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Data mining approach to explore emergency vehicle crash patterns: A comparative study of crash severity in emergency and non-emergency response modes

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ABSTRACT

Emergency vehicle crashes, involving police vehicles, ambulances, and fire trucks, pose a serious traffic safety concern causing severe injury and deaths to first responders and other road users. However, limited research is available focusing on the contributing factors and their interactions related to these crashes. This research aims to address this gap by 1) identifying patterns of emergency vehicle crashes based on severity levels in both emergency and non-emergency modes and 2) comparing the associations by response modes for the related fatal, nonfatal injury, and no-injury crashes. Two national crash databases, Fatality Analysis Reporting System (FARS) and Crash Report Sampling System (CRSS), were utilized for police-reported emergency vehicle crashes from January 2016 to February 2020. Association rule mining (ARM) was employed to reveal the association between factors that strongly contributed to these crashes. The generated rules were validated using the lift increase criterion (LIC). The results showed the complex nature of risk factors influencing the severity of emergency vehicle crashes. The fatal consequences of speeding with no seatbelt usage were evident for emergency mode, whereas none of these risky driving attributes was observed for non-emergency mode. In addition, the analysis identified the risk of fatal emergency vehicle crashes involving pedestrians in dark-lighted conditions in both response modes. Regarding nonfatal injury severity, angle collisions were more likely to occur at urban intersections during emergencies, while rear-end crashes were more frequent on segments with a posted speed limit of 40–45 mph during non-emergency incidents. The outcomes also revealed that the no-injury crashes involving fire trucks exhibited different patterns depending on the response mode. The findings of this study can guide in making effective strategies to improve safe driving behavior of first responders. The identified associations provide insights into the factors that can be controlled to ensure safe operation of emergency vehicles on the road.

1. Introduction

Emergency vehicles are designated and authorized to respond promptly during an emergency to ensure critical services for protecting health, property, life, and the environment. The three main categories of emergency vehicles include police vehicles, ambulances, and fire trucks. In the U.S., there are over 400,000 police vehicles, 45,000 ambulances, and 150,000 fire trucks dedicated to rescuing individuals during emergencies (Fahy et al., 2021; Gaines et al., 2015). First responders (e.g., police officers, emergency medical service personnel, and firefighters) often travel in emergency mode to arrive at the scene as quickly as possible. In the meantime, they need to ensure safe driving under numerous hazardous road and traffic circumstances, including reckless drivers, congested roads, and multi-faceted distractions (Hsiao et al., 2018). In addition to their emergency duties, each law enforcement officer (LEO) regularly performs several responsibilities, including investigating road collisions, patrolling, assisting motorists, and overseeing work zones. Therefore, they face a heightened risk of collisions and injuries associated with frequent driving involvement in emergencies under high work pressure (IAFF, 2006; LaTourrette, 2015). Recent and past crash statistics in the U.S. can provide a few insights into these hazards. Between 2016 and 2019, an average of 82 fatalities resulted

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from collisions involving emergency vehicles. The National Highway Traffic Safety Administration (NHTSA) reported approximately 88 fatal crashes involving emergency vehicles in 2019, representing a nearly 24% increase from 2016. More than 55% of these fatalities involved drivers or passengers of non-emergency vehicles, and approximately 76% of the crashes occurred during the emergency mode of travel. Although these deaths account for a small proportion of total traffic fatalities, the risks associated with emergency vehicle collisions and the resulting casualties are significantly higher when considering the exposure of these vehicle types (Maguire et al., 2002). The International Association of Fire Fighters (IAFF) and the U.S. Fire Administration (USFA) published the "Best Practices for Emergency Vehicle and Roadway Operations Safety in the Emergency Services" in 2010, which provides up-to-date safety guidelines for emergency vehicles (IAFF, 2006).

During emergencies, the first responders are often granted a 'code 3 running' option, allowing them to exceed the posted speed limits, use flashing lights and sirens, and bypass the traffic control signs and signals to optimize travel time (USFA, 2014). However, the implementation of this policy depends on the standard operating procedures (SOPs) of the corresponding agencies and state traffic regulations (Hsiao et al., 2018). It is important to note that authorized emergency speeding can result in severe injuries and fatalities (Missikpode et al., 2018). Although the weight of large emergency vehicles (e.g., fire trucks) provides additional protection to first responders, their size poses a threat to occupants of other vehicles, as well as road users (e.g., bicyclists and pedestrians), in crash incidents (Donoughe et al., 2012). Therefore, the distinct characteristics of emergency vehicles and driving during emergencies can significantly influence the likelihood of crashes. Besides, crash involvement of first responders generates unwanted delays in providing emergency assistance. Acknowledging this urgency, Congress has directed the NHTSA to explore the characteristics of emergency vehicle crashes (THUD, 2020), which advocates for an in-depth investigation to determine the complexities of underlying factors contributing to these collisions. From the safe system perspective, each crash results from a combination of multiple factors covering road, environment, infrastructure, and human characteristics (Das et al., 2023; FHWA, 2021; Hossain et al., 2021a). Following the concept, this study aims to identify the grouping of risk factors affecting the severity of emergency vehicle crashes. The relevant fatal and nonfatal crash information is utilized from two national crash databases, Fatality Analysis Reporting System (FARS) and Crash Report Sampling System (CRSS), from January 2016 to February 2020. The extracted crash information is combined to create two separate crash datasets based on response modes (emergency and non-emergency run). Finally, association rule mining (ARM) was applied in each dataset to reveal the meaningful associations among crash contributing factors for different crash severity levels.

2. Literature review

2.1. Contributing factors of emergency vehicle crashes

Several studies have concentrated on the multitude of contributing traits to distinguish the significant crash attributes related to emergency vehicle driving. While the majority of emergency vehicle drivers fall within the age range of 25 to 44 (Savolainen et al., 2009), older first responders aged 50 and above are more likely to be involved in collisions with high injury severity (Abdelwanis, 2013). However, the impact of aging on crashes can be minimal as most assigned drivers are well-trained and skilled professionals (Abdelwanis, 2013; Savolainen et al., 2009). It is worth mentioning that emergency vehicle drivers have to go through driver education training courses that satisfy the affiliated state and federal requirements (Savolainen et al., 2009; USFA, 2014). A few agencies and departments organize these training continually at regular intervals to reminisce the driving skills required in complex road surroundings (IAFF, 2006). Several studies have observed a high proportion of male emergency vehicle drivers (ranging from 70% to 85%) and have concluded that driver gender does not have a substantial impact on the risk of crashes (Abdelwanis, 2013; Clarke et al., 2009; Savolainen et al., 2009). Crash-involved first responders often drive without safety restraint devices (Peterson et al., 2009; Yasmin et al., 2012), although the severe consequences of unrestrained driving have been well-documented (Hossain et al., 2021b; Hossain et al., 2022). Hsiao et al. (2015) inferred that the seatbelt arrangement in fire trucks might not adequately accommodate firefighters wearing heavy personal protective equipment, highlighting the need for updated specifications to make the seatbelt system more flexible for larger emergency vehicles. Due to intense time pressure (Clarke et al., 2009), emergency vehicle drivers are more prone to speeding and other risky driving behaviors during emergency runs (De Graeve et al., 2003; Savolainen et al., 2009), which can significantly increase the likelihood of severe injuries (Savolainen et al., 2009).

Compared to other emergency vehicles, police vehicles show a higher risk of collisions during emergency responses (Missikpode et al., 2018). Ambulances and fire trucks, on the other hand, benefit from their larger size, which enhances their visibility to other road users. However, these vehicles are less capable of quickly altering speed than police cars. In relation to environmental characteristics, nonfatal collisions involving emergency vehicles predominantly occur during daylight hours and on weekdays (Drucker et al., 2013; Ray and Kupas, 2007; Savolainen et al., 2009). Conversely, fatal crashes are more frequent during the evening and midnight hours (Abdelwanis, 2013; Fu and Vaca, 2011). Drivers tend to show more risky and aggressive behaviors at night due to reduced traffic volume (Hossain et al., 2021b). Inclement weather conditions such as heavy rain, icy roads, and snow-covered roads can influence emergency vehicle driving (USFA, 2014), as it becomes more challenging for drivers to maintain control over their vehicles. At signalized intersections, non-emergency vehicle drivers occasionally fail to yield the right-of-way to the forthcoming emergency vehicles (Kahn et al., 2001), resulting in a higher severity of injuries (Polders et al., 2015). In light of this, the USFA strongly recommends that first responders visually confirm that all surrounding vehicles have yielded, even when operating in 'code 3 running', before proceeding through intersections (USFA, 2014).

The majority of fatal and severe crashes involving emergency vehicles tend to occur on roadways with high posted speed limits (Abdelwanis, 2013; Savolainen et al., 2009). These road classes often require a greater stopping distance, which can be critical for emergency vehicles with significant forward momentum (Robertson and Baker, 1976). Most stop-controlled and signalized intersections are centered in urban environments; therefore, a high fraction of severe crashes involving emergency vehicles is pronounced in those locations (Drucker et al., 2013; Ray and Kupas, 2007). Pirrallo and Swor (1994) indicated that a substantial percentage of ambulance crashes involved pedestrians, but no significant variations were observed between emergency and non-emergency response modes. Several studies have conveyed that injury crashes of emergency vehicles during emergency use are more prevalent at intersections and on roadways with traffic signals (Custalow and Gravitz, 2004; Drucker et al., 2013; Pirrallo and Swor, 1994; Sanddal et al., 2010). In relation to collision types, angle crashes are more likely to be associated with emergency vehicles, predominantly occurring at the turning phases of intersections (Abdelwanis, 2013; Ray and Kupas, 2007).

2.2. Study objectives

Most prior literature on emergency vehicle collisions has applied simple descriptive statistics (Donoughe et al., 2012; Ray and Kupas, 2007) or parametric modeling approaches (e.g., regression models) (Drucker et al., 2013; Missikpode et al., 2018; Savolainen et al., 2009; Yasmin et al., 2012) to examine the statistically significant risk factors influencing these incidents. However, these models rely on predefined hypotheses, such as mutually exclusive covariates, which may not always be valid (Hossain et al., 2023). For example, the impact of speeding may differ in dark conditions compared to daylight. No previous study has examined how the interaction of multiple factors influences the severity of emergency vehicle crashes. Moreover, the driving behavior of first responders during emergency responses differs from non-emergency situations (Drucker et al., 2013). This research aims to address this gap by 1) identifying patterns of emergency vehicle crashes based on severity levels in both emergency and non-emergency modes and 2) comparing the associations by response modes for the related fatal, nonfatal injury, and no-injury crashes. Two national crash databases, FARS and CRSS, are utilized for police-reported emergency vehicle crashes from January 2016 to February 2020. These databases, maintained by the NHTSA, follow a standardized coding manual. Numerous factors related to driver, road, environmental, and crash characteristics have been explored. It is important to mention that this study uses FARS and CRSS to extract fatal and nonfatal emergency vehicle crash information, respectively. Previous researchers have also utilized these data sources, either separately or combined, for various safety research purposes, such as assessing risk factors, estimating casualties, evaluating the effectiveness of traffic safety standards and programs, and more (Cox et al., 2023; Hossain et al., 2023; Kielminski et al., 2023; Tefft et al., 2013). ARM is applied to identify the co-existing characteristics of crashes. This unsupervised data mining method can handle datasets of varying sizes and complexity, allowing to interpret the variable interdependencies without compromising the integrity of the original dataset (Das et al., 2022; Hossain et al., 2021b; Rahman et al., 2021b). The study findings can improve the understanding of emergency vehicle crash scenarios, which can be helpful in targeting/developing effective educational, design, and enforcement strategies to proactively reduce such crashes and associated casualties.

3. Methodology

Association rules mining (ARM) identifies frequent itemsets (i.e., collection of variable attributes) that occur together in an event (i.e., individual emergency vehicle crash) (Agrawal et al., 1993; Montella et al., 2020). This method follows a straightforward and iterative process to reveal associations among factors without any predetermined hypotheses (Pande and Abdel-Aty, 2009). The apriori algorithm was employed in this study to identify crash patterns based on the severity of the crashes in both emergency and non-emergency response modes. In recent years, several researchers have utilized ARM as a decision support tool to discover the association rules from a multidimensional crash database, focusing on specific categories of variables (Das et al., 2022; Hossain et al., 2022; Hossain et al., 2021b; Hossain et al., 2022b).

Let $K = \{k_1, k_2, k_3, \cdots, k_n\}$ be a set of emergency vehicle crash database and each observation in K contains a subset of items (a set of variable attributes) in itemset, $J = \{j_1, j_2, j_3, \cdots, j_n\}$. A rule has the form $P \rightarrow Q$ where $P, Q \subseteq J$ and $P \cap Q = \varnothing$. P is the antecedent (left hand side-LHS) and Q is the consequent (right hand side-RHS). In an n-itemset rule, it is possible to have multiple items as the antecedent. For instance, consider a 3-itemset rule: {lighting condition = dark-lighted, speeding = yes} → {crash severity = fatal}. In this rule, the antecedent is represented by P = {lighting condition = dark-lighted, speeding = yes}, and the consequent is represented by Q = {crash severity = fatal}. It is important to note that these rules indicate interdependencies among factors rather than direct causation. To filter the generated rules, three parameters are mostly used: support (S), confidence (C), and lift (L). The parameter 'support' quantifies how frequently a rule or pattern ($P \rightarrow Q$) appears together in the entire dataset, while 'confidence' measures the proportion of how recurring $P \rightarrow Q$ compared to the frequency of P occurs in the dataset. The third parameter 'lift' specifies how often items are a part of the same independent crash events. The equations of these parameters are as follows:

$$Support(P) = \frac{P'}{N}$$

$$Support(Q) = \frac{Q'}{N}$$

$$Support(P \rightarrow Q) = \frac{(P' \cap Q')}{N}$$

$$Confidence(P \rightarrow Q) = \frac{Support(P \rightarrow Q)}{Support(P)}$$

$$Lift(P \rightarrow Q) = \frac{Support(P \rightarrow Q)}{Support(P) \times Support(Q)}$$

here, N is the number of emergency vehicle crashes, P' = frequency of occurrences with P, Q' = frequency of occurrences with Q, $(P' \cap Q')$ = frequency of occurrences with both P and Q. Fig. 1 displays a hypothetical example of how ARM estimates support, confidence, and lift.

In association rule discovery, 'lift' is critical to determine the strength of any rule since it implies how more often the antecedent(s) and the consequent are part of the identical crash compared to what would be expected if they were statistically independent (Kong et al., 2020). A lift value greater than 1 suggests a positive interrelation between P and Q, whereas a value less than 1 indicates a negative correlation between P and Q (Das et al., 2021; Samerei et al., 2021b). A lift value close to 1 specifies that P is independent of the likelihood of Q (Hossain et al., 2021b).

To validate each rule with more than two itemsets, it is necessary to ensure that adding each item in the antecedent leads to a significant increase in the lift value. This validation process is referred to as Lift Increase Criterion (LIC) (Gu et al., 2022; López et al., 2014; Montella et al., 2021; Rella Riccardi et al., 2023; Samerei et al., 2021b). A rule having one item r in the antecedent with a lift value L_{P_r} is considered the parent rule. After adding a new item $r+1$, the lift value $L_{P_{r+1}}$ of the new rule is compared with the previous lift value L_{P_r} to obtain LIC.

$$LIC = \frac{L_{P_r}}{L_{P_{r+1}}}$$

here, P_r is the antecedent with item r and P_{r+1} is the antecedent after a new item is included. The analysis in this study was conducted using the 'arules' package in the statistical software R (Hornik et al., 2005).

4. Data

Crash databases from NHTSA's FARS and CRSS between January 2016 and February 2020 were analyzed to discover the interconnected characteristics of emergency vehicle collisions with respect to response modes. It is important to note that federal and state governments imposed travel restrictions from March 2020 in response to the COVID-19 pandemic. Therefore, this study utilized the available years of crash data prior to the pandemic. FARS is a census of all fatal traffic crashes on public roadways in the U.S. where at least one person (either a motorist or non-motorist) died within 30 days of the crash. Conversely, CRSS is a representative sample of police-investigated crash reports in the U.S., covering a range of severities from no-injury to fatal incidents. These crashes are from 60 selected sites across the U.S. which are representative in terms of geography, population, miles driven, and overall crash statistics. Since 2016, the CRSS database has replaced NHTSA's General Estimates System (GES). Due to some differences in the sampling design, the GES dataset was not included in this study. Detailed information regarding the eligibility criteria for the CRSS dataset can be found in the Analytical Users' Manual provided by NHTSA (NHTSA, 2021).

Information regarding crashes involving at least one emergency vehicle was extracted from the FARS and CRSS databases as they follow

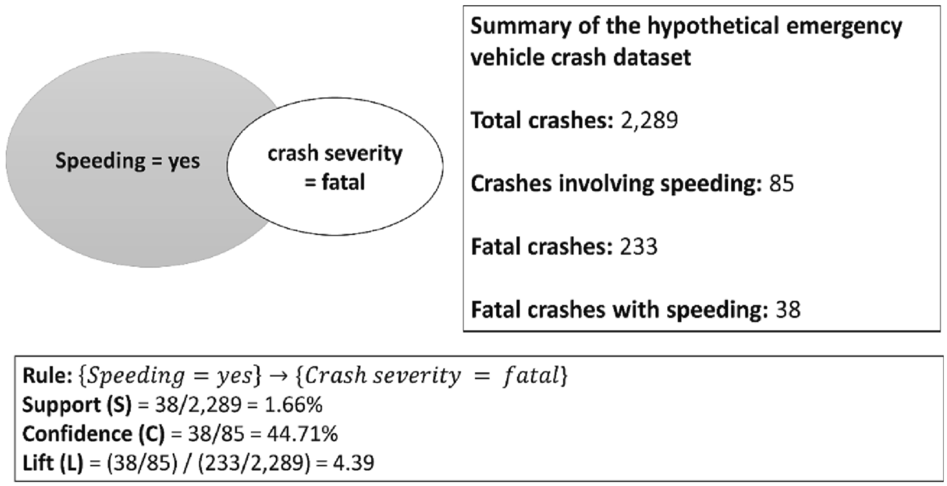

Fig. 1. A hypothetical example of estimating the three parameters of ARM.

a uniform coding manual. Within these databases, crash information is stored in several files, and each crash has been assigned a unique identification number (ST_CASE). For this study, three specific files (person, vehicle, and accident) were used to prepare the final crash datasets. Crashes included in this study were restricted to three primary types of emergency vehicles-police cars, ambulances, and fire trucks (SPEC_USE in [5,6,7]). Both databases specify whether the emergency vehicles were being used for emergencies or not (EMER_USE in [2,3,4,5,6]). In cases where multiple emergency vehicles were involved in a single crash, only the record of the first emergency vehicle was included. The emergency vehicle crashes obtained from CRSS with a reported maximum injury severity of A (suspected serious injury), B (suspected minor injury), C (possible injury), and O (no apparent injury) were included. Conversely, fatal crashes involving emergency vehicles were extracted from the FARS database. During this process, 11 out of 1,001 crashes from CRSS were excluded due to missing or unknown maximum injury severity level. For each crash, the unique crash identification number (ST_CASE) and vehicle number (VEH_NO) were used to extract the emergency vehicle driver information (PER_TYPE = 01).

For analysis, the crash contributing factors were selected based on previous related studies, the availability of variables in the original database, and engineering judgments. Approximately 95% of distraction information in the dataset comprised no distracted driving, unknown, not reported, and not specified. In addition, around 81% of emergency vehicle drivers were male. Therefore, these variables were not included in the final dataset. The 'crash severity' variable was categorized as fatal,

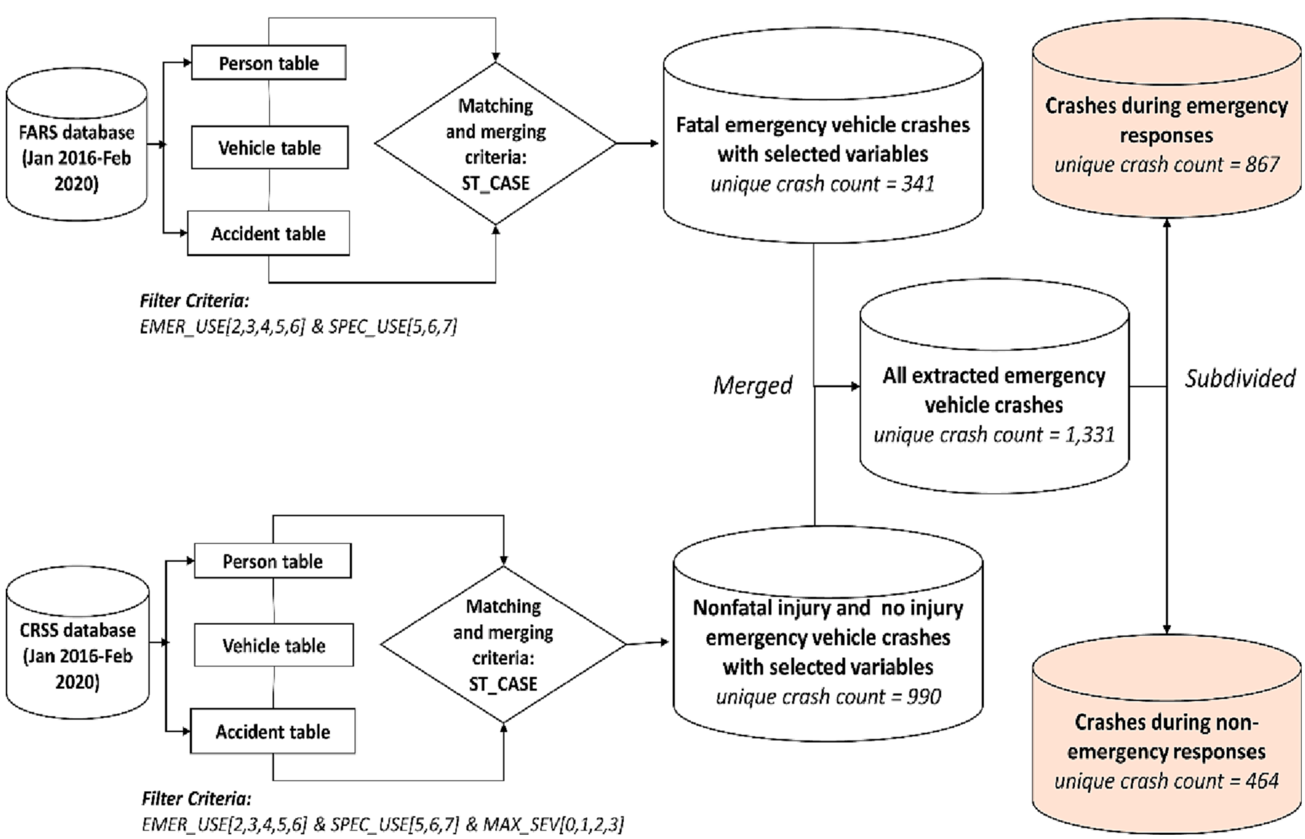

Fig. 2. Framework of preparing the final datasets.

nonfatal injury (suspected serious injury, suspected minor injury, possible injury), and no-injury. 'Day of the week (DOW)' was classified according to the NHTSA classification (weekday: Monday 6:00 am to Friday 5:59 pm and weekend: Friday 6:00 pm to Monday 5:59 am). Land use and trafficway were merged to form a new variable called 'Road type'. For example, if land use was urban and trafficway was two-way-divided, road type would be classified as urban-two-way-divided. Following the study objectives, the merged crash dataset was divided into two subsets based on emergency vehicle response modes. The dataset for emergency mode included 867 crashes, whereas the dataset for non-emergency mode comprised 464 crashes. Fig. 2 shows the framework of preparing the final datasets. Each of the two final datasets contained 15 identical variables with 65 categories. Table 1 shows the crash severity distribution by response modes. To assess whether there was a significant variation in the proportions of severity categories based on emergency vehicle response mode, a Chi-squared test was conducted with a confidence interval of 95%. This test compared the proportion of each severity attribute across different response mode categories. The obtained p-value indicated the statistical significance of crash severity in relation to emergency vehicle response mode (Table 1).

Table 2 shows summary statistics of emergency vehicle crashes by maximum crash severity with respect to response modes. Consistent with Savolainen et al. (2009), the majority of crashes involved drivers aged 25–34, regardless of whether they were in emergency or non-emergency runs. It is worth noting that young drivers exhibited a higher allocation in fatal crashes during non-emergency runs (20.22%), highlighting their usual elevated risk of being involved in severe collisions (Rahman et al., 2021a). Regarding fatal crashes, a higher prevalence of no seatbelt usage and speeding was observed in emergencies compared to non-emergency scenarios. This could be attributed to the urgency associated with reaching the destination in an emergency situation (Bui et al., 2018). Fire trucks were more likely to be involved in fatal and nonfatal injury crashes during emergency operations. Moreover, police vehicles had a higher incidence of crashes in both emergency and non-emergency response modes. Typically, police officers are the first responders dispatched to a wide range of unexpected incidents (Reaves, 2017). Weekend crashes were more prominent while vehicles were in emergency runs. Fatal crashes involving emergency vehicles were more prevalent from midnight to noon, indicating a period of increased vulnerability for these vehicles. In the emergency responses, a higher proportion of no-injury crashes occurred between 12:00 pm and 5:59 pm (33.64%) compared to the non-emergency mode. Both in the emergency and non-emergency response modes, there were disproportionately more crashes occurring in clear weather conditions. The potential explanation can be inherently more clear weather than adverse and/or lower traffic volume during inclement weather (Hsiao et al., 2018; Maze et al., 2006). In relation to fatal and nonfatal injury crashes, cloudy weather conditions were identified as more vulnerable during emergencies. This could be due to poor visibility and/or increased risky driving behaviors during emergency situations (Yasmin et al., 2012).

Nonfatal injury crashes during emergencies were slightly more frequent in dark-lighted conditions (28.07%), while in dark-not-lighted conditions, they were relatively lower (10.53%) compared to non-emergency mode. Emergency vehicle crashes were more discernable at intersections during emergency runs, parallel with multiple previous studies (Pirrallo and Swor, 1994; Savolainen et al., 2009). Urban areas exhibited a higher occurrence of emergency vehicle crashes, likely influenced by factors such as elevated traffic volume, greater emergency call frequency, and numerous intersections (Brown et al., 2000; Hsiao et al., 2018). In terms of response modes, fatal crashes on urban two-way non-divided roadways were more frequently observed during emergency operations. No significant variations were observed in the attributes related to the posted speed limit. When emergency vehicles were involved in conflicts with other vehicles, they appeared more vulnerable during emergency responses, accounting for 70.63% of fatal incidents. Compared to non-emergencies, a high proportion of fatal and nonfatal injury crashes were observed in emergency responses. Conversely, single-vehicle crashes with fatalities were overrepresented during non-emergency responses, also reported by Abdelwanis (2013). Additionally, rear-end collisions were more prevalent for emergency vehicles when not in emergency mode.s

Table 1
Severity distribution of emergency vehicle crashes response modes.

Severity class	Fatal		Nonfatal injury		No-injury	
Response mode	Freq.	%	Freq.	%	Freq.	%
Emergency	252	29.07	285	32.87	330	38.06
Non-emergency	89	19.18	141	30.39	234	50.43
p-value of chi-square test			<0.001			

5. Results and discussions

To achieve the objective of obtaining association rules containing antecedents leading to specific crash severity outcomes, ARM is applied in both datasets by fixing the maximum severity levels of crashes as a consequent. This study limited the maximum number of antecedents to 3 for a more straightforward interpretation of the generated rules (Pande and Abdel-Aty, 2009; Rahman et al., 2021b). A two-step approach was taken to analyze the crash datasets to identify co-existing characteristics influencing the severity of emergency vehicle crashes during emergency and non-emergency response modes.

Step 1: Setting appropriate minimum support and confidence values in ARM is crucial to obtain meaningful and interesting results (Kong et al., 2020; Montella et al., 2021). Choosing a low threshold can generate many uninteresting rules, whereas a high value could overlook the significant inherent relationship between categories (Das et al., 2022; Rahman et al., 2023). However, there are no predefined rules for selecting the threshold values of support (S), confidence (C), and lift (L). Following previous studies (Hossain et al., 2022; Kong et al., 2021; Tamakloe et al., 2022), a trial-and-error approach was employed to set the minimum values for the two datasets. The minimum values of support (S), confidence (C), and lift (L) were set ≥2%, ≥50%, and ≥1.5, respectively for the dataset containing emergency response crashes. In contrast, the threshold values of support (S), confidence (C), and lift (L) were set ≥2%, ≥50%, and ≥1.4, respectively for the dataset containing non-emergency response crashes. The initially generated rules were pruned to remove redundant and repeated associations (Hossain et al., 2021b).

Step 2: The rules with more than two items, sharing the same antecedent(s) as the parent rule, were rearranged based on the descending order of their lift values (Gu et al., 2022; López et al., 2014; Montella et al., 2021; Rella Riccardi et al., 2023; Tamakloe et al., 2022). After that, LIC was calculated for each rule with more than two items to identify the strongest rules for discussion. It is important to note that this study considered a minimum LIC value of 1.1, indicating that the extended rule was selected if it had at least a 10% increase in the lift value compared to the previous or parent rule (Samerei et al., 2021a, Samerei et al., 2021b). The association rules satisfying the LIC criterion are presented in Tables 3–6.

5.1. Rules by crash severity in emergency mode

Table 3 exhibits 16 rules (A#1-A#16) that illustrate the patterns of fatal emergency vehicle crashes during emergency responses. Rule A#2 indicates that the probability of emergency vehicles being involved in fatal collisions with pedestrians is 3.03 times in dark conditions with streetlighting. Oncoming vehicle headlights can significantly compromise drivers' vision during dark conditions (Farber, 2004); therefore, first responders often have to react quickly at night to ensure safe pedestrian-vehicle interactions (Tofighi et al., 2021). These limitations encountered in low lighting conditions can significantly contribute to

Table 2
Overview of emergency vehicle crashes by crash severity with respect to response modes.

Variable attribute	Emergency mode						Non-emergency mode					
	fatal		nonfatal injury		no-injury		fatal		nonfatal injury		no-injury	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%
driver age												
<25y	20	7.94	32	11.23	37	11.21	18	20.22	16	11.35	21	8.97
25-34y	100	39.68	115	40.35	126	38.18	32	35.96	42	29.79	73	31.20
35-44y	59	23.41	57	20.00	78	23.64	10	11.24	28	19.86	60	25.64
45-54y	55	21.83	48	16.84	58	17.58	17	19.10	34	24.11	49	20.94
>54y	11	4.37	13	4.56	17	5.15	9	10.11	10	7.09	17	7.26
unknown	7	2.78	20	7.02	14	4.24	3	3.37	11	7.80	14	5.98
no seatbelt use												
no	197	78.17	249	87.37	324	98.18	74	83.15	131	92.91	231	98.72
yes	55	21.83	36	12.63	6	1.82	15	16.85	10	7.09	3	1.28
speeding												
no	202	80.16	277	97.19	321	97.27	82	92.13	134	95.04	229	97.86
yes	50	19.84	8	2.81	9	2.73	7	7.87	7	4.96	5	2.14
vehicle type												
police	162	64.29	228	80.00	219	66.36	55	61.80	125	88.65	175	74.79
ambulance	51	20.24	42	14.74	62	18.79	24	26.97	15	10.64	34	14.53
fire truck	39	15.48	15	5.26	49	14.85	10	11.24	1	0.71	25	10.68
day of the week (DOW)												
weekday	139	55.16	186	65.26	212	64.24	62	69.66	105	74.47	162	69.23
weekend	113	44.84	99	34.74	118	35.76	27	30.34	36	25.53	72	30.77
crash time												
6–11:59am	92	36.51	88	30.88	82	24.85	29	32.58	41	29.08	49	20.94
12–5:59 pm	54	21.43	104	36.49	111	33.64	21	23.60	49	34.75	27	11.54
6–11:59 pm	35	13.89	53	18.60	95	28.79	12	13.48	33	23.40	59	25.21
12–5:59am	71	28.17	40	14.04	42	12.73	27	30.34	18	12.77	99	42.31
weather												
clear	172	68.25	178	62.46	228	69.09	62	69.66	98	69.50	150	64.10
cloudy	39	15.48	48	16.84	38	11.52	9	10.11	17	12.06	36	15.38
rain	13	5.16	37	12.98	26	7.88	12	13.48	18	12.77	20	8.55
snow	1	0.40	5	1.75	10	3.03	1	1.12	—	—	11	4.70
others	27	10.71	17	5.96	28	8.48	5	5.62	8	5.67	17	7.26
lighting condition												
daylight	100	39.68	161	56.49	199	60.30	31	34.83	83	58.87	143	61.11
dark-lighted	80	31.75	80	28.07	84	25.45	33	37.08	28	19.86	43	18.38
dark-not-lighted	61	24.21	30	10.53	39	11.82	21	23.60	24	17.02	40	17.09
others	11	4.37	14	4.91	8	2.42	4	4.49	6	4.26	8	3.42
intersection												
no	140	55.56	158	55.44	212	64.24	56	62.92	87	61.70	163	69.66
yes	112	44.44	127	44.56	118	35.76	33	37.08	54	38.30	71	30.34
posted speed limit												
<25mph	23	9.13	24	8.42	63	19.09	2	2.25	19	13.48	45	19.23
30-35mph	54	21.43	80	28.07	81	24.55	20	22.47	35	24.82	56	23.93
40-45mph	61	24.21	67	23.51	80	24.24	27	30.34	40	28.37	42	17.95
50-55mph	67	26.59	25	8.77	36	10.91	23	25.84	10	7.09	32	13.68
>60mph	37	14.68	19	6.67	15	4.55	16	17.98	11	7.80	20	8.55
others	10	3.97	70	24.56	55	16.67	1	1.12	26	18.44	39	16.67
road type												
rural-one-way	3	1.19	3	1.05	7	2.12	—	—	—	—	2	0.85
rural-two-way-divided	18	7.14	19	6.67	16	4.85	8	8.99	6	4.26	17	7.26
rural-two-way-not-divided	63	25.00	31	10.88	45	13.64	28	31.46	16	11.35	34	14.53
rural-trafficway-others	—	—	6	2.11	22	6.67	—	—	4	2.84	11	4.70
urban-no-trafficway	2	0.79	4	1.40	11	3.33	1	1.12	4	2.84	11	4.70
urban-one-way	3	1.19	7	2.46	14	4.24	1	1.12	8	5.67	14	5.98
urban-two-way-divided	73	28.97	66	23.16	64	19.39	27	30.34	38	26.95	41	17.52
urban-two-way-not-divided	88	34.92	82	28.77	107	32.42	23	25.84	48	34.04	80	34.19
urban-trafficway-others	2	0.79	67	23.51	44	13.33	1	1.12	17	12.06	24	10.26
movement prior to crash												
going straight	170	67.46	157	55.09	139	42.12	58	65.17	62	43.97	87	37.18
accelerate/decelerate	5	1.98	12	4.21	13	3.94	2	2.25	7	4.96	16	6.84
negotiating curve	22	8.73	12	4.21	17	5.15	13	14.61	14	9.93	16	6.84
stopped	19	7.54	32	11.23	40	12.12	4	4.49	24	17.02	37	15.81
turning left	16	6.35	23	8.07	25	7.58	6	6.74	9	6.38	18	7.69
turning right	2	0.79	13	4.56	24	7.27	—	—	7	4.96	14	5.98
others	18	7.14	36	12.63	72	21.82	6	6.74	18	12.77	46	19.66
most harmful event												
motor vehicle in-transport	178	70.63	228	80.00	233	70.61	50	56.18	103	73.05	139	59.40
live animal	—	—	2	0.70	24	7.27	—	—	7	4.96	35	14.96
parked motor vehicle	—	—	2	0.70	26	7.88	1	1.12	—	—	17	7.26
pedestrian	35	13.89	15	5.26	1	0.30	19	21.35	12	8.51	—	—
rollover/overturn	14	5.56	7	2.46	—	—	5	5.62	1	0.71	—	—
others	25	9.92	31	10.88	46	13.94	14	15.73	18	12.77	43	18.38

(continued on next page)

Table 2 (*continued*)

Variable attribute	Emergency mode						Non-emergency mode					
	fatal		nonfatal injury		no-injury		fatal		nonfatal injury		no-injury	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%
crash type												
single-vehicle	76	30.16	59	20.70	95	28.79	37	41.57	39	27.66	94	40.17
angle	103	40.87	129	45.26	84	25.45	26	29.21	35	24.82	29	12.39
head-on	31	12.30	12	4.21	5	1.52	17	19.10	3	2.13	2	0.85
rear-end	28	11.11	55	19.30	55	16.67	5	5.62	51	36.17	65	27.78
sideswipe	11	4.37	24	8.42	73	22.12	4	4.49	11	7.80	36	15.38
others	3	1.19	6	2.11	18	5.45	—	—	2	1.42	8	3.42

Table 3
Rules for 'crash severity = fatal' in emergency mode.

Rule ID	LHS	S%	C%	L	Count	LIC
n/a	speeding = yes	5.77	74.63	2.57	50	n/a
A#1	speeding = yes & no seatbelt use = yes	2.08	90.00	3.10	18	1.21
n/a	most harmful event = pedestrian	4.04	68.63	2.36	35	n/a
A#2	most harmful event = pedestrian & lighting condition = dark-lighted	2.54	88.00	3.03	22	1.28
A#3	most harmful event = pedestrian & DOW = weekend	2.54	88.00	3.03	22	1.28
n/a	no seatbelt use = yes	6.34	56.70	1.95	55	n/a
A#4	no seatbelt use = yes & road type = rural-two-way-not-divided	2.19	76.00	2.61	19	1.34
A#5	no seatbelt use = yes & crash time = 6–11:59 pm	2.42	72.41	2.49	21	1.28
A#6	no seatbelt use = yes & road type = urban-two-way-not-divided	2.31	68.97	2.37	20	1.22
A#7	no seatbelt use = yes & crash type = single-vehicle	2.08	64.29	2.21	18	1.13
A#8	no seatbelt use = yes & DOW = weekend	2.65	63.89	2.20	23	1.13
A#9	no seatbelt use = yes & driver age = 25-34y	2.88	62.50	2.15	25	1.10
n/a	posted speed limit = 50-55mph	7.73	52.34	1.80	67	n/a
A#10	posted speed limit = 50-55mph & intersection = yes	2.77	64.86	2.23	24	1.24
A#11	posted speed limit = 50-55mph & intersection = yes & crash type = angle	2.08	72.00	2.48	18	1.11
A#12	posted speed limit = 50-55mph & road type = rural-two-way-not-divided	3.46	61.22	2.11	30	1.17
A#13	posted speed limit = 50-55mph & road type = rural-two-way-not-divided & most harmful event = motor vehicle in-transport	2.65	79.31	2.73	23	1.30
A#14	posted speed limit = 50-55mph & DOW = weekend	2.88	59.52	2.05	25	1.14
A#15	posted speed limit = 50-55mph & DOW = weekend & movement prior to crash = going straight	2.31	74.07	2.55	20	1.24
n/a	posted speed limit=>60mph	4.27	52.11	1.79	37	n/a
A#16	posted speed limit=>60mph & lighting condition = dark-not-lighted	2.08	62.07	2.14	18	1.19

Table 4
Rules for 'crash severity = nonfatal injury' and 'crash severity = no-injury' in emergency mode.

Rule ID	LHS	S%	C%	L	Count	LIC
n/a	road type = urban-trafficway-others	7.73	59.29	1.80	67	n/a
B#1	road type = urban-trafficway-others & vehicle type = police	5.88	68.92	2.10	51	1.16
B#2	road type = urban-trafficway-others & vehicle type = police & movement prior to crash = going straight	3.58	77.50	2.36	31	1.12
B#3	road type = urban-trafficway-others & crash type = angle	4.27	67.27	2.05	37	1.13
B#4	road type = urban-trafficway-others & crash type = angle & intersection = yes	2.77	77.42	2.36	24	1.15
B#5	road type = urban-trafficway-others & lighting condition = dark-lighted	2.65	65.71	2.00	23	1.11
n/a	crash type = sideswipe	8.42	67.59	1.78	73	n/a
C#1	crash type = sideswipe & vehicle type = fire truck	2.54	95.65	2.51	22	1.42
C#2	crash type = sideswipe & crash time = 6–11:59am	2.19	82.61	2.17	19	1.22
C#3	crash type = sideswipe & driver age = 25-34y	3.81	78.57	2.06	33	1.16
C#4	crash type = sideswipe & driver age = 25-34y & lighting condition = daylight	2.54	88.00	2.31	22	1.12
C#5	crash type = sideswipe & posted speed limit = 30-35mph	2.54	75.86	1.99	22	1.12
C#6	crash type = sideswipe & vehicle type = ambulance	2.08	75.00	1.97	18	1.11
n/a	posted speed limit=<25mph	7.27	57.27	1.50	63	n/a
C#7	posted speed limit=<25mph & driver age = 35-44y	2.19	76.00	2.00	19	1.33
C#8	posted speed limit=<25mph & intersection = no	5.42	69.12	1.82	47	1.21
C#9	posted speed limit=<25mph & crash type = single-vehicle	3.46	66.67	1.75	30	1.16
C#10	posted speed limit=<25mph & crash type = single-vehicle & road type = urban-two-way-not-divided	2.19	73.08	1.94	19	1.11

Note: B#1-B#5: nonfatal injury as consequent, C#1-C#10: no-injury as consequent.

the risk of fatal collisions. Poor visibility can also explain emergency vehicle crashes on high-speed roadways in dark with no streetlighting (A#16). The generated rules also reveal a recurring pattern of fatal crashes involving pedestrians and emergency vehicles on weekends (A#3). Additionally, fatal crashes during emergencies on weekends are associated with roads having posted speed limits of 50–55 mph (A#15). The outcomes of speeding are more likely to be fatal if first responders drive without seatbelts during emergency runs (A#1). The association between speeding and unrestrained driving is reported to be vulnerable in multiple studies (Bogstrand et al., 2015; Hossain et al., 2021b). The rules show that unrestrained first responders during emergency runs are

Table 5
Rules for 'crash severity = fatal' in non-emergency mode.

Rule ID	LHS	S%	C%	L	Count	LIC
n/a	crash type = head-on	3.66	77.27	4.03	17	n/a
D#1	crash type = head-on & intersection = no	3.23	88.24	4.60	15	1.14
n/a	most harmful event = pedestrian	4.09	61.29	3.20	19	n/a
D#2	most harmful event = pedestrian & posted speed limit = 40-45mph	2.59	92.31	4.81	12	1.51
D#3	most harmful event = pedestrian & road type = urban-two-way-divided	2.59	80.00	4.17	12	1.31
D#4	most harmful event = pedestrian & crash time = 6–11:59 pm	2.59	80.00	4.17	12	1.31
D#5	most harmful event = pedestrian & crash time = 6–11:59 pm & movement prior to crash = going straight	2.37	91.67	4.78	11	1.15
D#6	most harmful event = pedestrian & lighting condition = dark-lighted	2.16	71.43	3.72	10	1.17
D#7	most harmful event = pedestrian & driver age = 25-34y	2.37	68.75	3.58	11	1.12
D#8	most harmful event = pedestrian & driver age = 25-34y & movement prior to crash = going straight	2.16	83.33	4.34	10	1.21

more likely to be involved in fatal collisions on two-way-divided roadways (A#4, A#6), on weekends (A#8), and during evening to midnight hours (A#5). With 'crash severity = fatal', emergency vehicles are more likely to collide with other motor vehicles on rural-two-way-undivided roadways with a posted speed limit of 50–55 mph (A#13). Furthermore, at intersections with a similar posted speed limit, the risk of fatal crashes involving emergency vehicles increases by 2.23 times (A#10), and these crashes are frequently classified as angle crashes (A#11). In these road conditions, drivers may require more time to decide whether to proceed or stop at the intersection (Liu et al., 2007). These circumstances, coupled with time pressure in emergency responses, can lead to premature decision-making (Hsiao et al., 2018). The fatal consequences of single-vehicle crashes are evident when first responders drive without seatbelts during emergencies (A#7), as reported in previous studies (Eustace et al., 2017; Hsiao et al., 2018).

Table 4 presents rules B#1-B#5, which describe the combination of attributes associated with nonfatal injury crashes in emergency response mode. It is noteworthy that all associations in these rules involve the attribute 'road type = urban-trafficway-others', indicating that the presence of a median was significantly underreported in the reporting of injury crashes while vehicles in emergencies. Rule B#3, with 'crash severity = nonfatal injury', suggests that vehicles in urban settings are 2.05 times more likely to be involved in angle crashes. This likelihood increases by 15% when intersections are included in the associations (B#4). The option of 'code 3 running' allows emergency vehicles to bypass traffic signs and signals, and drivers often change lanes swiftly to go for the right of way. However, emergency vehicle drivers may encounter situations where other vehicles do not yield to them as expected (Hsiao et al., 2018). Rule B#2 indicates that police officers, during emergency runs, are frequently involved in injury crashes when proceeding straight on urban roads. These roads in combination with dark-lighted conditions are linked to nonfatal injury collisions (B#5). Notably, none of the associations include factors related to driver characteristics, suggesting that they may have less influence on nonfatal injury crashes involving emergency vehicles.

In Table 4, rules C#1-C#10 provide insights into the co-existing categories influencing no-injury crashes during emergency responses. Rule C#2 (S: 2.19%, C: 82.61%, L: 2.17) can be explained as follows: a) 2.19% of fire trucks are involved in collisions with no-injury severity during morning to afternoon hours in emergency runs, b) Among all crashes involving fire trucks during the specified time frame, 95.95% result in no injuries, and c) The proportion of crashes with no-injury severity for fire trucks in the specified response mode and time period is 2.51 times higher than the same proportion in the complete dataset. Among emergency vehicles, fire trucks and ambulances are more frequently involved in sideswipe crashes with no-injury severity (C#1,

Table 6
Rules for 'crash severity = nonfatal injury' and 'crash severity = no-injury' in non-emergency mode.

Rule ID	LHS	S%	C%	L	Count	LIC
n/a	crash type = rear-end	10.99	42.15	1.39	51	n/a
E#1	crash type = rear-end & driver age = 45-54y	4.09	59.38	1.95	19	1.41
E#2	crash type = rear-end & driver age = 45-54y & movement prior to crash = stopped	2.59	66.67	2.19	12	1.12
E#3	crash type = rear-end & posted speed limit = 40-45mph	3.88	52.94	1.74	18	1.26
E#4	crash type = rear-end & posted speed limit = 40-45mph & road type = urban-two-way-divided	2.59	66.67	2.19	12	1.26
E#5	crash type = rear-end & posted speed limit = 40-45mph & intersection = no	2.16	58.82	1.94	10	1.11
E#6	crash type = rear-end & road type = urban-two-way-divided	5.17	52.17	1.72	24	1.24
E#7	crash type = rear-end & road type = urban-two-way-divided & movement prior to crash = stopped	2.80	68.42	2.25	13	1.31
E#8	crash type = rear-end & crash time = 6–11:59 pm	2.37	47.83	1.57	11	1.13
n/a	most harmful event = live animal	7.54	83.30	1.65	35	n/a
F#1	most harmful event = live animal & crash time = 6–11:59 pm	3.45	94.10	1.87	16	1.13
F#2	most harmful event = live animal & driver age = 35-44y	2.59	92.30	1.83	12	1.11
n/a	crash type = sideswipe	7.76	70.60	1.40	36	n/a
F#3	crash type = sideswipe & intersection = yes	2.59	80.00	1.59	12	1.13
F#4	crash type = sideswipe & crash time = 12–5:59 pm	4.09	79.20	1.57	19	1.12
F#5	crash type = sideswipe & road type = urban-two-way-not-divided	3.02	77.80	1.54	14	1.10
n/a	vehicle type = fire truck	5.39	69.40	1.38	25	n/a
F#6	vehicle type = fire truck & most harmful event = parked motor vehicle	2.16	100	1.98	10	1.44
F#7	vehicle type = fire truck & posted speed limit=<25mph	2.59	100	1.98	12	1.44
n/a	posted speed limit=<25mph	9.70	68.20	1.35	45	n/a
F#8	posted speed limit=<25mph & driver age = 45-54y	2.59	80.00	1.59	12	1.17
F#9	posted speed limit=<25mph & crash time = 6–11:59 pm	3.45	80.00	1.59	16	1.17

Note: E#1-E#8: nonfatal injury as consequent, F#1-F#9: no-injury as consequent.

C#6). This observation aligns with the findings of Carrick and Srinivasan (2023), who noted that sideswipe crashes tend to have lower levels of injury severity compared to other types of collisions. In the generated rules with 'crash severity = no-injury', single-vehicle crashes are more frequent on urban-two-way-not-divided roadways with a posted speed limit of ≤ 25 mph (C#10). Interestingly, 'intersection = yes' does not appear in the generated rules, indicating that most of the no-injury crashes during emergency responses occur on roadway segments rather than at intersections (C#8).

5.2. Rules by crash severity in non-emergency mode

Table 5 shows 8 rules (D#1-D#8) that describe the concurrent attributes influencing fatal emergency vehicle crashes during non-emergency runs. The interaction between 'movement prior to crash = going straight' and 'most harmful event = pedestrian' is highly associated with emergency vehicle crashes from evening to midnight hours (D#5). In non-emergency responses, road and environmental characteristics significantly affect fatal crashes involving pedestrians. For instance, such crashes are more likely to happen on roadways with a posted speed limit of 40–45 mph (D#2), on urban-two-way-divided roadways (D#3), and in dark conditions with streetlighting (D#6). Earlier, Das and Dutta (2020) highlighted the risks associated with driving on urban-divided road networks. Rule D#8 indicates that first responders aged 25–34 have a higher likelihood of being involved in pedestrian-related fatal collisions while going straight. In terms of collision types, the analysis reveals the deadly consequences of head-on crashes on road segments during non-emergency runs (D#1). Head-on crashes often result in severe injuries, especially when involving larger vehicles (Abdelwanis, 2013; Liu and David Fan, 2019). None of the associations include 'no seatbelt use = yes' and 'speeding = yes', implying that risky driving tendencies are less prevalent among first responders during non-emergency mode of travel.

Table 6 shows the generated rules (E#1-E#8) with 'crash severity = nonfatal injury' as consequent in non-emergency mode. Notably, all associations involve rear-end collisions, which are more prevalent during evening to midnight hours (E#8). Rule E#2 indicates the increased likelihood of rear-end crashes among first responders aged 45–54 when their vehicles are momentarily stopped, such as at a traffic signal. The presence of a dilemma zone requires drivers to make quick decisions on whether to stop or proceed before a red signal. Within this zone, abrupt stops by one driver can lead to conflicts with following vehicles (Hsiao et al., 2018; Polders et al., 2015; Schrock et al., 2016). Rear-end crashes on roadways with a posted speed limit of 40–45 mph are associated with urban-two-way-divided roadways (E#4) and segments (E#5). In the context of nonfatal injury crashes during non-emergencies, the combination of 'road type = urban-two-way-divided' and 'movement prior to crash = stopped' increases the risk of rear-end collisions by 2.25 times (E#7).

In Table 6, rules F#1-F#9 provide information about affiliated attributes contributing to no-injury crashes during non-emergency responses. Rule F#7 (S: 2.59%, C: 100%, L: 1.98) states that 2.59% of crashes involving fire trucks on roadways with a speed limit of ≤ 25 mph in non-emergency runs result in no injuries. Furthermore, 100% of crashes involving fire trucks on these roads have no injuries. The proportion of no-injury crashes involving fire trucks on roadways with a speed limit of ≤ 25 mph in the specified response mode is 1.98 times higher than the same proportion in the complete dataset. The generated rules also indicate that fire truck drivers are more likely to be involved in no-injury collisions with parked motor vehicles (F#6). Sideswipe collisions during non-emergency responses are more frequent at intersections (F#3), in the afternoon to evening hours (F#4), and on urban-two-way-not-divided roadways (F#5). Failure to yield the right of way and rapid lane changes are common reasons for sideswipe crashes at intersections (Abdel-Aty and Keller, 2005), which are closely related to the driving habits of first responders (Hsiao et al., 2018). During evening to midnight hours, no-injury crashes involving emergency vehicles are more prevalent on low-speed roadways (F#9) and when colliding with live animals (F#1).

5.3. Comparison of emergency and non-emergency responses

The generated rules highlight the fatal consequences of speeding without seatbelt usage in emergency mode. However, none of these risky driving attributes are observed in the rules for non-emergency runs. Fatal crashes at intersections are more common during emergencies compared to their counterparts. Fatal outcomes are observed in non-emergency response modes in cases of head-on collisions on road segments. Conversely, in emergency modes, vehicles are more likely to be involved in angle crashes at intersections with high posted speed limits. The contribution of road classes to fatal emergency vehicle crashes involving pedestrians differs between response modes. Two-way-not-divided roadways are strongly associated with emergency mode, while urban-two-way-divided roadways are highly affiliated with non-emergency runs. The risk of emergency vehicle crashes involving pedestrians is evident in dark-lighted conditions in both response modes, leading to deadly consequences. Fatal crashes from evening to midnight hours are associated with unrestrained driving in emergency mode. Conversely, during the same time frame, emergency vehicles in non-emergency situations are found to be more vulnerable to pedestrian-related incidents.

Regarding nonfatal injury severity, angle collisions are more likely to occur at urban intersections during emergencies, while rear-end crashes are more frequent on segments with a posted speed limit of 40–45 mph in non-emergency mode. Urban roadways are strongly affiliated with injury crashes involving emergency vehicles in both response modes. In terms of vehicle movement prior to the crash, crashes in emergency responses are strongly associated with straight movement. However, crashes in non-emergency responses are more likely to occur when the vehicle is momentarily stopped in traffic or other locations. The no-injury crashes involving fire trucks exhibit different patterns depending on the response mode. In emergency mode, these crashes are more likely to be sideswiped, whereas in non-emergency responses, first responders of fire trucks frequently collide with parked motor vehicles. The characteristics of the emergency vehicles, such as fire trucks and ambulances, are more prominent in sideswipe crashes with no-injury during emergency responses. Conversely, the characteristics of the road, such as intersections and urban-two-way-not-divided roads, are found to be influential in non-emergency responses. The patterns of no-injury crashes also differ in terms of low-speed roads between the response modes. For instance, in emergency runs, the crashes are more likely to be single-vehicle incidents, whereas in non-emergency mode, they tend to occur more frequently from evening to midnight hours.

6. Conclusions

Emergency vehicle crashes pose a serious traffic safety concern causing severe injury and deaths to first responders and other road users. Therefore, identifying the chain of characteristics influencing these crashes has become crucial. However, there is limited research that specifically investigates the contributing factors and their interactions in emergency vehicle crashes. To address this gap, this study utilized data from two national crash databases (FARS and CRSS) spanning over four years (January 2016 to February 2020) to analyze the association of factors contributing to different levels of crash severity in both emergency and non-emergency modes of travel. One of the major contributions of this study is to discover the effect of response modes on emergency vehicle crash patterns. Additionally, this study is the first to uncover the co-existing risk factors associated with crash severity in emergency vehicle crashes. Using the apriori algorithm of ARM, the study developed rules to identify combinations of risk factors that strongly contribute to these crashes. The generated rules were filtered based on support, confidence, and lift, and then validated by the lift increase criterion. Compared to traditional parametric modeling, ARM can handle datasets more effectively without relying on predefined hypotheses. The findings of this study can guide in making effective strategies to improve safe driving behavior of first responders. The identified associations provide insights into the factors that can be controlled to ensure safe operation of emergency vehicles on the road.

This study shows the complex nature of emergency vehicle crashes by identifying the intricate associations between risk factors. Several states have devised mandatory training programs to improve the safe driving skills of first responders (Pietzsch, 2015). Moreover, the Division of Occupational Health, Safety, and Medicine of the IAFF has introduced emergency vehicle safety programs to educate first responders on how to ensure their own safety while driving in emergency situations (IAFF, 2022). The associations revealed in this research provide valuable insights into the underlying risk factors related to emergency vehicle crashes, which can be incorporated into training materials to strengthen existing educational interventions. In fatal crash scenarios, it was observed that emergency vehicle drivers often engage in speeding while responding to emergency incidents. Further research is needed to determine if the vehicles displayed flashing warning lights and sounded sirens, which can tell whether the 'code 3 running' law was properly followed or not. Additionally, the framework of the emergency vehicle dispatching system can be improved to minimize unexpected time delays during emergencies (Chen et al., 2013), thereby reducing the time pressure associated with emergency runs. This study also highlighted the involvement of pedestrians in fatal emergency vehicle collisions. It is crucial to develop educational and media campaigns to enhance public awareness regarding appropriate actions to take when an emergency vehicle approaches. A similar concept is applicable to enhance the enforcement and effectiveness of the 'move-over' law. It should be noted that the 'move-over' law says that motorists must move over and change lanes when first responders are stopped on the side of the roadway with activated emergency signals (Carson, 2008). In addition, emergency vehicle warning systems (e.g., emergency vehicle approaching message) can be promoted to alert other motorists about the location and movement of emergency vehicles during emergency runs (Lidestam et al., 2020).

In this study, the cumulative effect of unrestrained driving and speeding exhibited fatal consequences. Therefore, strict compliance with seatbelt policy needs to be assured through improving situational awareness and enhancing the effective enforcement of seatbelt law. The outcomes of ARM showed a strong association between dark-lighted conditions and fatal emergency vehicle crashes, particularly when pedestrians were involved. Therefore, there is a scope to reduce the related crashes by improving road visibility. While retroreflective stripes on clothing have proven effective in improving pedestrian conspicuity (Black et al., 2021), transportation planners have also prioritized modern technologies such as adaptive lighting and LED lighting to enhance road illumination (Wood, 2020). Earlier, Pearsall (2010) suggested installing warning lights with varying intensity levels, as a single intensity may not be appropriate for both day and nighttime conditions. Additionally, the study proposed placing retroreflective materials at lower heights on emergency vehicles to maximize the benefit of approaching vehicles' headlamps. The study findings indicated that fatal crashes in emergency mode were more likely to occur on rural-two-way-undivided roads with speed limits exceeding 50 mph. In contrast, non-emergency mode crashes with comparable severity outcomes were associated with urban-two-way-divided roads and roadways with a posted speed limit of 40–45 mph. Road safety assessments focusing on geometric features and functional elements can be prioritized to implement solutions such as redesigning traffic signal timing (Qin and Khan, 2012) or installing adaptive traffic control systems (Djahel et al., 2013). In terms of passenger cars and large trucks, the effectiveness of crash avoidance technologies such as side view assist, lane departure warning, vehicle stability control, forward collision warning, and adaptive headlights are found to be effective in reducing several types of collision (e.g., rear-end, head-on, single-vehicle, sideswipe) (Jermakian, 2012, 2011). Further research is needed to evaluate the safety effectiveness of these in-vehicle technologies specifically for emergency vehicles. Addressing the safety of first responders requires a comprehensive approach that incorporates environmental improvements, technological advancements, educational initiatives, and enforcement efforts.

This study has some limitations that can be addressed in future studies. One limitation is the potential for reporting biases, both in terms of underreporting and overreporting, which could have influenced the study findings. To enhance the reliability of the data, future investigations can explore alternative comprehensive data sources or employ more robust data collection methods. Furthermore, future studies can explore occupant, demographic, and situational factors that directly or indirectly impact first responders' driving behavior. Understanding the patterns of emergency vehicle crashes considering the presence of civilians in the vehicle could be an extensive area of research. Additionally, while this study focused on analyzing 4-itemsets, conducting further research to explore longer patterns involving multiple factors would be valuable. Integrating real-world observations with laboratory experiments can provide a more comprehensive approach to target specific countermeasures effectively. It would also be beneficial to conduct research examining crash mechanisms, such as the sequence of events, within the identified crash scenarios involving emergency vehicles.

Author contributions

The authors confirm contribution to the paper as follows: study conception and design: Hossain M.M.; data preparation: Hossain M.M.; analysis and interpretation of results: Hossain M.M., Zhou H.; draft manuscript preparation: Hossain M.M., Das S., Zhou H. All authors reviewed the results and approved the final version of the manuscript.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

Abdel-Aty, M., Keller, J., 2005. Exploring the overall and specific crash severity levels at signalized intersections. Accid. Anal. Prev. 37 (3), 417–425. https://doi.org/10.1016/j.aap.2004.11.002.

Abdelwanis, N., 2013. Characteristics and Contributing Factors of Emergency Vehicle Crashes. Clemson University. Dissertation.

Agrawal, R., Imieliński, T., Swami, A., 1993. Mining association rules between sets of items in large databases 207–216. doi:10.1145/170035.170072.

Black, A.A., Bui, V., Henry, E., Ho, K., Pham, D., Tran, T., Wood, J.M., 2021. Using retroreflective cloth to enhance drivers' judgment of pedestrian walking direction at night-time. J. Safety Res. 77, 196–201. https://doi.org/10.1016/j.jsr.2021.03.002.

Bogstrand, S.T., Larsson, M., Holtan, A., Staff, T., Vindenes, V., Gjerde, H., 2015. Associations between driving under the influence of alcohol or drugs, speeding and seatbelt use among fatally injured car drivers in Norway. Accid. Anal. Prev. 78, 14–19. https://doi.org/10.1016/j.aap.2014.12.025.

Brown, L.H., Khanna, A., Hunt, R.C., 2000. Rural vs urban motor vehicle crash death rates: 20 Years of FARS data. Prehospital Emerg. Care 4 (1), 7–13. https://doi.org/10.1080/10903120090941551.

Bui, D.P., Hu, C., Jung, A.M., Pollack Porter, K.M., Griffin, S.C., French, D.D., Crothers, S., Burgess, J.L., 2018. Driving behaviors associated with emergency service vehicle crashes in the U.S. fire service. Traffic Inj. Prev. 19 8, 849–855. https://doi.org/10.1080/15389588.2018.1508837.

Carrick, G., Srinivasan, S., 2023. Characterizing incident responder crashes involving move over law violations. Transport. Res. Record: J. Transport. Res. Board 2677 (2), 741–752.

Carson, J.L., 2008. Traffic Incident Management Quick Clearance Laws: A National Review of Best Practices. Federal Highway Administration (FHWA), U.S. Department of Transportation.
Chen, C.Y., Chen, P.Y., Chen, W.T., 2013. A novel emergency vehicle dispatching system. IEEE Veh. Technol. Conf. doi:10.1109/VTCSpring.2013.6691836.
Clarke, D.D., Ward, P., Bartle, C., Truman, W., 2009. Work-related road traffic collisions in the UK. Accid. Anal. Prev. 41 (2), 345–351. https://doi.org/10.1016/j.aap.2008.12.013.
Cox, A.E., Mueller, A.S., Cicchino, J.B., 2023. Safety potential of crash avoidance features, improved headlights, and V2V-enhanced technologies for older drivers. J. Safety Res. 85, 200–209.
Custalow, C.B., Gravitz, C.S., 2004. Emergency medical vehicle collisions and potential for preventive intervention. Prehospital Emerg. Care 8 (2), 175–184. https://doi.org/10.1016/S1090-3127(03)00279-X.
Das, S., Dutta, A., 2020. Extremely serious crashes on urban roadway networks: Patterns and trends. IATSS Res 44 (3), 248–252.
Das, S., Kong, X. "Jack", Hossain, M.M., 2022. Exploration on prior driving modes for automated vehicle collisions. Int. J. Urban Sci. https://doi.org/10.1080/12265934.2022.2142650.
Das, S., Tamakloe, R., Zubaidi, H., Obaid, I., Alnedawi, A., 2021. Fatal pedestrian crashes at intersections: trend mining using association rules. Accid. Anal. Prev. 160, 106306.
Das, S., Hossain, M.M., Ashifur Rahman, M., Kong, X., Sun, X., Al Mamun, G.M., 2023. Understanding patterns of moped and seated motor scooter (50 cc or less) involved fatal crashes using cluster correspondence analysis. Transportmetrica A: Transport Sci. 19 (2) https://doi.org/10.1080/23249935.2022.2029613.
De Graeve, K., Deroo, K.F., Calle, P.A., Vanhaute, O.A., Buylaert, W.A., 2003. How to modify the risk-taking behaviour of emergency medical services drivers? Eur. J. Emerg. Med. 10 (2), 111–116. https://doi.org/10.1097/00063110-200306000-00009.
Djahel, S., Salehie, M., Tal, I., Jamshidi, P., 2013. Adaptive traffic management for secure and efficient emergency services in smart cities. 2013 IEEE Int. Conf Pervasive Comput. Commun. Work. PerCom Work. 2013, 340–343. https://doi.org/10.1109/PerComW.2013.6529511.
Donoughe, K., Whitestone, J., Gabler, H.C., 2012. Analysis of firetruck crashes and associated firefighter injuries in the United States. Ann. Adv. Automot. Med. 56, 69–76.
Drucker, C., Gerberich, S.G., Manser, M.P., Alexander, B.H., Church, T.R., Ryan, A.D., Becic, E., 2013. Factors associated with civilian drivers involved in crashes with emergency vehicles. Accid. Anal. Prev. 55, 116–123.
Eustace, D., Elmagri, H.F., Hovey, P.W., Board, T.R., 2017. Exploring Contributing Factors of Injury Severity of Drivers of Emergency Vehicles in Ohio 13p. Transportation Research Board 96th Annual Meeting.
Fahy, R., Evarts, B., Stein, G.P., 2021. U.S. Fire Department Profile 2019. National Fire Protection Association (NFPA).
Farber, G., 2004. Seeing With Headlights. NHTSA Workshop on Headlamp, Washington, DC.
FHWA, 2021. Zero Deaths and Safe System, Safe System and Traditional Approach Principles.
Fu, J., Vaca, F.E., 2011. Characteristics of law enforcement officers' fatalities in motor vehicle crashes. Ann. Emerg. Med. 58 (6), 568. https://doi.org/10.1016/j.annemergmed.2011.10.012.
Gaines, L., Weikersheimer, P., Gaines, L., 2015. Status and Issues for Idling Reduction in the United States Alternative Fuel and Advanced Vehicle Technology Market Trend. Argonne National Laboratory.
Gu, C., Xu, J., Gao, C., Mu, M., Guangxun, E., Ma, Y., 2022. Multivariate analysis of roadway multi-fatality crashes using association rules mining and rules graph structures: A case study in China. PLoS One 17 10 October. doi:10.1371/journal.pone.0276817.
Hornik, K., Grün, B., Hahsler, M., 2005. arules-A computational environment for mining association rules and frequent item sets. J. Stat. Softw. 14 (15), 1–25.
Hossain, M.M., Rahman, M.A., Sun, X., Mitran, E., 2021a. Investigating underage alcohol-intoxicated driver crash patterns in louisiana. Transp. Res. Rec. 2675 (11), 769–782. https://doi.org/10.1177/03611981211019742.
Hossain, M.M., Sun, X., Mitran, E., Rahman, M.A., 2021b. Investigating fatal and injury crash patterns of teen drivers with unsupervised learning algorithms. IATSS Res. 45 (4), 561–573. https://doi.org/10.1016/j.iatssr.2021.07.002.
Hossain, A., Sun, X., Thapa, R., Codjoe, J., 2022. Applying association rules mining to investigate pedestrian fatal and injury crash patterns under different lighting conditions. Transp. Res. Rec. 2676 (6), 659–672. https://doi.org/10.1177/03611981221076120.
Hossain, A., Sun, X., Islam, S., Alam, S., Mahmud Hossain, M.d., 2023. Identifying roadway departure crash patterns on rural two-lane highways under different lighting conditions: Association knowledge using data mining approach. J. Safety Res. 85, 52–65.
Hossain, M.M., Zhou, H., Rahman, M.A., Das, S., Sun, X., 2022. Cellphone-distracted crashes of novice teen drivers: Understanding associations of contributing factors for crash severity levels and cellphone usage types. Traffic Inj. Prev. 23 (7), 390–397. https://doi.org/10.1080/15389588.2022.2097667.
Hossain, M.M., Zhou, H., Das, S., Sun, X., Hossain, A., 2023. Young drivers and cellphone distraction: Pattern recognition from fatal crashes. J. Transp. Saf. Secur. 15 (3), 239–264.
Hsiao, H., Whitestone, J., Wilbur, M., Lackore, J.R., Routley, J.G., 2015. Seat and seatbelt accommodation in fire apparatus: anthropometric aspects. Appl. Ergon. 51, 137–151. https://doi.org/10.1016/j.apergo.2015.04.004.
Hsiao, H., Chang, J., Simeonov, P., 2018. Preventing emergency vehicle crashes: status and challenges of human factors issues. Hum. Factors 60 (7), 1048–1072. https://doi.org/10.1177/0018720818786132.
IAFF, 2006. Best Practices for Emergency Vehicle and Roadway Operations Safety in the Emergency Services. International Association of Fire Fighters (IAFF).
IAFF, 2022. Emergency Vehicle Safety Program. International Association of Fire Fighters (IAFF). https://www.iaff.org/vehicle-safety/.
Jermakian, J.S., 2011. Crash avoidance potential of four passenger vehicle technologies. Accid. Anal. Prev. 43 (3), 732–740. https://doi.org/10.1016/j.aap.2010.10.020.
Jermakian, J.S., 2012. Crash avoidance potential of four large truck technologies. Accid. Anal. Prev. 49, 338–346. https://doi.org/10.1016/j.aap.2010.10.033.
Kahn, C.A., Pirrallo, R.G., Kuhn, E.M., 2001. Characteristics of fatal ambulance crashes in the United States: an 11-year retrospective analysis. Prehospital Emerg. Care 5 (3), 261–269. https://doi.org/10.1080/10903120190939751.
Kielminski, D., Atkinson, E., Peters, D., Willson, S., Atkinson, T., 2023. Crash characteristics for classic/historic vehicles and comparisons to newer vehicles. J. Safety Res. 84, 18–23. https://doi.org/10.1016/j.jsr.2022.10.004.
Kong, X., Das, S., Jha, K., Zhang, Y., 2020. Understanding speeding behavior from naturalistic driving data: Applying classification based association rule mining. Accid. Anal. Prev. 144, 105620.
Kong, X., Das, S., Zhang, Y., 2021. Mining patterns of near-crash events with and without secondary tasks. Accid. Anal. Prev. 157, 106162.
LaTourrette, T., 2015. Risk factors for injury in law enforcement officer vehicle crashes. Policing 38 (3), 478–504.
Lidestam, B., Thorslund, B., Selander, H., Näsman, D., Dahlman, J., 2020. In-car warnings of emergency vehicles approaching: effects on car drivers' propensity to give way. Front. Sustain. Cities 2. https://doi.org/10.3389/frsc.2020.00019.
Liu, Y., Chang, G.L., Tao, R., Hicks, T., Tabacek, E., 2007. Empirical observations of dynamic dilemma zones at signalized intersections. Transp. Res. Rec. 2035, 122–133. https://doi.org/10.3141/2035-14.
Liu, P., David Fan, W., 2019. Modeling head-on crash severity on ncdot freeways: a mixed logit model approach. Can. J. Civ. Eng. 46 (6), 322–328. https://doi.org/10.1139/cjce-2018-0262.
López, G., Abellán, J., Montella, A., De Oña, J., 2014. Patterns of Single-vehicle crashes on two-lane rural highways in granada province, Spain: In-depth analysis through decision rules. Transp. Res. Rec. 2432 (1), 133–141. https://doi.org/10.3141/2432-16.
Maguire, B.J., Hunting, K.L., Smith, G.S., Levick, N.R., 2002. Occupational fatalities in emergency medical services: A hidden crisis. Ann. Emerg. Med. 40 (6), 625–632. https://doi.org/10.1067/mem.2002.128681.
Maze, T.H., Agarwal, M., Burchett, G., 2006. Whether weather matters to traffic demand, traffic safety, and traffic operations and flow. Transport. Res. Record 1948 (1), 170–176.
Missikpode, C., Peek-Asa, C., Young, T., Hamann, C., 2018. Does crash risk increase when emergency vehicles are driving with lights and sirens? Accid. Anal. Prev. 113, 257–262. https://doi.org/10.1016/j.aap.2018.02.002.
Montella, A., de Oña, R., Mauriello, F., Rella Riccardi, M., Silvestro, G., 2020. A data mining approach to investigate patterns of powered two-wheeler crashes in Spain. Accid. Anal. Prev. 134, 105251.
Montella, A., Mauriello, F., Pernetti, M., Rella Riccardi, M., 2021. Rule discovery to identify patterns contributing to overrepresentation and severity of run-off-the-road crashes. Accid. Anal. Prev. 155, 106119.
NHTSA, 2021. Crash Report Sampling System Analytical User's Manual, 2016–2020. National Highway Traffic Safety Administration (NHTSA).
Pande, A., Abdel-Aty, M., 2009. Market basket analysis of crash data from large jurisdictions and its potential as a decision support tool. Saf. Sci. 47 (1), 145–154. https://doi.org/10.1016/j.ssci.2007.12.001.
Pearsall, B., 2010. Keeping Officers Safe on the Road. National Institute of Justice (NIJ), 265.
Peterson, K., Amandus, H., Wassell, J.T., 2009. Reducing firefighter vehicle crash fatalities. Fire Eng. 162 (6), 79–84.
Pietzsch, R.N., 2015. Effectiveness of Mandatory Driver Training Programs for fire Service Drivers. Eastern Kentucky University.
Pirrallo, R.G., Swor, R.A., 1994. Characteristics of fatal ambulance crashes during emergency and non-emergency operation. Prehosp. Disaster Med. 9 (2), 125–132.
Polders, E., Daniels, S., Hermans, E., Brijs, T., Wets, G., 2015. Crash patterns at signalized intersections. Transp. Res. Rec. 2514, 105–116. https://doi.org/10.3141/2514-12.
Qin, X., Khan, A.M., 2012. Control strategies of traffic signal timing transition for emergency vehicle preemption. Transp. Res. Part C Emerg. Technol. 25, 1–17. https://doi.org/10.1016/j.trc.2012.04.004.
Rahman, M.A., Hossain, M.M., Mitran, E., Sun, X., 2021a. Understanding the contributing factors to young driver crashes: a comparison of crash profiles of three age groups. Transp. Eng. 5, 100076.
Rahman, M.A., Das, S., Sun, X., Sun, M., Hossain, M.M., 2023. Using unsupervised learning to investigate injury-associated factors of animal-vehicle crashes. Int. J. Injury Control Safety Promot. 30 (2), 210–219.
Rahman, M.A., Sun, X., Sun, M., Shan, D., 2021b. Investigating characteristics of cellphone distraction with significance tests and association rule mining. IATSS Res 45 (2), 198–209.
Ray, A.M., Kupas, D.F., 2007. Comparison of rural and urban ambulance crashes in Pennsylvania. Prehospital Emerg. Care 11 (4), 416–420. https://doi.org/10.1080/10903120701536966.
Reaves, B., 2017. Police Vehicle Pursuits, 2012–2013. U.S, Department of Justice.
Rella Riccardi, M., Mauriello, F., Scarano, A., Montella, A., 2023. Analysis of contributory factors of fatal pedestrian crashes by mixed logit model and association rules. Int. J. Injury Control Safety Promot. 30 (2), 195–209.

Robertson, L.S., Baker, S.P., 1976. Motor vehicle sizes in 1440 fatal crashes. Accid. Anal. Prev. 8 (3), 167–175. https://doi.org/10.1016/0001-4575(76)90018-X.

Samerei, S.A., Aghabayk, K., Mohammadi, A., Shiwakoti, N., 2021a. Data mining approach to model bus crash severity in Australia. J. Safety Res. 76, 73–82. https://doi.org/10.1016/j.jsr.2020.12.004.

Samerei, S.A., Aghabayk, K., Shiwakoti, N., Karimi, S., 2021b. Modelling bus-pedestrian crash severity in the state of Victoria, Australia. Int. J. Inj. Contr. Saf. Promot. 28 (2), 233–242. https://doi.org/10.1080/17457300.2021.1907597.

Sanddal, T.L., Sanddal, N.D., Ward, N., Stanley, L., 2010. Ambulance crash characteristics in the US defined by the popular press: a retrospective analysis. Emerg. Med. Int. 2010, 1–7. https://doi.org/10.1155/2010/525979.

Savolainen, P.T., Dey, K.C., Ghosh, I., Karra, T.L.N., Lamb, A., 2009. Investigation of Emergency Vehicle Crashes in the State of Michigan. U.S. Department of Justice.

Schrock, S.D., Udaipurwala, M.T., Fitzsimmons, E.J., 2016. Evaluation of intersection confirmation lights with targeted enforcement to reduce red light running violations at freeway ramp intersections. Transp. Res. Rec. 2584, 1–7. https://doi.org/10.3141/2584-01.

Tamakloe, R., Das, S., Nimako Aidoo, E., Park, D., 2022. Factors affecting motorcycle crash casualty severity at signalized and non-signalized intersections in Ghana: Insights from a data mining and binary logit regression approach. Accid. Anal. Prev. 165, 106517.

Tefft, B.C., Williams, A.F., Grabowski, J.G., 2013. Teen driver risk in relation to age and number of passengers, United States, 2007–2010. Traffic Inj. Prev. 14 (3), 283–292. https://doi.org/10.1080/15389588.2012.708887.

THUD, 2020. S. Rept. 116-109 - Transportation, Housing and Urban Development, and Related Agencies (THUD) appropriations bill.

Tofighi, M., Asgary, A., Tofighi, G., Podloski, B., Cronemberger, F., Mukherjee, A., Liu, X., 2021. Applying machine learning models to first responder collisions beside roads: Insights from "two vehicles hit a parked motor vehicle" data. Appl. Sci. 11, 23. https://doi.org/10.3390/app112311198.

USFA, 2014. Emergency Vehicle Safety Initiative, FA-336. U.S. Fire Administration.

Wood, J.M., 2020. Nighttime driving: visual, lighting and visibility challenges. Ophthalmic Physiol. Opt. 40 (2), 187–201. https://doi.org/10.1111/opo.12659.

Yasmin, S., Anowar, S., Tay, R., 2012. Effects of drivers' actions on severity of emergency vehicle collisions. Transp. Res. Rec. 2318, 90–97. https://doi.org/10.3141/2318-11.