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Demographic risk factors and injury severity scores in Substance-use behaviour related traffic crashes

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A R T I C L E I N F O

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A B S T R A C T

Alcohol and drugs, including Tetrahydrocannabinol (THC), significantly impact roadway safety by impairing cognitive functions, coordination, and reaction times, leading to increased crash risk and severity. This study examines the prevalence of alcohol and drugs among 4,586 injured roadway users (drivers, riders, and passengers) in the U.S. from 2019 to 2021, utilizing an XGBoost model to identify key variables associated with Injury Severity Score (ISS) in substance-related traffic crashes, and highlighting influential factors such as injury location, demographic characteristics (age, race), safety compliance, and alcohol and drug presence. These risk factors were further analyzed through Cluster Correspondence Analysis (CCA) to reveal patterns and trends affecting injury severity across different demographic and behavioral groups. The findings reveal that 55.8% of the injured tested positive for substances, with cannabinoids being the most common, followed by alcohol, stimulants, and opioids. This study identified six core crash clusters, each with distinct characteristics, including older drivers, impaired young drivers, specific driver ethnicities, and motorcyclists. Key findings from clusters indicate that older drivers, despite high safety compliance and negative substance tests, faced crash risks potentially due to age-related limitations. Impaired young adult crashes are characterized by risky behavior, including alcohol and THC use combined with low safety compliance, while motorcyclists with high substance involvement and inconsistent helmet use, are identified as a high-risk group, frequently experiencing severe leg injuries. These insights underscore the need for comprehensive traffic safety policies targeting substance use and promoting effective safety measures to mitigate crash risks and improve road safety.

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1. Introduction

1.1. Background

Alcohol and drug use poses a significant risk to mortality and morbidity of both the driver and bystander. In 2020, 11,654 fatalities were reported due to alcohol use (National Center for Statistics and Analysis, 2022). Alcohol impairs cognitive functions, coordination, and reaction times, leading to increased crash risk and more severe outcomes, particularly at higher blood alcohol concentrations (BAC). Tetrahydrocannabinol (THC), the active component in cannabis, also affects driving performance by impairing attention, judgment, and motor skills, which can elevate the likelihood of crashes. The presence of alcohol or drugs in crash-involved drivers or passengers is often linked to more severe crash outcomes, with drugged driving, including THC use, contributing to higher fatality rates and serious injuries (National Center for Statistics and Analysis, 2022). Nearly half of roadway users in the U.S. who sustained serious or fatal injuries were found to have one or more drugs in their system. Among these, cannabinoids were the most common at 25.1 %, with alcohol at 23.1 %, stimulants at 10.8 %, and opioids at 9.3 % (Thomas et al., 2022). The associations between drug positivity and factors such as age, sex, time, and day of crash were identified. Although the results offer insights into drug prevalence, they were not interpreted as indicators of impairment or risk in the absence of further contextual information.

Previous studies underscored the significant impact of alcohol and THC on road safety and crash severity. Cherpitel et al. (2022), Høye and Hesjevoll (2023), and Dong et al. (2024b) found that increased BAC and cannabis use heighten the risk of crashes and road traffic injuries (RTIs) by compromising driving performance, impacting cognitive abilities and reaction times. Beirness et al. (2021) revealed that THC was the most detected drug among fatally injured drivers in Ontario and similarly, Khiabani et al. (2006) found a strong correlation between higher blood THC levels and impairment, reflecting its detrimental effect on driving performance. Toxicological analyses of drivers fatally injured in road accidents in Spain revealed that over half had tested positive for alcohol (with blood alcohol levels above 0.3 g/l), drugs of abuse, and/or psychopharmaceuticals, either individually or in combination (National Institute of Toxicology and Forensic Sciences, 2022).

Previous reports from traffic and transport authorities along with related studies have predominantly focused on descriptive statistics of specific substances without offering a comprehensive analysis of drug and alcohol prevalence among fatally injured drivers and passengers. Moreover, there is very few research that analyzed Injury Severity Score (ISS). These studies often failed to incorporate contextual factors such the locations of injuries on the body, types of vehicles involved, safety measures (including seatbelt use, helmet use, and airbag deployment), and demographic variables, along with their effects on ISS. This study addresses existing gaps by providing an in-depth analysis of alcohol and substance presence, safety measures, injury locations post-crash, and the use of various vehicle categories among drivers and passengers. Using Cluster Correspondence Analysis (CCA), it examines crash data to uncover underlying patterns and trends, offering valuable insights into the dynamics of driver and passenger crash injuries that extend beyond the scope of existing literature and typical government reports. The analysis is based on a comprehensive three-year dataset (2019–2021) from the U.S., focusing on the factors contributing to roadway user crashes, particularly alcohol and drug usage, safety measures, and injured body locations. Following this introduction, the next section reviews related literature, followed by the methodology, which includes data description and a concise explanation of the theory behind CCA. The results and discussion are presented in subsequent sections. Notably, this study contributes significantly to the field by exploring ISS alongside contextual factors associated with impairment related post-collision data. One of its key contributions is the identification of specific clusters using CCA which enables a detailed examination of crash dynamics and various drug related parameters offering a deeper understanding of substance related crashes.

2. Study contributions

This study addresses critical gaps in understanding the impact of alcohol and drug use, particularly THC, on roadway safety and injury outcomes for both drivers and passengers. While prior studies primarily offer descriptive statistics and conventional models on substance involvement, they rarely explore the complex interrelationships between drug and alcohol prevalence, injury severity, and contextual factors like injury locations, vehicle types, and safety measures (e.g., seatbelt and helmet use). By utilizing a comprehensive dataset spanning 2019–2021 and employing CCA, this research provides a comprehensive view into these interrelationships, revealing specific clusters that highlight the dynamics of substance-related crashes and the factors that influence injury severity. This approach uncovers complex patterns within high-dimensional crash data, facilitating the understanding of the hidden relationships affecting crash injury outcomes.

3. Literature review

This literature review seeks to thoroughly analyze the effects of substance use, particularly alcohol and drugs, on traffic crash outcomes and related policies. Recent studies highlighting trends and effects of substance use on traffic crashes globally will be explored, with a focus on the influence of BAC on driving performance and behaviour. Additionally, the role of THC and other drugs in road traffic injuries and fatalities will be investigated. Various interventions and strategies designed to mitigate the risks associated with impaired driving will also be discussed. This study aims to synthesize current knowledge and identify gaps for future research, ultimately contributing to enhanced public safety and more effective policy development.

3.1. Blood alcohol concentration (BAC) and traffic crash

BAC measures the amount of alcohol in a specific volume of blood, expressed by weight. A BAC of 0.08 g per deciliter (g/dL) significantly raises the risk of a crash (Scherer & Fell, 2019). Due to this increased danger, it is illegal to drive with a BAC of 0.08 or higher in all 50 states. Research on the impacts of BAC on driving performance and behaviour has yielded important insights into how alcohol impairs driving across various contexts (Aktaş & Akgür, 2022; Dong et al., 2024a; Eby et al., 2017; Høye & Hesjevoll, 2023; Yadav & Velaga, 2019). The 2022 Federal Motor Carrier Safety Administration (FMCSA) Drug and Alcohol Testing Survey reported that 0.9 % of commercial drivers tested positive for drugs and 0.29 % had BACs of 0.04 % or higher (United States. Department of Transportation, 2024). Dong et al. (2024b, 2024a) highlighted that varying BAC levels impair cognitive functions and significantly delay reaction times, affecting performance in both manual and automated driving systems. Similarly, Høye and Hesjevoll (2023b) through a *meta*-analysis of 60 studies found that higher BAC levels exponentially increase the risk of crashes and injuries, with notable variations based on geographical regions and the severity of outcomes. This is consistent with the findings of Yadav and Velaga (2019), who used a driving simulator to demonstrate that elevated BAC levels contribute to more aggressive driving patterns, including greater acceleration and brake pedal force, which can further exacerbate traffic safety issues. Tivesten et al. (2023) explored how alcohol affects the visual attention of drivers on a test track, showing that intoxication increased off-path glances and altered visual focus across different driving modes, suggesting potential enhancements for driver monitoring systems. This complements the insights from Baldock et al. (2022), who found that substance use, including alcohol, plays a significant role in both pre- and post-crash scenarios, exacerbating outcomes and highlighting the need for alternative pain management therapies.

Internationally, in Cameroon, Oyono et al. (2022) reported that 30.9 % of road users injured in traffic crashes had BAC above the legal limit, with the highest rates among motorcycle riders during weekends, suggesting a need for improved measures to reduce alcohol-impaired driving. This finding aligns with the study by Damsere-Derry et al. (2018), which observed a high prevalence of alcohol among nonfatally injured crash victims in northern Ghana, particularly among motorcyclists, recommending enhanced BAC enforcement and road safety education. Surveys have also provided valuable information on public perceptions and legal standards. A survey regarding the 0.05 BAC limit proposed by the NTSB found that while the lower limit could save lives, there are concerns about the effectiveness of current sobriety tests and the need for enhanced public education (Fiorentino & Martin, 2018). This sentiment is echoed in the study by Eby et al. (2017), which revealed moderate support for lowering the BAC standard in the U.S., yet highlighted the necessity for better public education on BAC laws and their impact on driving behaviour.

3.2. Impacts of substance use on road traffic injuries (RTIs)

Recent studies have investigated the influence of substance use, particularly alcohol and drugs, on traffic crash outcomes and related policies (Alexandrescu et al., 2024; M. B. Johnson, 2022; Singichetti et al., 2024; Tatar et al., 2022). Analyzing Fatality Analysis Reporting System (FARS) data from 2010 to 2017, Johnson (2022) found that alcohol-involved crashes were underrepresented in high-skill-demand situations like intersections and with moving objects but were 24 % more likely to involve stationary objects, suggesting that alcohol impairs cognitive and psychomotor driving skills. Alexandrescu et al. (2024) revealed that 38 % of drivers had alcohol levels above the limit and 47 % tested positive for other drugs, with those having prior drink/drug driving offenses significantly tested positive for drugs. A recent study of unintentional drug toxicity deaths in Québec from 2012 to 2021 highlighted an increase in mortality rates over time, peaking in 2020 and remaining high in 2021, with notable shifts in drug detection, including an increase in Fentanyl and novel Benzodiazepines (Do et al., 2024). They further highlighted that a greater proportion of fatally injured drivers were found positive for drugs rather than alcohol. Using a difference-in-differences approach, the impact of Florida's Prescription Drug Monitoring Program (PDMP) on drug-related fatal vehicle crashes was evaluated, revealing a significant decline in opioid-related fatal crashes post-PDMP implementation, with roughly two fewer deaths per month. However, no significant reductions were observed for crashes involving other prescription drugs, cocaine, or marijuana (Tatar et al., 2022).

Studies have consistently shown that drug-impaired driving is more common among young drivers, with a higher prevalence of illegal drug use, such as THC, compared to alcohol consumption (M. Baldock, 2023; Peck et al., 2008; Poetto et al., 2024). Poetto et al. (2024) reported the key factors included a high prevalence of drug use, with 9 % of drivers testing positive (mainly for THC and cocaine), and demographic trends showing most were males under 30. This finding is consistent with Alcañiz et al. (2021), who reported that drug-impaired driving was more frequent in young males during daytime, while alcohol use was higher on conventional roads, weekends, and at night. Similarly, Beirness et al. (2021) found that THC use was more common than alcohol, especially among males, and multi-substance detection was frequent, with alcohol-related fatalities peaking on weekends in single-vehicle crashes, while

Table 1
Contributing Factors to Substance Use and Road Traffic Injuries.

Factors	Studies
Demographic (male, age)	(Ahlström et al., 2018; Alcañiz et al., 2021; M. Baldock, 2023; Mills et al., 2021a; Peck et al., 2008; Poetto et al., 2024)
Driver condition (impair cognitive functions, aggressive driving, speeding, altered visual focus)	(Dong et al., 2024b; Dong et al., 2024a; A. S. Hasan et al., 2022; S. L. Johnson, 2008; Tivesten et al., 2023; Yadav & Velaga, 2019)
Crash type (single vehicle crash)	(Alexandrescu et al., 2024; Beirness et al., 2021)
Temporal characteristics (weekday, weekend, daytime, nighttime)	(Alcañiz et al., 2021; Beirness et al., 2021; Oyono et al., 2022)
Spatial characteristics (geographical regions)	(Høye & Hesjevoll, 2023)

drug-related crashes were more evenly distributed throughout the week. Additionally, a systematic review by Hasan et al. (2022) on illegal drug driving identified key factors associated with this behaviour, including a tendency towards sensation-seeking and impulsivity among young, single males who use cannabis. Furthermore, Hasan et al. (2023) explored factors to drug driving in Australia included problematic drug use, knowledge of penalties, and the use of detection avoidance strategies, with cannabis being the most common drug. Table 1 summarizes the contributing factors to substance use and road traffic injuries.

3.3. Interventions and strategies for addressing alcohol and drug impairment in driving

National Transportation Safety Board (NTSB) report emphasized the need for improved countermeasures and laws regarding drug-impaired driving, reflecting the growing concerns about cannabis and other drugs (National Transportation Safety Board, 2022). Effective strategies for mitigating the impacts of alcohol and drug impairment on driving involved a combination of technological, educational, and rehabilitative approaches. Ahlström et al. (2023) demonstrated that increasing breath alcohol concentration (BrAC) impairs attention and leads to dangerous driving behaviours, such as speeding and reduced visual focus on the road, underscoring the need for advanced driver assistance systems to counteract these effects. Castro et al. (2023) found that traffic offenders with high rates of substance abuse and lower educational levels struggle to dissociate substance use from driving, suggesting that mere license revocations are inadequate. Comprehensive rehabilitation programs and interventions targeting these underlying issues are necessary. Research by Allen et al. (2023) and Zaouk et al. (2023) on the Driver Alcohol Detection System for Safety (DADSS) revealed that integrating such systems into vehicles could significantly reduce drunk driving incidents, aligning with a risk-based approach to enhance safety. Additionally, Mills et al. (2021b) identified that younger drivers are more influenced by safe transport advocates and are at higher risk for drug driving. Strategies targeting this demographic, including public education and peer influence programs, can promote better self-regulation and planning for safe alternatives. Combining these technological, educational, and rehabilitative strategies offers a multifaceted approach to addressing impaired driving and improving road safety.

4. Research gap

Recent studies have identified significant impacts of substance use, particularly alcohol and THC, on traffic crash outcomes, highlighting increased risks of road traffic injuries and fatalities associated with both substances. Some studies have emphasized the need for stricter control policies and highlighted regional variations in alcohol and drug-related crashes. However, these studies predominantly focused on specific substances. They lacked a comprehensive analysis that integrates contextual factors such as demographics, vehicle types, and safety measures (e.g., seatbelt use, helmet use, and airbag deployment). Moreover, the combined effects of multiple substances and the detailed examination of injury severity among drivers and passengers remain underexplored. This study aims to address these gaps by providing a detailed analysis of alcohol and substance presence, safety measures, and post-crash injury locations in the body, using CCA to identify patterns and trends in crash data. Utilizing a comprehensive three-year (2019–2021) dataset from the U.S., this research seeks to enhance understanding of the dynamics of driver and passenger crashes, contributing developing of more effective traffic safety policies and interventions.

5. Methodology

This section outlines the research methodology used in this paper. Before applying CCA, data preparation, variable importance

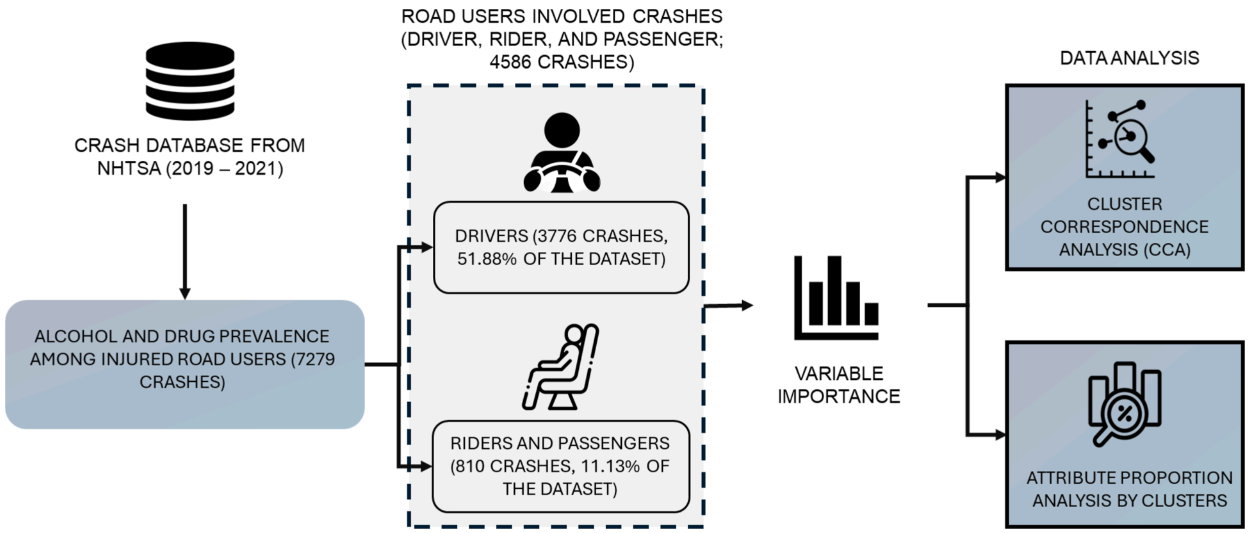


Fig. 1. Flow chart of study design.

analysis, and exploratory data analysis were conducted. The application of CCA offers a significant advantage by allowing a detailed examination of relationships between categorical variables, such as demographic factors, injury severity, and substance use. This method facilitates pattern recognition by providing an intuitive visual interpretation of the complex interactions. The methodology is detailed in the following sub-sections.

5.1. Data preparation and study design

This study obtained three years (2019–2021) of crash data collected by the National Highway Traffic Safety Administration (NHTSA) from seven different locations in the U.S. including Jacksonville and Miami in Florida, Charlotte in North Carolina, Baltimore in Maryland, Worcester in Massachusetts, Iowa City in Iowa, and Sacramento in California (Thomas et al., 2022). The dataset has 7,279 roadway users' toxicological analyses information that includes road users' demographic information, Injury Severity Score (ISS), injury location and type, safety measures (helmet use, seatbelt use, airbag deployment), and presence of alcohol, cannabinoids (Active THC), stimulants, opioids. Among these, around 4,586 data are regarding drivers and passengers used in this study. Injury location in the body categories encompasses various body parts affected during incidents. Head and neck injuries are categorized distinctly, while hand injuries include areas such as the lower and upper left arm, left hand, left wrist, and corresponding right-side locations. Leg injuries encompass ankles, feet, and upper and lower legs on both sides, and chest-related injuries cover the chest, ribs, back, hips, and specific side impacts. Internal injuries are focused on abdominal and torso areas. The ISS ranges from 1 to 75. The ISS is classified into five levels: Minor Injury (1 to 8), Moderate Injury (9 to 15), Serious Injury (16 to 24), Severe Injury (25 to 49), and Critical Injury (50 to 75) following the scoring method of VanDerHeyden and Cox (2008), Yadollahi et al. (2020), Camilloni et al. (2010), Cassidy et al. (2014), and Reynolds et al. (2011). Fig. 1 depicts the procedure followed for data preparation and the execution of correspondence analysis on the prepared data in this research.

5.2. Exploratory data analysis

The dataset facilitated the examination of drug and alcohol prevalence patterns in two groups of roadway users (driver and passenger), offering essential insights into the substances frequently linked with injury severity on the roads. The descriptive statistics presented in Table 2 provide an overview of the demographics and injury characteristics of drivers and passengers based on data collected from various locations including Jacksonville and Miami in Florida, Charlotte in North Carolina, Baltimore in Maryland, Worcester in Massachusetts, Iowa City in Iowa, and Sacramento in California. The dataset used in this study comprises 4,586 observations related to crash injuries, categorized into five injury severity levels based on the ISS: Minor Injury (ISS Score: 1 to 8) (75.49 %), Moderate Injury (ISS Score: 9 to 15) (12.06 %), Serious Injury (ISS Score: 16 to 24) (6.96 %), Severe Injury (ISS Score: 25 to 49) (5.15 %), and Critical Injury (ISS Score: 50 to 75) (0.35 %). Most injured were drivers (82.34 %), with passengers accounting for 17.66 %. Among drivers, 5.53 % of severe injuries (ISS Score: 25 to 49) occurred. The data also provides insights into the time of injury data collection, showing a higher crash occurrence during the daytime (54.97 %) compared to nighttime (45.03 %). Weekday incidents were more prevalent (66.59 %) than weekend incidents (33.41 %). The data reveals that cars, accounting for 60.03 % of vehicle types involved in crashes, had a severe injury rate of 4.43 % (122 cases), while critical injuries were minimal at 0.36 %. Similarly, motorcycles represent 18.05 % of the total crash incidents and among them 11.59 % (139 cases) showed moderate injuries but significantly higher rates of serious (9.66 %) and severe injuries (9.06 %).

Age also plays a significant role among 37.88 % of individuals aged 21–34, 5.35 % (93 cases), 5.35 % (93 cases), and 0.46 % (8 cases) suffered from serious, severe, and critical injuries respectively which are the highest compared to other age groups. Furthermore, males experienced high injury rates compared to females accounting for 12.77 % (379 cases), 7.72 % (229 cases), and 6.30 % (187 cases) of moderate, serious, and severe injuries respectively. Among racial groups, white individuals, who constitute 42.56 % of the dataset, exhibited the highest rates of moderate (12.86 %, 251 cases), serious (9.02 %, 176 cases), and severe injuries (6.10 %, 119 cases) compared to other races. Regarding injury body location, chest and other injuries were most common, comprising 36.07 % of the dataset, with 11.49 % (190 cases) being moderate, 7.13 % (118 cases) serious, and 4.78 % (79 cases) severe.

Seat belt usage significantly influences injury severity in vehicular incidents. Among those not wearing seat belts, 9.23 % (65 cases) suffered severe injuries. Additionally, the presence of airbags also impacted injury outcomes, where individuals with front and side airbags deployed had higher rates of severe (4.74 %, 52 cases) and serious injuries (5.83 %, 64 cases) compared to those without any airbag deployment, indicating a potential mitigating effect on injury severity. The presence of safety features like seat belts and airbags significantly influenced injury outcomes; 80.70 % (2350 cases) of individuals using seat belts reported minor injuries, whereas non-users faced 9.52 % (67 cases) and 9.23 % (65 cases) of serious and severe injuries. Additionally, airbags also impacted on injury outcomes, where individuals with front and side airbags deployed had higher rates of minor injuries (78.71 %). For individuals with a higher alcohol concentration (.15+%), there is an evident increase in the percentage of moderate to severe injuries, with 12.43 % experiencing moderate injuries and 8.59 % suffering from serious injuries. Additionally, of the individuals with THC levels ranging from 2-4 ng/mL, which constitute 8.33 % (382 cases) of the population, 79.32 % (303 cases) experienced minor injuries, while 4.97 % (19 cases) sustained severe injuries. For individuals testing positive for multiple drug classes, the rates of more severe injuries increase noticeably. Those with three drug classes show 17.67 % (44 cases) of severe injuries and 2.01 % (5 cases) of critical injuries. Meanwhile, alcohol consumption also shows a marked influence. Individuals testing positive for alcohol alone experience moderate (13.89 %, 71 cases), serious (8.61 %, 44 cases), and severe injuries (5.87 %, 30 cases) at notable rates.

The XGBoost model was utilized to determine the most important variables associated with ISS. The top 10 variables, ranked by their importance scores, are illustrated in Fig. 2 where darker shades signify higher importance values. 'Injury Location' was identified

Table 2
Descriptive Statistics of the Variables.

Variable and Attribute	Overall	Minor Injury (ISS Score: 1 to 8)	Moderate Injury (ISS Score: 9 to 15)	Serious Injury (ISS Score: 16 to 24)	Severe Injury (ISS Score: 25 to 49)	Critical Injury (ISS Score: 50 to 75
Total Crashes	4586 (100 %)	3462 (75.49 %)	553 (12.06 %)	319 (6.96 %)	236 (5.15 %)	16 (0.35 %)
Seating Position						
Driver	3776 (82.34 %)	2830 (74.95 %)	456 (12.08 %)	268 (7.10 %)	209 (5.53 %)	13 (0.34 %)
Passenger	810 (17.66 %)	632 (78.02 %)	97 (11.98 %)	51 (6.30 %)	27 (3.33 %)	3 (0.37 %)
Time of the Collection						
Daytime collection	2521 (54.97 %)	1960 (77.75 %)	277 (10.99 %)	161 (6.39 %)	116 (4.60 %)	7 (0.28 %)
Nighttime collection	2065 (45.03 %)	1502 (72.74 %)	276 (13.37 %)	158 (7.65 %)	120 (5.81 %)	9 (0.44 %)
Day of the Week						
Weekday	3054 (66.59 %)	2347 (76.85 %)	339 (11.10 %)	208 (6.81 %)	150 (4.91 %)	10 (0.33 %)
Weekend	1532 (33.41 %)	1115 (72.78 %)	214 (13.97 %)	111 (7.25 %)	86 (5.61 %)	6 (0.39 %)
Vehicle Type						
Car	2753 (60.03 %)	2127 (77.26 %)	319 (11.59 %)	175 (6.36 %)	122 (4.43 %)	10 (0.36 %)
Motorcycle	828 (18.05 %)	530 (64.01 %)	139 (16.79 %)	80 (9.66 %)	75 (9.06 %)	4 (0.48 %)
Other	98 (2.14 %)	76 (77.55 %)	9 (9.18 %)	9 (9.18 %)	4 (4.08 %)	0 (0 %)
SUV	450 (9.81 %)	370 (82.22 %)	37 (8.22 %)	31 (6.89 %)	11 (2.44 %)	1 (0.22 %)
Truck	320 (6.98 %)	253 (79.06 %)	33 (10.31 %)	18 (5.63 %)	15 (4.69 %)	1 (0.31 %)
Van	76 (1.66 %)	64 (84.21 %)	5 (6.58 %)	3 (3.95 %)	4 (5.26 %)	0 (0 %)
Age						
18–20	324 (7.06 %)	259 (79.94 %)	33 (10.19 %)	15 (4.63 %)	15 (4.63 %)	2 (0.62 %)
21–34	1737 (37.88 %)	1336 (76.91 %)	207 (11.92 %)	93 (5.35 %)	93 (5.35 %)	8 (0.46 %)
35–44	816 (17.79 %)	618 (75.74 %)	96 (11.76 %)	69 (8.46 %)	32 (3.92 %)	1 (0.12 %)
45–64	1179 (25.71 %)	872 (73.96 %)	155 (13.15 %)	83 (7.04 %)	66 (5.60 %)	3 (0.25 %)
65+	529 (11.54 %)	376 (71.08 %)	62 (11.72 %)	59 (11.15 %)	30 (5.67 %)	2 (0.38 %)
Gender						
Male	2968 (64.72 %)	2161 (72.81 %)	379 (12.77 %)	229 (7.72 %)	187 (6.30 %)	12 (0.40 %)
Female	1618 (35.28 %)	1301 (80.41 %)	174 (10.75 %)	90 (5.56 %)	49 (3.03 %)	4 (0.25 %)
Race						
White	1952 (42.56 %)	1401 (71.77 %)	251 (12.86 %)	176 (9.02 %)	119 (6.10 %)	5 (0.26 %)
African or African American	1444 (31.49 %)	1153 (79.85 %)	151 (10.46 %)	74 (5.12 %)	60 (4.16 %)	6 (0.42 %)
Hispanic	900 (19.62 %)	654 (72.67 %)	137 (15.22 %)	57 (6.33 %)	48 (5.33 %)	4 (0.44 %)
Asian	68 (1.48 %)	62 (91.18 %)	4 (5.88 %)	1 (1.47 %)	0 (0 %)	1 (1.47 %)
Native American or Alaska Native	25 (0.55 %)	21 (84.00 %)	1 (4.00 %)	2 (8.00 %)	1 (4.00 %)	0 (0 %)
More Than One Race	26 (0.57 %)	19 (73.08 %)	1 (3.85 %)	2 (7.69 %)	4 (15.38 %)	0 (0 %)
Hawaiian or Pacific Islander	5 (0.11 %)	5 (100 %)	0 (0 %)	0 (0 %)	0 (0 %)	0 (0 %)
Primary Body Injury Location						
Chest and Other	1654 (36.07 %)	1260 (76.18 %)	190 (11.49 %)	118 (7.13 %)	79 (4.78 %)	7 (0.42 %)
Hand Injury	553 (12.06 %)	462 (83.54 %)	51 (9.22 %)	32 (5.79 %)	8 (1.45 %)	0 (0 %)

(continued on next page)

Table 2 (*continued*)

Variable and Attribute	Overall	Minor Injury (ISS Score: 1 to 8)	Moderate Injury (ISS Score: 9 to 15)	Serious Injury (ISS Score: 16 to 24)	Severe Injury (ISS Score: 25 to 49)	Critical Injury (ISS Score: 50 to 75
Head/neck Injury	1426 (31.09 %)	1085 (76.09 %)	149 (10.45 %)	104 (7.29 %)	84 (5.89 %)	4 (0.28 %)
Internal Injury	272 (5.93 %)	196 (72.06 %)	21 (7.72 %)	26 (9.56 %)	27 (9.93 %)	2 (0.74 %)
Leg Injury	681 (14.85 %)	459 (67.40 %)	142 (20.85 %)	39 (5.73 %)	38 (5.58 %)	3 (0.44 %)
Seat Belt Use						
No	704 (15.35 %)	467 (66.34 %)	103 (14.63 %)	67 (9.52 %)	65 (9.23 %)	2 (0.28 %)
Yes	2912 (63.50 %)	2350 (80.70 %)	297 (10.20 %)	160 (5.49 %)	96 (3.30 %)	9 (0.31 %)
NA	970 (21.15 %)	645 (66.49 %)	153 (15.77 %)	92 (9.48 %)	75 (7.73 %)	5 (0.52 %)
Airbag Deployed						
Deployed front	1042 (22.72 %)	821 (78.79 %)	108 (10.36 %)	69 (6.62 %)	40 (3.84 %)	4 (0.38 %)
Deployed front and side	1097 (23.92 %)	857 (78.12 %)	118 (10.76 %)	64 (5.83 %)	52 (4.74 %)	6 (0.55 %)
Deployed side	168 (3.66 %)	119 (70.83 %)	28 (16.67 %)	11 (6.55 %)	10 (5.95 %)	0 (0 %)
Not deployed	937 (20.43 %)	776 (82.82 %)	80 (8.54 %)	44 (4.70 %)	36 (3.84 %)	1 (0.11 %)
No airbag	211 (4.60 %)	145 (68.72 %)	31 (14.69 %)	20 (9.48 %)	14 (6.64 %)	1 (0.47 %)
NA	1131 (24.66 %)	744 (65.78 %)	188 (16.62 %)	111 (9.81 %)	84 (7.43 %)	4 (0.35 %)
Helmet Use						
No	381 (8.31 %)	242 (63.52 %)	73 (19.16 %)	36 (9.45 %)	30 (7.87 %)	0 (0 %)
Yes	474 (10.34 %)	314 (66.24 %)	68 (14.35 %)	44 (9.28 %)	44 (9.28 %)	4 (0.84 %)
NA	3731 (81.36 %)	2906 (77.89 %)	412 (11.04 %)	239 (6.41 %)	162 (4.34 %)	12 (0.32 %)
Alcohol Range						
Negative	3620 (78.94 %)	2756 (76.13 %)	436 (12.04 %)	236 (6.52 %)	180 (4.97 %)	12 (0.33 %)
.02 %-.049 %	82 (1.79 %)	57 (69.51 %)	9 (10.98 %)	11 (13.41 %)	5 (6.10 %)	0 (0 %)
.05 %-.079 %	84 (1.83 %)	57 (67.86 %)	14 (16.67 %)	6 (7.14 %)	7 (8.33 %)	0 (0 %)
.08 %-.149 %	253 (5.52 %)	189 (74.70 %)	26 (10.28 %)	19 (7.51 %)	16 (6.32 %)	3 (1.19 %)
.15+%	547 (11.93 %)	403 (73.67 %)	68 (12.43 %)	47 (8.59 %)	28 (5.12 %)	1 (0.18 %)
Tetrahydrocannabinol Range (THC)						
Negative	3428 (74.75 %)	2588 (75.50 %)	414 (12.08 %)	241 (7.03 %)	174 (5.08 %)	11 (0.32 %)
1 ng/mL	277 (6.04 %)	199 (71.84 %)	33 (11.91 %)	26 (9.39 %)	19 (6.86 %)	0 (0 %)
2–4 ng/mL	382 (8.33 %)	303 (79.32 %)	35 (9.16 %)	23 (6.02 %)	19 (4.97 %)	2 (0.52 %)
5–9 ng/mL	288 (6.28 %)	220 (76.39 %)	37 (12.85 %)	21 (7.29 %)	9 (3.13 %)	1 (0.35 %)
>=10 ng/mL	211 (4.60 %)	152 (72.04 %)	34 (16.11 %)	8 (3.79 %)	15 (7.11 %)	2 (0.95 %)
11-Hydroxy- Tetrahydrocannabinol Range (THCOH)						
Negative	3874 (84.47 %)	2921 (75.40 %)	456 (11.77 %)	280 (7.23 %)	205 (5.29 %)	12 (0.31 %)
1 ng/mL	249 (5.43 %)	199 (79.92 %)	28 (11.24 %)	11 (4.42 %)	9 (3.61 %)	2 (0.80 %)
2–4 ng/mL	320 (6.98 %)	240 (75.00 %)	46 (14.38 %)	21 (6.56 %)	11 (3.44 %)	2 (0.63 %)
5–9 ng/mL	107 (2.33 %)	79 (73.83 %)	13 (12.15 %)	6 (5.61 %)	9 (8.41 %)	0 (0 %)
>=10 ng/mL	36 (0.78 %)	23 (63.89 %)	10 (27.78 %)	1 (2.78 %)	2 (5.56 %)	0 (0 %)
Number of Drug Class Positive						

(*continued on next page*)

Table 2 (*continued*)

Variable and Attribute	Overall	Minor Injury (ISS Score: 1 to 8)	Moderate Injury (ISS Score: 9 to 15)	Serious Injury (ISS Score: 16 to 24)	Severe Injury (ISS Score: 25 to 49)	Critical Injury (ISS Score: 50 to 75
0	2942 (64.15 %)	1611 (54.76 %)	482 (16.38 %)	411 (13.97 %)	408 (13.87 %)	30 (1.02 %)
1	2367 (51.61 %)	1249 (52.77 %)	438 (18.50 %)	333 (14.07 %)	312 (13.18 %)	35 (1.48 %)
2	962 (20.98 %)	476 (49.48 %)	136 (14.14 %)	168 (17.46 %)	172 (17.88 %)	10 (1.04 %)
3	249 (5.43 %)	115 (46.18 %)	46 (18.47 %)	39 (15.66 %)	44 (17.67 %)	5 (2.01 %)
4	25 (0.55 %)	11 (44.00 %)	4 (16.00 %)	6 (24.00 %)	4 (16.00 %)	0 (0 %)
5	4 (0.09 %)	0 (0 %)	0 (0 %)	0 (0 %)	4 (100 %)	0 (0 %)
Alcohol Only Positive						
No	4075 (88.86 %)	3098 (76.02 %)	482 (11.83 %)	275 (6.75 %)	206 (5.06 %)	14 (0.34 %)
Yes	511 (11.14 %)	364 (71.23 %)	71 (13.89 %)	44 (8.61 %)	30 (5.87 %)	2 (0.39 %)
Alcohol Cannabinoids Positive						
No	4366 (95.20 %)	3296 (75.49 %)	530 (12.14 %)	298 (6.83 %)	227 (5.20 %)	15 (0.34 %)
Yes	220 (4.80 %)	166 (75.45 %)	23 (10.45 %)	21 (9.55 %)	9 (4.09 %)	1 (0.45 %)
Alcohol Stimulants Positive						
No	4529 (98.76 %)	3417 (75.45 %)	550 (12.14 %)	314 (6.93 %)	233 (5.14 %)	15 (0.33 %)
Yes	57 (1.24 %)	45 (78.95 %)	3 (5.26 %)	5 (8.77 %)	3 (5.26 %)	1 (1.75 %)
Alcohol Sedatives Positive						
No	4560 (99.43 %)	3445 (75.55 %)	549 (12.04 %)	318 (6.97 %)	232 (5.09 %)	16 (0.35 %)
Yes	26 (0.57 %)	17 (65.38 %)	4 (15.38 %)	1 (3.85 %)	4 (15.38 %)	0 (0 %)
Alcohol Opioids Positive						
No	4567 (99.59 %)	3446 (75.45 %)	552 (12.09 %)	317 (6.94 %)	236 (5.17 %)	16 (0.35 %)
Yes	19 (0.41 %)	16 (84.21 %)	1 (5.26 %)	2 (10.53 %)	0 (0 %)	0 (0 %)
Alcohol Antidepressants Positive						
No	4585 (99.98 %)	3461 (75.49 %)	553 (12.06 %)	319 (6.96 %)	236 (5.15 %)	16 (0.35 %)
Yes	1 (0.02 %)	1 (100 %)	0 (0 %)	0 (0 %)	0 (0 %)	0 (0 %)
Alcohol OTC Positive						
No	4577 (99.80 %)	3455 (75.49 %)	552 (12.06 %)	318 (6.95 %)	236 (5.16 %)	16 (0.35 %)
Yes	9 (0.20 %)	7 (77.78 %)	1 (11.11 %)	1 (11.11 %)	0 (0 %)	0 (0 %)
Alcohol Other Positive						
No	4577 (99.80 %)	3454 (75.46 %)	553 (12.08 %)	318 (6.95 %)	236 (5.16 %)	16 (0.35 %)
Yes	9 (0.20 %)	8 (88.89 %)	0 (0 %)	1 (11.11 %)	0 (0 %)	0 (0 %)

as the most influential factor, followed by 'Race, 'Seatbelt Use', 'Age', 'Airbag Deployed', 'Number of Drug Class Positive', 'Alcohol Range', 'Vehicle Type', 'THC Range', and 'Helmet Use'. These variables have been selected for subsequent CCA to identify patterns and interactions.

5.3. Analytical Method/Theory

5.3.1. Cluster Correspondence analysis (CCA)

CCA is a sophisticated technique for examining categorical data, focusing on the relationships between categorical variables (Sourial et al., 2010). It is widely utilized by researchers dealing with high-dimensional datasets. These techniques simplify complex data by projecting it into a lower-dimensional space, thereby extracting crucial insights from structured data (van de Velden et al., 2017). This method aims to create meaningful clusters within a dataset based on a set of observable variables. CCA emphasizes identifying cluster allocations and scaling figures for the categories of categorical variables to enhance the variance between groups. Initially introduced by van de Velden et al. (2017), CCA combines correspondence analysis with K-means cluster analysis to achieve cluster allocation and optimal scaling values (coordinates) for the categories of p categorical variables, thereby maximizing variation between groups. van de Velden et al. (2017) achieved this by arranging cluster memberships according to variable categories and assessing both cluster assignments and category significance (coordinates in a compressed space), aiming to concurrently optimize the

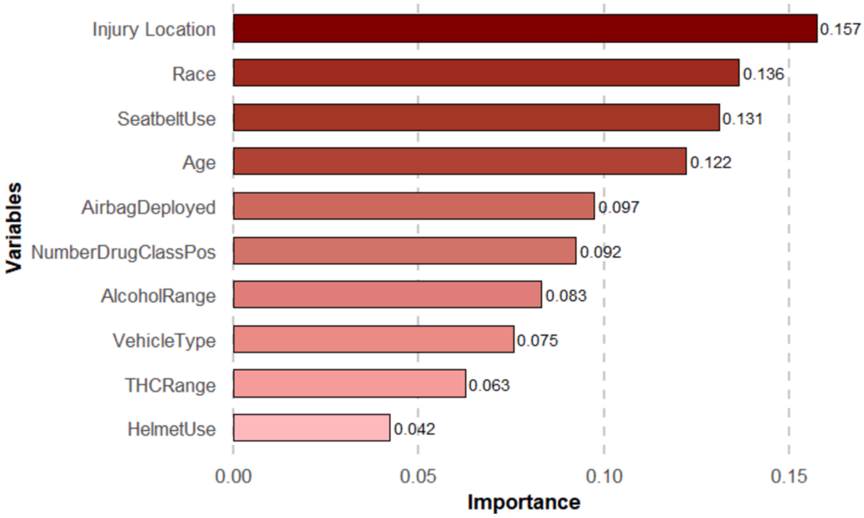


Fig. 2. Variable importance plot.

variances both between clusters and categories. This method yields simple visualizations that facilitate the interpretation of a standard biplot. The following discussion will demonstrate the mathematical algorithm employed in CCA.

Cluster Selection: The implementation of the CCA algorithm requires selecting clusters beforehand, guided by the Calinski-Harabasz (C–H) index. The CCA algorithm reaches convergence when the C–H index, which assesses the ratio between-cluster variance to within-cluster variance, no longer decreases over successive iterations. A higher C–H index value signifies better convergence.

CCA Algorithm: Originally, a standard data matrix X, which includes n observations across q categorical variables, must be converted into a distinct matrix Z, referred to as the super indicator matrix. This conversion utilizes a one-hot encoding technique, transforming each categorical variable into a binary format. This transformation yields $Z = [\boldsymbol{Z}_1, \boldsymbol{Z}_2, \ldots, \boldsymbol{Z}_q]$, where each Zj is an n $\times$ pj matrix representing the encoded j-th categorical variable with Pj categories. The transformed matrix Z maintains the original n rows but expands to $Q = \sum_{j=1}^{q} Pj$ columns in total. Furthermore, Zk represents an n $\times$ K binary matrix, specifying each observation's association with K clusters. To analyze the connections between clusters and categorical variables, a cross-tabulation between the indicator matrix and the membership matrix is performed, producing a $K \times pj$ matrix, referred to as $F = \boldsymbol{Z}_K^{\top}\boldsymbol{Z}$.

The process of applying Correspondence Analysis (CA) to this matrix involves deriving optimal scaling values for both rows (clusters) and columns (categories) to maximize the variance between clusters. This ensures that clusters are distinctly separated based on categorical variable distributions, while categories are effectively distinguished by their varying distributions across clusters. However, since cluster memberships are initially unknown, the method involves iterating between CA and K-means clustering. Specifically, optimal category quantifications (column coordinates) and cluster allocations are obtained by alternating between performing CA on the contingency matrix and applying K-means clustering to the reduced space coordinates derived from CA (van de Velden et al., 2017). The CCA algorithm can be summarized in the following steps:

1. Initiate cluster assignment $\boldsymbol{Z}_K$, potentially by randomly distributing objects into clusters.
2. Obtain category quantifications B through Correspondence Analysis on the contingency matrix $\boldsymbol{Z}_K^{\top}\boldsymbol{Z}$.
3. Compute individual coordinates by averaging the centered scores with category quantifications from the initial step:.$\boldsymbol{Y} = \frac{1}{q}\left(\boldsymbol{I} - \frac{\boldsymbol{1}\boldsymbol{1}^{\top}}{n}\right)ZB$
4. Update $\boldsymbol{Z}_K$ by employing K-means clustering on Y.
5. Repeat the process from step 2 with $\boldsymbol{Z}_K$ as the cluster allocation matrix, until stability is achieved, meaning no changes in $\boldsymbol{Z}_K$, Y, and G) (van de Velden et al., 2017).
6. The resulting Zk provides G, the optimal cluster centroid matrix, and the category quantification matrix B. These coordinate matrices, G and B, are used to generate a biplot of the clusters and categories. To improve the interpretation of the biplots, both matrices are scaled by a constant value $\gamma = \left(\frac{K}{Q} \cdot \frac{TrB^{T}B}{TrG^{T}G}\right)^{1/4}$. The scaled coordinate matrices $\boldsymbol{G}_s = \gamma\boldsymbol{G}$, and $\boldsymbol{B}_s = \frac{1}{\gamma}\boldsymbol{B}$ maintain the same average squared deviation from the origin, facilitating clearer biplot presentations for the analysis (van de Velden et al., 2017).

In this study, the *'clustrd'* package within the R statistical software (Markos et al., 2019) framework was used to apply CCA to the datasets of driver and passenger crashes.

6. Results

The key variables influencing ISS, as identified by the XGBoost model, include 'Injury Location' as the most critical factor, followed by significant factors such as 'Race,' 'Seatbelt Use,' 'Age,' 'Airbag Deployment,' 'Number of Drug Classes Positive,' 'Alcohol Range,' 'Vehicle Type,' 'THC Range,' and 'Helmet Use,' each contributing notably to injury outcomes. These variables were subsequently used to conduct CCA to explore potential patterns and interactions between demographic and behavioral factors and their impact on ISS. The two-dimensional solution generated from the CCA consists of six clusters. Table 3 below details the sizes of the clusters, their sum of squares, and the coordinates of the cluster centroids in two dimensions. The sum of squares for each cluster indicates the variability within that cluster relative to its number of observations. Fig. 3 depicts the two-dimensional projections (Dim. 1 and Dim. 2 represent dimension 1 and dimension 2, respectively) of the data points associated with driver and passenger crashes, following the CCA, along with the cluster centroids. The position of the centroid of each cluster have been identified in Dimension 1 and Dimension 2. Cluster 1, with 1,370 crashes, comprises 29.9 % of the dataset. The centroid's position at −0.0068 for Dimension 1 and 0.0098 for Dimension 2 places it close to the origin, suggesting a balanced representation across these dimensions. The cluster's within-cluster sum of squares is 0.0190, indicating moderate cohesion among the crashes. Cluster 2 includes 1,199 crashes, making up 26.1 % of the data. It features a centroid shifted slightly towards negative values in both dimensions (−0.0048 in Dim. 1 and −0.0089 in Dim. 2) with a sum of squares at 0.0222, implying a slightly higher dispersion among the crashes compared to Cluster 1. Cluster 3 contains 917 crashes, accounting for 20 % of the total. Its centroid at −0.0050 in Dimension 1 and 0.0024 in Dimension 2 indicates a position not far from the origin, with a sum of squares at 0.0215, suggesting a moderate spread around the centroid. Cluster 4, the smallest in terms of sample size, holds 436 crashes (9.5 %). The centroid is markedly displaced to the positive side in Dimension 1 (0.0264) and moderately in Dimension 2 (0.0088), with a lower sum of squares at 0.0096, indicating a tighter grouping of data points. Cluster 5, with 347 crashes (7.6 %), has its centroid located at 0.0273 in Dimension 1 and −0.0080 in Dimension 2. With a sum of squares of 0.0109, this cluster exhibits a moderate level of dispersion like Cluster 4. Lastly, Cluster 6 encompasses 317 crashes (6.9 %) and has the centroid furthest from the origin, positioned at −0.0041 in Dimension 1 and −0.0191 in Dimension 2. The sum of squares is the lowest at 0.0075, indicating a closer clustering of crashes around the centroid than the other clusters.

6.1. *Clusters of driver and passenger crashes*

To understand the patterns and characteristics of driver and passenger crashes, the specific clusters identified through CCA are examined and explained in the following subsections. Fig. 4 **(a, b),** Fig. 5 **(a, b),** and Fig. 6 **(a, b)** illustrate the primary attributes of the clusters that display the highest standardized residuals, either positive or negative. A positive residual indicates a higher-than-average frequency of the attribute within the cluster, while a negative residual signifies a lower-than-average frequency. The length of each bar represents the prominence of the attribute in terms of its frequency within that cluster. For clarity, attributes with positive values on the right side will be discussed to highlight associative characteristics within each cluster.

6.1.1. *Cluster 1 (C1) − older adult crashes*

Fig. 4**a** depicts various attributes associated with older adult crashes in Cluster 1, comprising 29.9 % of the data analyzed. The length of each bar represents the frequency or significance of the attribute within this cluster in relation to the cluster's center. The center, set at zero on the horizontal axis, serves as the baseline. The figure highlights the top twenty attributes with the strongest associations in this cluster, showing positive and negative correlations as indicated by the direction of the bars. Seven attributes with positive residual means extending to the right, such as *'Number of Drug Class Positive: 0', 'Age: 65+', "Seat Belt Use: Yes', Air Bag Deployment: Not deployed, 'THC Range: Negative', 'Vehicle Type: SUV',* and *'Alcohol Range: Negative'* have a positive association with this cluster. Notably, *'Number of Drug Class Positive: 0' and 'Age: 65+'* exhibit the strongest positive associations, indicating that crashes involving older adults without substance use are prevalent in this cluster. Based on the association of these attributes, this cluster can be labeled as 'Older Adult Crashes'. This cluster further suggests that individuals aged 65+, despite having no drugs or alcohol in their system, consistently wearing seatbelts, driving or riding SUVs, and not experiencing airbag deployment still end up being involved in crashes. This could be attributed to physical frailty and cognitive limitations that negatively impact their safety, as suggested by Albert et al. (2018).

Table 3
Location of the Cluster Centroids and Other Cluster Measures.

Cluster	Size (Percentage)	Sum of Squares	Dimension 1 (Dim. 1)	Dimension 2 (Dim. 2)
Cluster 1	1370 (29.9 %)	0.0190	−0.0068	0.0098
Cluster 2	1199 (26.1 %)	0.0222	−0.0048	−0.0089
Cluster 3	917 (20 %)	0.0215	−0.0050	0.0024
Cluster 4	436 (9.5 %)	0.0096	0.0264	0.0088
Cluster 5	347 (7.6 %)	0.0109	0.0273	−0.0080
Cluster 6	317 (6.9 %)	0.0075	−0.0041	−0.0191

Note: Dim: dimension or axis.

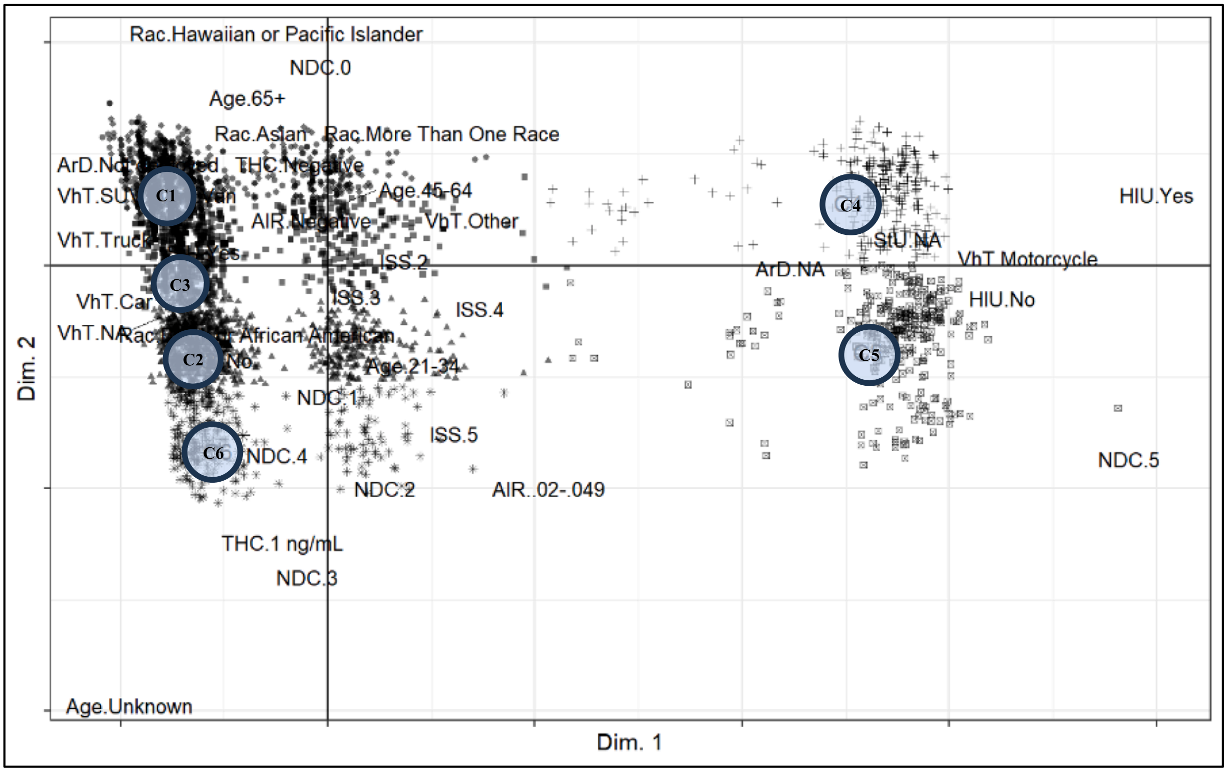


Fig. 3. Two-dimensional projection of crash attributes among fatally and seriously injured drivers and passengers.

6.1.2. Cluster 2 (C2) – impaired young adult crashes

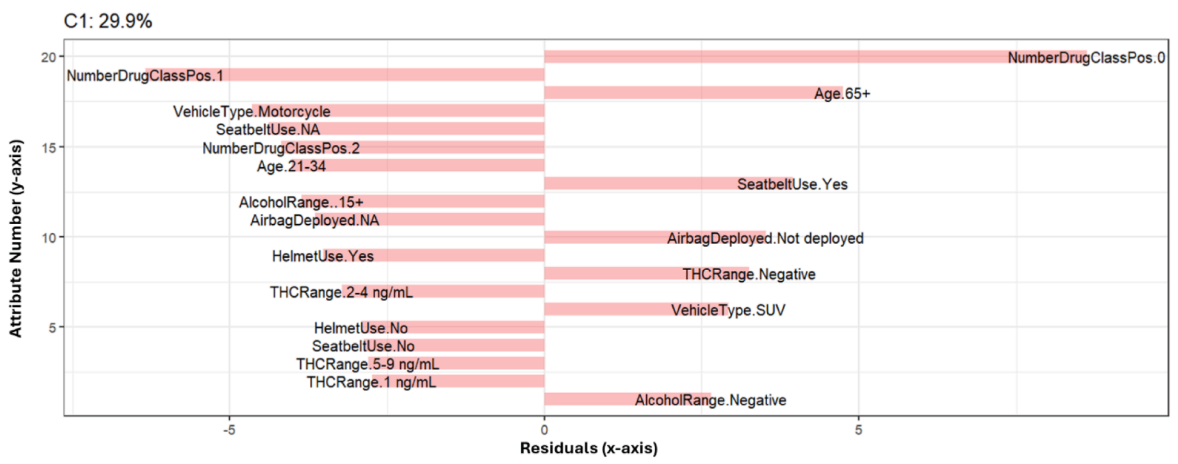
Cluster 2 is represented in Fig. 4**b.** The bar chart shows the characteristics of Cluster 2, which represents 26.1 % of the crash data analyzed. This cluster is characterized by eleven attributes with positive residuals extending to the right in Yellow: one drug in the system, alcohol concentration of 0.15 % or higher, THC levels ranging from 1 ng/mL, 2–4 ng/mL, 5–9 ng/mL, to 10 ng/mL or more, vehicle type car, and individuals aged 21–34 who are not using a seatbelt but have a front airbag deployed. This indicates a correlation among individuals aged 21–34 who are not using a seatbelt, with a front airbag deployed, alcohol levels of 0.15 % or higher, and THC concentrations ranging from 1 ng/mL to 10 ng/mL in their system, while driving or using a car. These factors together suggest a pattern of risky driving behaviour among young adults, potentially leading to crashes due to the combination of substance use and lack of seatbelt usage. This observation is consistent with the findings of Simons-Morton et al. (2019), who noted that young adults exhibit riskier driving behaviours compared to older adults, resulting in a Kinematic Risky Driving (KRD) incidence rate that is 2.86 times higher. This increased risk may stem from young adults' propensity for making driving-related errors (Curry et al., 2011) and their involvement in various risky driving activities (Mirman et al., 2012) combined with the usage of alcohol and THC (the psychoactive component of cannabis) (O'Kane et al., 2002; Osilla et al., 2023; Wolff & Johnston, 2014). Interventions aimed at reducing alcohol-impaired driving among adolescents have helped lower the incidence of underage drinking and driving (Carpenter et al., 2007; Liang & Huang, 2008). However, these measures might not be as effective in addressing cannabis-impaired driving, as the expectations and impacts of cannabis use can vary from those of alcohol (Kristjansson et al., 2012). More targeted strategies are required to address this.

6.1.3. Cluster 3 (C3) – car crashes with low substance presence

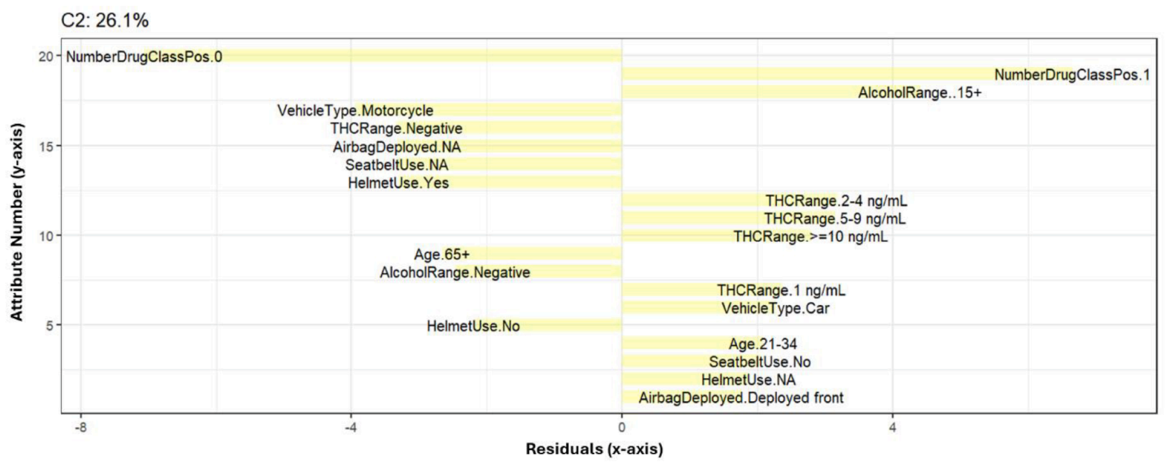
Cluster 3 is represented in Fig. 5**a.** The bar chart shows the characteristics of Cluster 3, which represents 20 % of the crash data analyzed. This cluster is characterized by seven attributes with positive residuals: negative THC and alcohol tests, absence of seatbelt use, car as the vehicle type, airbags deployed both front and side, and the presence of one drug in the system. This demonstrates a strong association among individuals while not under the influence of THC or alcohol, not using seatbelt combined with minimal drug presence in their system, and airbag deployed front and side. It can also be suggested that even minimal substance use is associated with an increased risk of vehicular crashes and impaired judgment, such as the negligence of seatbelt usage. This finding aligns with the research conducted by Bogstrand et al. (2015) and Foxwell et al. (2023), who found that alcohol and drug impairment is associated with not using a seatbelt and highlighted the significant impact of not wearing a seatbelt. Valen et al. (2019) indicated that the lack of seatbelt use is associated with an increased risk of fatality.

6.1.4. Cluster 4 (C4) – Motorcyclist crashes with leg injuries and low substance presence

Cluster 4 is represented in Fig. 5**b.** The bar chart shows the characteristics of Cluster 4, which represents 9.5 % of the crash data



(a) Cluster 1 - Older adult crashes



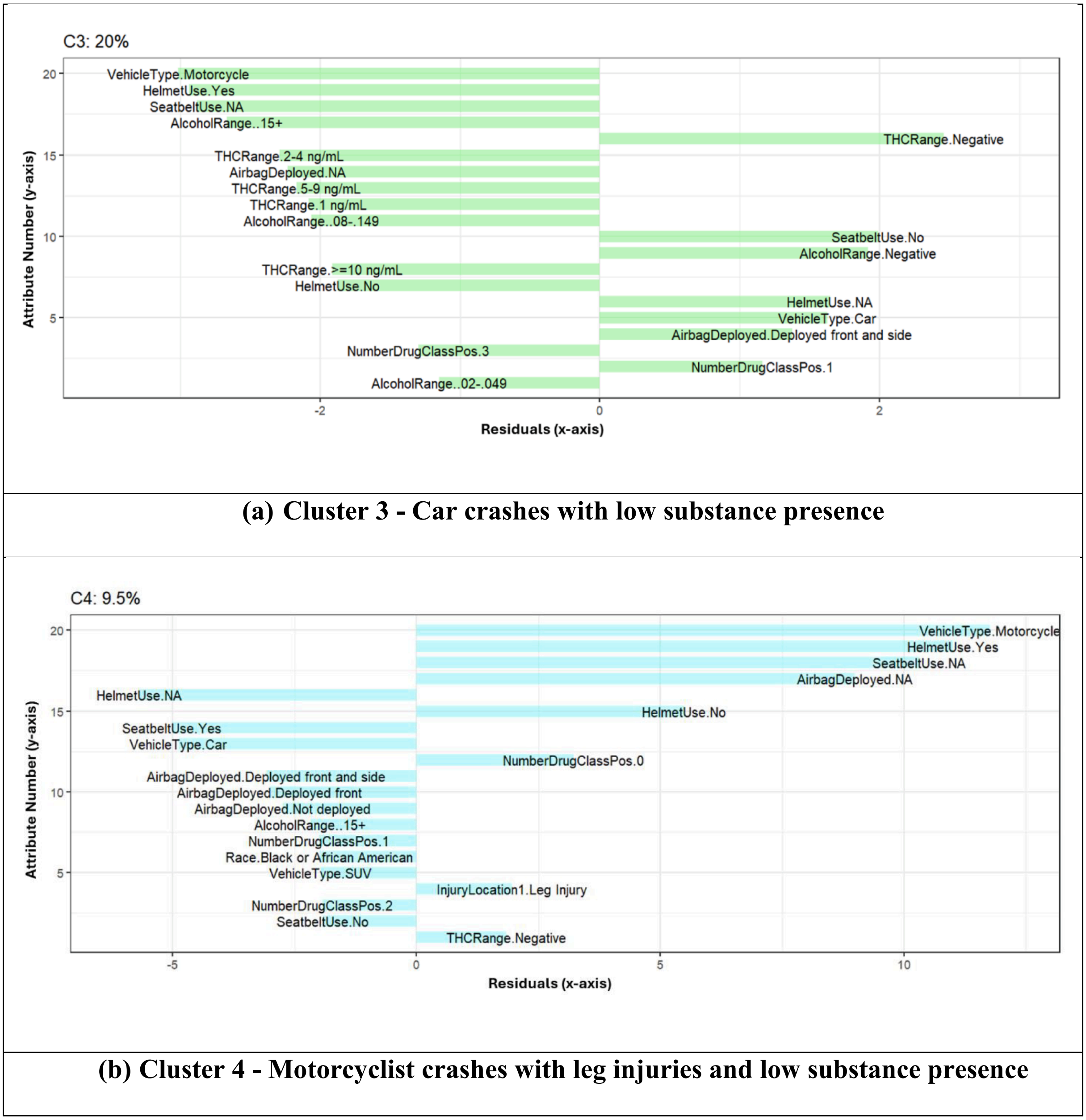
(b) Cluster 2 - Impaired young adult crashes

Fig. 4. Distribution of standardized residuals for cluster 1 and cluster 2.

analyzed. This cluster possesses eight attributes with positive residuals: motorcycle usage as the vehicle type, inconsistent helmet use, the absence of drugs in the system for most of them, and a high occurrence of leg injuries. Although most individuals in this group tested negative for alcohol and THC, Table 4 indicates the presence of low levels of alcohol and other substances within the group, with BAC ranging from 0.02 % to 0.049 %. While THC is absent, other drugs are notably prevalent; 17.20 % of the individuals have one type of drug detected, and 2.52 % have two types of drugs in their system. This cluster demonstrates a correlation among the attributes, suggesting that motorcyclists, whether they wear helmets or not, tend to experience leg injuries more frequently in crashes. This finding is consistent with Ross (1983) and Ankarath et al. (2002), who reported that motorcycle crashes commonly led to severe injuries, with leg injuries being notably frequent among riders.

6.1.5. *Cluster 5 (C5) – impaired Motorcyclist crashes*

Fig. 6**a** illustrates Cluster 5, which is depicted in the bar chart. This cluster accounts for 7.6 % of the analyzed crash data and showcases its specific characteristics. This cluster features ten attributes with positive residuals: motorcycle use, inconsistent helmet usage, the presence of a drug, alcohol levels ranging from 0.02 % to over 0.149 %, and a THC level of 2–4 ng/mL. These factors correlate, indicating



(a) Cluster 3 - Car crashes with low substance presence

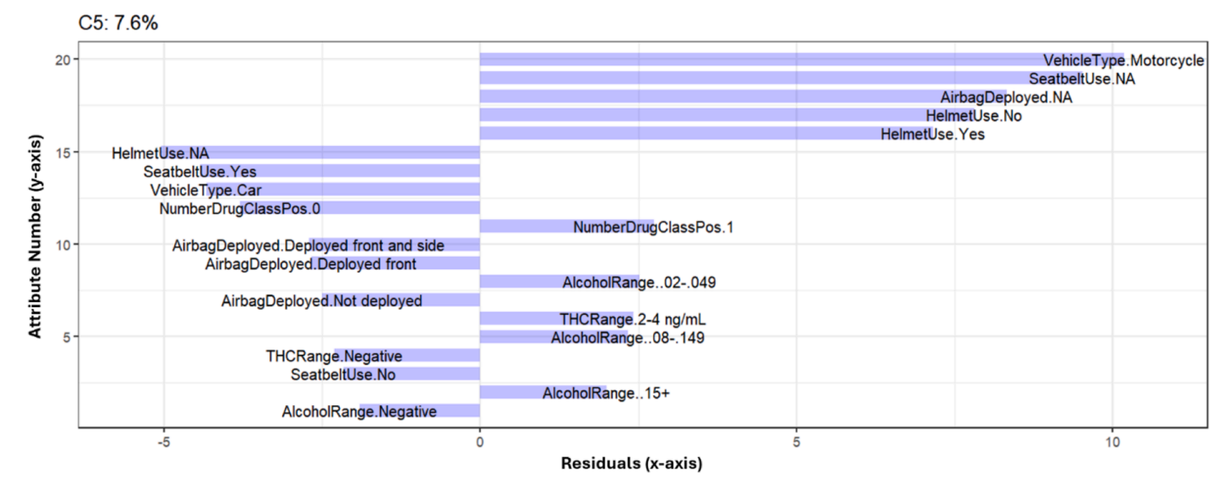
(b) Cluster 4 - Motorcyclist crashes with leg injuries and low substance presence

Fig. 5. Distribution of standardized residuals for cluster 3 and cluster 4.

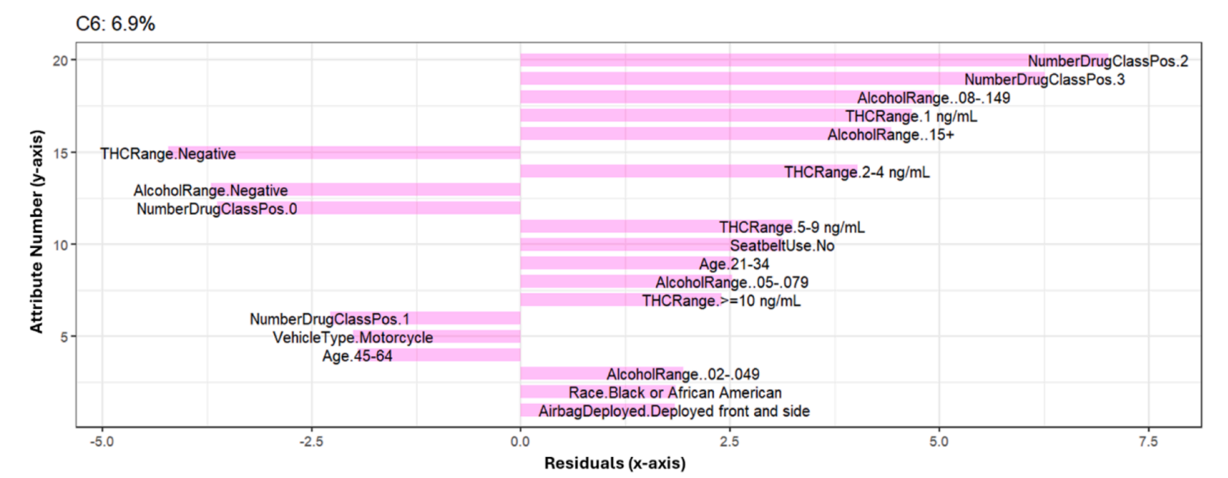
that motorcyclists with this profile frequently engage in behaviours associated with increased substance presence, contributing to crash risks. The presence of drug/alcohol usage can be highly correlated with motorcyclists' crashes. This result aligns with the findings of Islam (2024) and Asgarian et al. (2019), who noted a significant correlation between the prevalence of alcohol and fatally injured motorcyclists. Specifically, alcohol-impaired motorcyclists (BAC $\geq$ 0.08 %) encounter far greater risks in single-motorcycle crashes, with a 10.4 times higher probability of severe injuries compared to their non-alcohol-impaired counterparts (BAC $<$ 0.08 %) (Islam, 2024). This highlights the critical impact of substance use on increasing the severity of injuries in motorcycle accidents.

6.1.6. Cluster 6 (C6) – Impaired African or African American young adult crashes

Fig. 6**b** illustrates Cluster 6, depicted in the bar chart. This cluster accounts for 6.9 % of the analyzed crash data and showcases its specific characteristics. This cluster is distinguished by fourteen attributes with positive residuals, including the presence of two or three drugs in the system alongside varying alcohol levels from 0.02 % to above 0.15 %, THC levels ranging from 1 ng/mL to more than 10 ng/mL, the absence of seatbelt use, individuals aged 21–34, and those identified as African or African American with airbags deployed both front and side. There is a correlation among these factors highlighting a pattern where young adults, particularly those



(a) Cluster 5 - Impaired motorcyclist crashes



(b) Cluster 6 - Impaired African or African American young adult crashes

Fig. 6. Distribution of standardized residuals for cluster 5 and cluster 6.

who are African or African American are at a greater risk of drug use and varying levels of alcohol consumption (Torres et al., 2014), often not wearing seatbelts. At the same time, their vehicles typically have airbags deployed during crashes. This finding also corresponds with the research conducted by Randle et al. (2020), who observed notably higher rates of alcohol impairment among African or African American young adults. Additionally, Hicks et al. (2022) and Wu et al. (2016) found a high prevalence of cannabis use within this demographic. Similarly, Popkin and Council (1993), as well as Arria et al. (2011), identified that African or African American individuals are involved in a higher number of crashes compared to their white counterparts. Additionally, evidence suggests that these individuals are more likely to drive after consuming alcohol and tend to operate vehicles with slightly higher BAC.

6.2. Comparative analysis of contributing attributes in clusters

The percentage distribution of variable categories by clusters is shown in Table 4. The percentages are derived by calculating the frequency of each category within a cluster and then converting these frequencies into percentages relative to the total number of

Table 4
Proportion of contributing factors in different clusters.

Variable	Category	All Data	Cluster 1 (29.9 %)	Cluster 2 (26.1 %)	Cluster 3 (20 %)	Cluster 4 (9.5 %)	Cluster 5 (7.6 %)	Cluster 6 (6.9 %)
Age	18–20	7.06	7.88	9.01	4.80	6.42	3.46	7.57
	21–34	37.88	15.77	50.21	42.42	33.72	48.99	67.19
	35–44	17.79	15.40	19.02	19.19	17.20	21.04	16.72
	45–64	25.71	34.96	18.85	23.66	34.17	24.50	7.26
	65+	11.54	25.99	2.92	9.92	8.49	2.02	0.95
Race	White	42.56	46.64	35.53	43.84	53.67	46.40	28.39
	African or African American	31.49	24.74	40.12	32.61	13.76	29.97	50.79
	Hispanic	19.62	20.00	19.68	17.78	26.38	19.31	14.20
	Asian	1.48	3.21	0.75	0.76	0.92	0.58	0.63
	Native American or Alaska Native	0.55	0.58	0.42	0.65	0.46	0	0.63
	Hawaiian or Pacific Islander	0.11	0.36	0	0	0	0	0
	More Than One Race	0.57	1.02	0.25	0.22	1.15	0.29	0.32
Alcohol Range	Negative	78.94	100	57.96	97.60	99.77	48.70	17.67
	.02 %-.049 %	1.79	0	2.67	0.11	0.23	7.78	6.62
	.05 %-.079 %	1.83	0	3.50	0.22	0	4.03	8.20
	.08 %-.149 %	5.52	0	9.34	0.22	0	15.27	27.13
	.15+%	11.93	0	26.52	1.85	0	24.21	40.38
THC Range	Negative	74.75	100	47.12	98.04	100	39.19	6.94
	1 ng/mL	6.04	0	11.59	0.44	0	13.54	27.44
	2–4 ng/mL	8.33	0	17.10	1.09	0	20.75	29.97
	5–9 ng/mL	6.28	0	13.84	0.33	0	14.70	21.45
	>=10 ng/mL	4.60	0	10.34	0.11	0	11.82	14.20
Number of Drug Class Positive	0	64.15	97.96	0	44.17	80.28	0	0
	1	51.61	2.04	74.73	43.95	17.20	65.71	10.73
	2	20.98	0	20.18	10.91	2.52	26.51	63.09
	3	5.43	0	4.17	0.87	0	6.92	25.55
	4	0.55	0	0.92	0.11	0	0.58	0.63
	5	0.09	0	0	0	0	0.29	0
Vehicle Type	Car	60.03	64.38	76.90	73.83	0	0.29	85.49
	Motorcycle	18.05	0.36	2.00	4.03	97.48	95.10	2.21
	SUV	9.81	18.03	8.92	8.83	0	0	4.73
	Truck	6.98	10.36	7.01	9.05	0	0	3.47
	Van	1.66	2.63	2.00	1.64	0.23	0	0
	Other	2.14	2.70	1.50	1.53	2.29	4.61	0.95
Seatbelt Use	Yes	63.50	91.68	70.48	69.47	0	0.58	54.26
	No	15.35	5.26	23.02	23.88	3.44	0.29	38.17
	NA	21.15	3.07	6.51	6.65	96.56	99.14	7.57
Airbag Deployed	Deployed front	22.72	25.77	30.78	26.50	0	0	24.29
	Deployed front and side	23.92	22.41	31.11	31.30	0	0.29	40.69
	Deployed side	3.66	4.67	4.59	3.93	0	0	4.10
	Not deployed	20.43	34.67	19.68	18.65	0.69	0.29	16.09
	No airbag	4.60	4.01	5.00	7.09	3.67	1.15	3.47
	NA	24.66	8.47	8.84	12.54	95.64	98.27	11.36
Helmet Use	Yes	10.34	0.22	0.17	0	66.51	51.30	0.32
	No	8.31	0.80	2.25	2.40	33.49	48.41	2.21
	NA	81.36	98.98	97.58	97.60	0	0.29	97.48
Primary Body Injury Location	Chest and Other	36.07	42.48	34.45	35.01	28.67	31.41	32.81
	Hand Injury	12.06	12.26	11.01	9.49	20.87	13.26	9.15
	Head/neck Injury	31.09	26.06	35.86	34.02	21.10	29.97	41.32
	Internal Injury	5.93	8.83	5.42	5.56	2.52	3.75	3.47
	Leg Injury	14.85	10.36	13.26	15.92	26.83	21.61	13.25
ISS	Minor Injury (ISS Score: 1 to 8)	75.49	81.17	77.65	74.48	68.58	60.52	71.61
	Moderate Injury (ISS Score: 9 to 15)	12.06	8.98	10.93	0	15.14	17.87	12.62
	Serious Injury (ISS Score: 16 to 24)	6.96	6.42	6.51	6.22	7.11	12.10	7.26
	Severe Injury (ISS Score: 25 to 49)	5.15	3.36	4.75	4.58	8.94	8.65	6.94
	Critical Injury (ISS Score: 50 to 75)	0.35	0.07	0.17	0.44	0.23	0.86	1.58

observations in that cluster. A higher percentage indicates a greater prevalence of crashes for that category within the cluster. This method effectively highlights the most common categories for each variable across different clusters. The main insights derived from this analysis are outlined below.

Cluster 1 represents crashes involving predominantly older individuals aged 45–64 (34.96 %) and 65+ (25.99 %). A significant proportion of these individuals did not have airbags deployed during the crash (34.67 %), but among those with airbags, they were mostly deployed in front (25.77 %). The majority had no drugs in their system (97.96 %), with a high seatbelt usage rate (91.68 %). The racial distribution was mainly white (46.64 %) and African or African American (24.74 %).Despite the regular use of safety measures like seat belts and absence of substance use, older adults predominantly sustain minor, moderate, and severe injuries (ISS of 1 to 8, 81.17 %; ISS of 9 to 15, 8.98 %; and ISS of 25 to 49, 3.36 %), reflecting the cluster's unique risk profile shaped by age-related vulnerabilities. Most of these older individuals primarily suffered from injuries in chest and other areas (42.48 %). This finding aligns with Mueller Orsay et al. (1990) and Coley et al. (2008), who reported frequent neck strains in belted elders. Similarly, Porter and Zhao (1998) and Bourbeau et al. (1993) noted a higher incidence of sternal fractures and neck strains among belted occupants.

Cluster 2 represents crashes involving younger individuals with significant substance use. This cluster is characterized by a younger demographic, primarily aged 21–34 (50.21 %) and 35–44 (19.02 %). The racial makeup included many African or African American (40.12 %) and White (35.53 %) individuals. During crash occurrence, airbags were frequently deployed, either front and side (31.11 %) or front only (30.78 %). A notable characteristic of this cluster is the high prevalence of alcohol use, with 9.34 % having a BAC between 0.08 % and 0.149 %, and 26.52 % exceeding 0.15 %. Additionally, many tested positive for THC at various levels, with11.59 % at 1 ng/mL, 17.10 % at 2–4 ng/mL, 13.84 % at 5–9 ng/mL, and 10.34 % having THC levels of 10 ng/mL or higher. Furthermore, most individuals had one (74.73 %) or two (20.18 %) drugs in their system. The legal BAC limit in US is currently 0.08 % (Van Dyke & Fillmore, 2017), while seven states have also enforced legal THC limits for driving, primarily based on THC levels in blood (Wong et al., 2014). For example, Colorado, Montana, and Washington have established a limit of 5.0 μg/L THC in blood, whereas Nevada and Ohio set urine limits of 10.0 μg/L THC and 2.0 μg/L THC in blood. The combination of THC and alcohol or other drugs results in increased impairment, further exacerbating driving risks. The large proportion of individuals in this cluster exceeding both legal BAC and THC limits, highlights their engagement in extremely risky driving behaviours, involving multiple substance use that severely impair judgment, reaction times, and overall driving ability. The propensity for risky behaviours is further reflected in the higher incidence of moderate to severe injuries (ISS of 9 to 15, 10.93 %; ISS of 16 to 24, 6.51 %; ISS of 25 to 49, 4.75 %), emphasizing the serious consequences of combined substance use and non-compliance with seatbelt regulations. The findings from this cluster are in line with Reinfurt et al. (1996).

Cluster 3 represents crashes involving individuals with moderate safety practices and low substance use. The cluster primarily consists of individuals aged 21–34 (42.42 %) and 35–44 (19.19 %), with a racial distribution of mostly White (43.84 %) and African or African American (32.61 %). Cars were the predominant vehicle type (73.38 %), and airbags were often deployed either front and side (31.30 %) or front only (26.50 %) during crash. Most individuals tested negative for alcohol (97.60 %) and THC (98.04 %), with approximately equal representation between those with no drugs detected (44.17 %) and those with one drug present (43.95 %). Many of them sustained minor injuries (ISS of 1 to 8 in 74.48 % of cases), suggesting that moderate safety measures and low substance use likely contributed to lower injury severity observed in this cluster. This observation is consistent with broader trends noted in previous literatures, such as those identified by Smink et al. (2008) and Watt et al. (2006).

Cluster 4 represents crashes predominantly involving motorcyclists with poor safety practices. This cluster primarily consists of individuals aged 45–64 (34.17 %) and 21–34 (33.72 %), with the racial composition mainly White (53.67 %) and Hispanic (26.38 %). Findings from this cluster indicate that motorcyclists, despite lower substance involvement, face a significant risk of moderate to severe injuries as indicated by ISS (ISS of 9 to 15, 15.14 %; ISS of 16 to 24, 7.11 %; ISS of 25 to 49, 8.94 %), emphasizing the inherent dangers of motorcycling.

Cluster 5 represents crashes involving younger motorcyclists with significant substance use. This cluster primarily consists of individuals aged 21–34 (48.99 %) and 35–44 (21.04 %), with a racial distribution of White (46.40 %) and African or African American (29.97 %). A notable 15.27 % of individuals had a BAC between 0.08 % and 0.149 %, while 24.21 % exceeded 0.15 %. Additionally, the majority had one (65.71 %) or two (26.51 %) drugs in their system. THC levels were varied, with 13.54 % at 1 ng/mL, 20.75 % at 2–4 ng/mL, 14.70 % at 5–9 ng/mL, and 11.82 % exceeding 10 ng/mL. This cluster underscores the high-risk behaviour of younger motorcyclists who exceed legal limits for alcohol and other substances, leading to a greater incidence of moderate to severe injuries compared to other groups. The ISS data further supports this, with 17.87 % moderate injuries (ISS of 9 to 15), 12.10 % serious injuries (ISS of 16 to 24), 8.65 % severe injuries (ISS of 25 to 49), and 0.86 % critical injuries (ISS of 50 to 75). In comparison to clusters 4 and 5, it is evident that higher concentrations of narcotics in the bloodstream are associated with more severe injuries and fatalities among motorcyclists. Motorcyclists who do not consume substances have a lower probability of injury in the event of a crash compared to those who consume substances. These findings are consistent with the work of Cheng and Ng (2012).

Cluster 6 demonstrates crashes involving young African or African American adults with substantial substance use and low safety practices. This cluster is characterized by a predominantly young demographic aged 21–34 (67.19 %). A notable proportion had airbags deployed front and side (40.69 %) or front only (24.29 %). There is a notable presence of alcohol, with 27.13 % of individuals having a BAC between 0.08 % and 0.149 %, and 40.38 % exceeding 0.15 %. Additionally, the presence of THC levels is higher, with 27.44 % at 1 ng/mL, 29.97 % at 2–4 ng/mL, 21.45 % at 5–9 ng/mL, and 14.20 % at 10 ng/mL or higher. Most individuals had two (63.09 %) or three (25.55 %) drugs in their system and the primary vehicle type was cars (85.49 %). This group represents a high-risk demographic, where substantial substance uses exceeding legal limits, combined with poor safety practices, contributes to increased injury severity. A significant portion experienced moderate to severe injuries (ISS of 9 to 15: 12.62 %, ISS of 16 to 24: 7.26 %, ISS of 25 to 49: 6.94 %, and ISS of 50 to 75: 1.58 %). Compared to other clusters in this study, this group ranked second in terms of high injury severity. These findings are supported by the research of Simons-Morton et al. (2019).

7. Conclusions

This study aimed to address the significant problem of alcohol and drug use, including THC, and its impact on roadway safety and injury severity, utilizing a three-year dataset (2019–2021) from NHTSA. Key variables associated with ISS are identified through an XGBoost model, including injury location, demographic characteristics (race, age), safety compliance factors (seatbelt and helmet use), and alcohol and substance presence. These factors were further examined through CCA to provide insights into the prevalence of alcohol and substances across various injury severity levels among drivers and passengers. The findings revealed six distinct clusters characterized by demographic factors, driver age, ethnicity, vehicle types, safety measures, and primary body injury location. Specifically, the study identified patterns of substance use, safety practices, and their correlation with injury severity, highlighting risky behaviours among different demographic groups including young adults, motorcyclists, older adults, and African American young adults. The findings indicate that alcohol and drugs are prevalent in a significant portion of traffic crashes, with alcohol detected in 23.1 % and cannabinoids in 25.1 % of cases. The analysis highlighted that young adult aged 21–34 years exhibited high levels of THC and alcohol with poor safety practices, such as not using seat belts, which correlated with severe crash injury outcomes. In contrast, older adults aged 65 years or older adhered more strictly to safety measures and had lower substance detection rates, yet still minorly injured in crashes due to age-related vulnerabilities. Motorcyclists showed especially high rates of substance use and lower safety gear utilization, resulting in more severe injuries and fatalities.

The use of CCA in this research showcases its potential as a powerful analytical tool for uncovering underlying patterns in risk factor and ISS in substance related traffic crashes, contributing to the uniqueness of this study. By distinguishing six clusters based on demographics, safety compliance, and injury locations, this analysis highlights specific patterns of substance use and safety practices linked to injury severity. The framework developed here provides a basis for data-informed interventions targeting impaired driving risks across diverse roadway user groups. The study's findings have several important implications. First, it underscores the critical need for targeted traffic safety policies and interventions that address the specific behaviours and risk factors identified within each cluster. Integrating contextual factors such as demographics, vehicle types, and safety measures provides a more holistic understanding of crash dynamics, which can inform the development of more effective countermeasures. Implementing stricter control policies for substance use, enhancing public education on the risks of impaired driving, and promoting safety measures such as seatbelts and airbags are recommended. Policy implications include the need for more rigorous enforcement of impaired driving laws, the expansion of roadside drug testing, and the introduction of graduated licensing programs for younger drivers to address risky behaviours. Additionally, incorporating advanced driver assistance systems (ADAS) in vehicles can help mitigate the effects of impaired driving.

Despite its comprehensive approach, this study has some limitations. While CCA is a powerful tool for identifying relationships, it does not account for all potential confounding variables that could influence these relationships, such as road conditions, weather, or other environmental factors not included in the dataset. Additionally, while the analysis revealed distinct clusters, the underlying patterns of behaviour and injury severity may be influenced by unmeasured economic factors such as income level and education that were not captured in the data. Furthermore, driving styles—such as reckless, aggressive, or distracted driving—were not captured in this dataset, limiting our ability to explore their impact on crash outcomes. Lastly, while this study focuses on identifying clusters and patterns, it does not directly address the effectiveness of interventions or policies designed to reduce substance-related crashes. Future research could fill this gap by investigating how various interventions (e.g., public awareness campaigns, increased policing, or technological innovations like ignition interlock devices) impact different clusters. Such studies would not only refine our understanding of risk factors but also provide actionable insights for policymakers striving to improve road safety.

CRediT authorship contribution statement

Mahmuda Sultana Mimi: Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Rohit Chakraborty:** Writing – review & editing, Writing – original draft, Validation. **Swastika Barua:** Writing – review & editing, Writing – original draft. **Subasish Das:** Writing – review & editing, Writing – original draft, Supervision, Data curation, Conceptualization. **Md Nasim Khan:** Writing – review & editing, Writing – original draft. **Bahar Dadashova:** Writing – review & editing, Writing – original draft.

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.

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Data availability

The authors do not have permission to share data.

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