-level roads’ can be distinguished by a large frequency (Figures 2 and 3) and their presence in antecedents in several strongly associated rules (rules 4, 5, 7, 10, 13, 16, 19, 24, 30).
- Vehicle type has been identified to be linked to driver gender in cellphone-related SVROR crashes. More distinctively, male drivers driving light trucks (rules 12, 19, 25) alongside other driving conditions are more likely to be involved in crashes, whereas female drivers driving passenger cars are involved in crashes in different scenarios (rules 15, 17, 21, 26).
- No specific driver age group was featured in the top 30 high-lift rules. Although only young drivers are conventionally perceived to be linked to cellphone distracted driving crashes, the impact of cellphone distraction in SVROR crashes has expanded to other age groups.
- Drivers who engage in cellphone use and are at fault in SVROR crashes are less likely to wear seatbelts. Driver’s non-usage of restraints has been present in multiple rules; as a consequent, this driving behavior can be associated with a few antecedents more than once—male drivers, absence of passengers, and non-incapacitating injury crashes (rules 1, 2, 3, 9).
- Passenger cars and light trucks can be found as consequents in several rules; however, they are associated with a specific set of characteristics. Crashes with passenger cars have been related more to female drivers driving in unlighted dark conditions in the absence of passengers (rules 15, 17). Crashes with light trucks, on the other hand, are associated with male drivers driving away from intersections on unseparated rural two-lane roads in unlighted dark conditions (rules 19, 25).
- The absence of passengers is a substantially strong trigger for cellphone use that leads to SVROR crashes, which could further be coupled with the non-use of restraints, another negative driving behavior (rules 7, 9, 22).
- Crashes with non-incapacitating injuries and no injuries could be found in several rules presented; however, fatal or incapacitating injuries, involved in only 1.5% of the crashes in the datasets, did not feature any of the top 30 high-lift rules. ‘No injury’ crashes have been present in consequents in the top 30 rules; rather, they can only be found only in antecedents in several rules.

- Non-incapacitating injury as consequents (rules 22, 28, 29) has been linked with the non-usage of safety restraints and the absence of passengers. Unlike non-incapacitating injury crashes, drivers were properly restrained in no injury crashes (rule 15)

Quantitative Findings by Interest Measures. Each rule represents a separate prevalent crash scenario in which the presence of crash characteristics can be quantified. Rules can be interpreted based on the user requirement and representative support, confidence, or lift values. For example, rule 1 with the highest lift in Table 2 is *driver_gender = male, passenger_presence = none, severity_type = non-incapacitating_injury → restraint_usage = not_used* (support = 5%, confidence = 24%, lift = 2.132). The support value implies that 5% of the SVROR crashes with reported cellphone use resulted in a non-incapacitating injury involving the absence of passengers with male drivers at fault who did not use restraints. The confidence value implies that, among the collective association of the antecedents in those crashes, 24% did not use restraints.

The lift values quantify the likelihood of crash involvement of one particular factor (consequent) in relation to a collective association of factors (antecedents) (*59*). Additionally, a comparison of rules for the presence of factors provides insights on the likelihood of crashes as well. Key meaningful interpretations of cellphone-related SVROR crashes based on lift values are as follows:

- The high lift value of 2.132 in rule 1 can be interpreted as the proportion of a specific crash condition (cellphone-related SVROR crash with a male driver without passenger presence resulted in a non-incapacitating injury) with non-usage of restraints was 2.132 times the proportion of all crashes with those specific crash conditions.
- The likelihood that a driver at fault did not use restraints (that is, driver protection system—seatbelt/helmet) in crashes that resulted in non-incapacitating injury is 2.052 times more likely with a male driver (rule 2) and 1.805 times more likely on a two-way roadway with no physical separation (rule 13).
- Conversely, non-usage of restraints could pose about 1.7 times more likelihood of a non-incapacitating injury (rule 29), and 1.75 times in absence of passengers (rule 22).
- Close to intersections and under lighted dark conditions, the likelihood of a cellphone-related SVROR crash increases from 1.754 (rule 20) to 1.768 (rule 18) because of passenger absence.
- The presence of a horizontal curve could have 1.819 times the likelihood of an SVROR crash with a driver's cellphone use during weekends in absence of passengers on an unlighted two-way roadway with no physical separation (rule 10).
- Regardless of passenger presence in clear weather, the likelihood of this crash on a horizontal curve comes down to 1.728 considering the remaining conditions are the same (rule 24).

Rules by Injury Severity. Identifying contributing factors associated with specific injury types can prioritize factors and enable researchers to compare and contrast factors by injury type. The top 30 high-lift rules identified in Table 3 offer a multitude of collective associations regardless of crash severity. Using this approach, one rule (rule 29) offers information on non-incapacitating injury in relation to its association with the non-use of restraints. However, by specifying injury type in the consequent, the ARM algorithm provides rules specific to injury types. Since the frequency of crashes by injury type is unequal, ordering the rules by support value is more logical. Specifically, in the cases of fatal and incapacitating injury crashes where the frequency is considerably small, a lift value could be disproportionately high or low with regard to the frequency of one contributing factor. Table 4 presents the top 10 rules segregated by each severity group and ordered by support values.

Apart from the normal driving conditions (that is, weekday, daylight, clear weather, and no alcohol), with female drivers (rules A2, A8), one passenger present (rules A3, A10), and non-use of restraints (rule A4), there were two notable specific individual findings for fatal and incapacitating injury crashes. Although the presence of a passenger is less likely to trigger cellphone use, the presence of multiple occupants (both driver and passenger) in the vehicle should increase the risk of fatal and incapacitating injury. In non-incapacitating injury crashes, the important factors are non-use of restraints, female drivers, two-way roadways with no separation, away from intersections, curve-level roadway, van and SUV, and so forth. The absence of passengers and no restraint use are two associative negative factors that can be found in multiple top 10 rules (rules B2, B10). Consistent with the earlier findings of no injury crashes in Table 2, they are more associated with the proper use of restraints. Interestingly, no injury crashes are also associated with male drivers, weekends, absence of passengers, straight-level roads, two-way roads with no separation, no alcohol, and so forth.

The strength of ARM is in its performance measures such as lift. Rules with high lift values indicate that these patterns are more likely to occur compared to other probable patterns. From a geometric point of view,

Table 4. Top 10 Strong Rules for Each of the Three Severity Groups in Descending Order by Support Value

#	Antecedent	Support (S) (%)	Confidence (C) (%)	Lift (L)
A	**Fatal and severe injury crashes, S $\geqslant$ 0.005, C $\geqslant$ 0.015, L $>$ 1.2**			
A1	alcohol = BAC:0, day_of_the_week = weekday	0.9	1.8	1.203
A2	driver_gender = female	0.7	1.9	1.269
A3	passenger_presence = one	0.6	6.5	4.329
A4	restraint_usage = not_used	0.6	5.3	3.482
A5	alcohol = BAC:0, day_of_the_week = weekday, lighting_condition = daylight	0.6	2.3	1.509
A6	day_of_the_week = weekday, lighting_condition = daylight	0.6	2.2	1.434
A7	alcohol = BAC:0, lighting_condition = daylight, weather_condition = clear	0.6	2.1	1.362
A8	driver_gender = female, alcohol = BAC:0	0.6	1.9	1.283
A9	lighting_condition = daylight, weather_condition = clear	0.6	1.9	1.272
A10	passenger_presence = one, weather_condition = clear	0.5	7.7	5.09
	Non-incapacitating injury crashes, S $\geqslant$ 0.05, C $\geqslant$ 0.7, L $>$ 1.2			
B1	restraint_usage = not_used	7.6	68.4	1.698
B2	passenger_presence = none, restraint_usage = not_used	6.6	70.5	1.75
B3	restraint_usage = not_used, road_type = two-way_road_with_no_physical_separation	6.3	72.1	1.789
B4	restraint_usage = not_used, weather_condition = clear	6.2	69.8	1.732
B5	alcohol = BAC:0, restraint_usage = not_used	6.2	68.5	1.7
B6	vehicle_type = van_suv, weather_condition = clear, road_type = two-way_road_with_no_physical_separation	6	56.3	1.398
B7	day_of_the_week = weekday, weather_condition = clear, alignment = curve-level	5.7	55.3	1.372
B8	driver_gender = female, lighting_condition = daylight, distance_from_intersection = greater_than_500ft	5.7	55.3	1.372
B9	vehicle_type = van_suv, road_type = two-way_road_with_no_physical_separation, distance_from_intersection = greater_than_500ft	5.5	56.9	1.412
B10	passenger_presence = none, restraint_usage = not_used, weather_condition = clear	5.5	73	1.812
	No injury crashes, S $\geqslant$ 0.1, C $\geqslant$ 0.65, L $>$ 1.2			
C1	driver_gender = male, restraint_usage = properly_used, day_of_the_week = weekend	16.4	71.4	1.228
C2	driver_gender = male, passenger_presence = none, restraint_usage = properly_used, weather_condition = clear, alignment = straight-level	15.8	69.9	1.201
C3	driver_gender = male, passenger_presence = none, restraint_usage = properly_used, road_type = two-way_road_with_no_physical_separation, alignment = straight-level	15.6	69.9	1.202
C4	driver_gender = male, passenger_presence = none, restraint_usage = properly_used, day_of_the_week = weekend	14.9	72.1	1.239
C5	driver_gender = male, alcohol = BAC:0, restraint_usage = properly_used, day_of_the_week = weekend	13.1	71.6	1.23
C6	driver_gender = male, restraint_usage = properly_used, weather_condition = clear, road_type = two-way_road_with_no_physical_separation, alignment = straight-level	12.8	71.2	1.223
C7	driver_gender = male, restraint_usage = properly_used, day_of_the_week = weekend, road_type = two-way_road_with_no_physical_separation	12.7	72.2	1.242
C8	driver_gender = male, alcohol = BAC:0, passenger_presence = none, restraint_usage = properly_used, day_of_the_week = weekend	12	73	1.254
C9	driver_gender = male, passenger_presence = none, restraint_usage = properly_used, weather_condition = clear, road_type = two-way_road_with_no_physical_separation, alignment = straight-level	11.8	71.6	1.23
C10	driver_gender = male, passenger_presence = none, restraint_usage = properly_used, day_of_the_week = weekend, road_type = two-way_road_with_no_physical_separation	11.5	72.9	1.252

Note: BAC = blood alcohol concentration; bold texts represent threshold of support, confidence, and lift values applied for each severity group.

curves, two-lane undivided roadways, and no lighting at night pose risks associated with cellphone distraction-related crashes. Improving roadways by providing more space to return to the lane, proper lighting at night, adequate curve signs, and reduction of speed limits can improve safety. From the behavioral point of view, male drivers, not using restraints, and single occupant driving pose risks associated with cellphone distraction-related traffic crashes. Driver education and the increase of safety message distribution can be beneficial in improving safety. Based on the newly adopted Safe System approach, roads should be designed in such a way that roadway users can avoid crashes or near-crash situations because of any errors they make while using the roadways.

Conclusions

As cellphone use-related distracted driving is likely to significantly affect road safety in upcoming years, an unprecedented increase in cellphone use calls for an extended investigation of its associated significant crash types. Cellphone use is one of the most distinguishable risky driving behaviors, whereas SVROR crashes are one of the most consequential driving outcomes of human errors. The convergence of these two specific areas underlines the urgency of studying the link between cellphone use and SVROR crashes. This paper mitigates the research gap by providing an improved understanding of the collective contribution of multiple characteristics leading to SVROR crashes because of cellphone use. Using the popular unsupervised algorithm ARM, this research particularly investigated the key patterns of crash, roadway, and vehicle features on a 5-year crash dataset from Louisiana.

The results from the top 30 high-lift association mining rules have been described in two different approaches: qualitative patterns of associative characteristics and quantitative measures of crash likelihood. The visualization of the association of crash characteristics facilitates the understanding of the simultaneous presence of important features. The association rules generated in this research provide strong implications for several interesting interconnections; a few examples are poor visibility because of unlighted dark condition away from intersections on two-way roads with no physical separation, nighttime driving during the weekends on curve roads with no streetlights, male drivers driving without safety restraints in the absence of passengers resulting in non-incapacitating injury, and so forth. In specific crash scenarios as a combination of multiple characteristics in the form of antecedents, the lift values in the rules quantify the likelihood of crash contributory factors such as the absence of passengers or non-usage of restraints in the form of one antecedent. Rules segregated by injury types as consequents reveal female drivers and non-use of restraints are more likely to be associated with both 'fatal and incapacitating' and 'non-incapacitating' injury types of crashes. The presence of one passenger is associated with fatal and incapacitating injury crashes, whereas curve-level roads are associated with non-incapacitating injury crashes. The notable factors of no injury crashes are male drivers, absence of passengers, weekends, and so forth. The magnitude of contributory factors should be greatly beneficial in understanding the mechanism of cellphone-related SVROR crashes and the effectiveness in strategic applications of countermeasures.

The results of this study strongly implicate the practicality of countermeasures. Improving nighttime visibility on two-lane roadways away from intersections could help prevent vehicles with cellphone distracted drivers from running off the roadway. Researchers should look into different measures to warn drivers near intersections, as streetlights may not be sufficient for preventing cellphone distracted drivers from roadway departure crashes. Restraint usage makes a difference between non-incapacitating injury and no injury severity outcomes from an SVROR crash with a cellphone distracted at-fault driver. It could also be investigated if the safety programs for preventing cellphone distracted driving in young drivers need to be expanded toward a relatively older generation of drivers.

This study provides a foundation for understanding the associative crash characteristics of cellphone-related SVROR crashes. This study does not include operating speed data as the current crash database does not have operating speed information on about 85% of crashes. The inadequate reporting of operating speed compelled the researchers not to include this variable to avoid biased results (*64*). Additionally, identifying crash factors segregated by cellphone distraction type would be more convenient, provided more specific information on cellphone use type is known. In the current crash data collection from Louisiana, specific cellphone use, categorized by talking, texting/manipulating, and so forth, is also not included in the crash database as suggested in the guidelines of the national motor vehicle data collection from the collaboration national organizations (*65*). Any strategic policy-based approach that works by identifying a demographic of drivers for targeted safety education, or enforcement implementation to prevent cellphone-related crashes, including SVROR, could be facilitated by sufficient reporting of cellphone distraction types. Underreporting of distraction-related crashes needs to be further studied at local levels.

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Author Contributions

The authors confirm their contribution to the paper as follows: study conception and design: M. Ashifur Rahman and S. Das; data collection: M. Ashifur Rahman; analysis and interpretation of results: M. Ashifur Rahman and S. Das; draft manuscript preparation: M. Ashifur Rahman, S. Das, and X. Sun. All authors reviewed the results and approved the final version of the manuscript.

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