Unraveling Crash Causation: A Deep Dive into Non-Motorists on Personal Conveyance

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ABSTRACT

Non-motorists using personal conveyances, like skateboards, face increased safety challenges due to reduced visibility, particularly at intersections and in low light conditions. Safety studies on non-motorists using personal conveyances rely on limited hospital datasets or controlled/naturalistic riding conditions, lacking comprehensive identification of e-scooter riding risk factors. To address this research gap, this study collected real-world traffic crash data and quantified safety risks related to key contributing factors. Utilizing the 2020–2021 Fatality Analysis Reporting System (FARS) fatal crash data, this study examined the patterns of crashes associated with non-motorists using personal conveyances at segments and intersections. The findings provide valuable insights into key risk factors that can guide stakeholders, municipalities, and campus administrators in developing effective mitigation strategies to reduce safety risks associated with non-motorists using personal conveyances. By addressing these safety concerns, personal conveyances devices can be integrated as a safe and sustainable shared mobility option in urban and campus environments.

Keywords: non-motorists, personal conveyance, traffic crashes, crash severity, Bayesian network.

INTRODUCTION

Personal conveyances encompass a wide array of devices used by non-motorists and pedestrians for mobility and leisure, which may be motorized or human-powered, excluding those propelled through pedaling (NHTSA, 2023). This category includes rideable toys, motorized rideable toys, and personal mobility assistance devices, such as self-balancing devices, wheelchairs, and mobility scooters. These options are popular in urban areas for their environmental benefits and convenience in first- and last-mile travel. However, users face challenges like risky behaviors and conflicts with other road users, leading to concerns about non-motorist injuries. Non-motorists, often vulnerable road users, lack comprehensive regulations, raising safety concerns. The absence of crash data hinders understanding non-motorist safety, and this study addresses the research gap by analyzing 2020-2021 crash data in the United States using Bayesian Network analysis.

This study will investigate factors contributing to injury crashes involving non-motorist safety and personal conveyances, offering insights into the complex dynamics between non-motorists and other road users in urban areas. Through a thorough analysis, the research seeks to recommend evidence-based policy interventions and safety measures, designed to mitigate risks associated with personal conveyances and enhance the well-being of sustainable transportation users. Ultimately, the study strives to contribute to creating safer and more accessible environments for non-motorists, promoting the adoption of sustainable transportation options and ensuring the safety of those using personal conveyances for mobility and leisure.

LITERATURE REVIEW

The rising popularity of eco-friendly non-motorized travel modes has spurred research on usage patterns and safety. This literature review consolidates findings from various studies to comprehensively understand challenges and opportunities in non-motorist crashes.

Safety Studies on Crashes

Several studies have examined the factors related to the non-motorist crashes and the non-motorized modes. Salas-Niño (2022) studied the legal framework for micro-mobility devices in a major U.S. city, finding a higher number of non-motorist injuries compared to traditional vehicles. This highlights the global need for effective safety regulations. Brunner et al. (2022) examined threat response and crash avoidance in non-motorists, emphasizing the importance of response latency and capabilities. Their study, involving 36 participants, simulated safety impacts of automated driving and traffic measures. Haworth et al. (2021) compared safety behaviors of shared and private non-motorists in Brisbane, Australia. They found a decline in shared e-scooter usage linked to a reduction in illegal behaviors, coinciding with an increase in private e-scooter usage.

Shah et al. (2021) and Pobudzei et al. (2023) investigated e-scooter and bicycle crashes, identifying distinct crash types. E-scooter crashes exhibited specific patterns. Approximately 10% of these crashes resulted in injuries or fatalities, and most crashes were concentrated in the city center. E-scooter casualties were more frequent on weekends and during evening and nighttime hours. A higher percentage of these casualties were intoxicated, and hit-and-run cases surpassed those involving cyclists (Pobudzei et al., 2023). These underscores the importance of tailoring safety interventions and campaigns for e-scooters (Shah et al., 2021).

Mayer et al. (2020) investigated the road safety implications of e-scooters in Austria and Germany, where they derived measures to enhance road safety concerning e-scooters. Huemer et al. (2022) observed 4,514 e-bike and e-scooter riders in Braunschweig, Germany, finding 13.4% engaged in distracting tasks like using headphones, leading to more violations and reduced safety gear use. Cluster analysis identified high-risk groups of young and middle-aged male riders of electric bikes and e-scooters, suggesting targeted campaigns for these demographics to address safety concerns. Sandt et al. (2022) tackled emerging e-scooter safety issues, outlining community efforts for injury prevention. The digest covered usage patterns, safety trends, contributing factors to crashes, injuries, fatalities, and city initiatives for e-scooter management and regulation. Ma et al. (2021) explored e-scooter safety risks through naturalistic riding experiments, emphasizing significant impacts like severe vibrations, especially on concrete pavements, and proximity to objects in constrained riding environments. The findings underscore heightened safety challenges for e-scooter riders.

Clewlow et al. (2022) described the U.S. Department of Transportation's Safety Data Initiative (SDI), which utilized GPS trip trace data to improve road networks and safety for vulnerable road users. Their work showcased the potential for data-driven insights in enhancing safety for a wide range of road users. Azimian and Jiao (2022) addressed e-scooter injury crashes in Austin, focusing on variables like demographics, income, land use, and education. Their results highlighted the need for infrastructure development, educational campaigns, and stricter enforcement to enhance e-scooter safety.

Safety Studies on Non-Motorists using other Personal Conveyances

Several types of personal conveyance devices such as roller skates, skateboards, baby carriages, toy skates have been used by non-motorists. In California, users of skateboards, roller skates, and push scooters cover up to 48 million miles per year (Fang and Handy, 2019). In 2012, 14 skateboarders died in automobile collisions in California. The estimated fatality rate suggests 20.9 to 23.0 deaths per 100 million miles traveled (Fang and Handy, 2017). A study compared the injury severity of skateboarders and long boarders. Longboard riders, due to increased dimensions allowing higher speeds, experienced significantly more fatal or severe injuries like skull fractures, traumatic brain injuries, and intracranial hemorrhage compared to traditional skateboarders (Fabian et al., 2014). Valdez (2016) offered safety guidelines for self-balancing motorized skateboard riders, recommending an age restriction (children under 13) and advising against using the device in or near moving traffic.

Previous studies in traffic safety analysis lack sufficient research on non-motorist safety analysis. Yasmin et al., (2021) tackled limitations in non-motorized crash prediction models arising from a lack of true exposure data. They addressed these issues by creating an integrated framework that combines non-motorized demand and crash prediction for comprehensive mobility and safety analysis. The proposal includes developing aggregate-level models for non-motorist generation and attraction, trip exposure matrices for safety evaluation, and crash frequency and severity proportion models at a zonal level.

Safety Studies on Bayesian Networks

Bayesian networks aid in motorcycle crash severity analysis by revealing relationships between potential factors. The Bayes' rule can predict future events based on preceding ones. (Das et al., 2023). Several studies used Bayesian networks for traffic crash analysis and pedestrian safety for determining the influence of the contributing factors on predicting crash outcomes (Kitali et al., 2021).The models can bring out the most probable factor or even combination that leads to an accident (Davis, 2003; Ma et al., 2018). In case of complex interrelationships that include multiple crash attributes and crash outcomes, the Bayesian networks were proved to be effective (De Oña et al., 2013).

The Bayesian Network approach is suitable for handling uncertain data types, like uncertainty in information provided by respondents, making it effective for acceptability estimation. Unlike traditional regression models, Bayesian Approaches offer flexibility in understanding interdependence between multiple factors and assessing counterfactual scenarios (Garces et al., 2016).Moreover, Bayesian Networks can also be used to investigate the impact of influential factors on crash severity for large vehicles such as large-trucks (Wu et al., 2023).

The discussed studies emphasize key insights into non-motorist safety, identifying factors like rider behaviors, environmental conditions, and infrastructure design. However, additional research is needed to uncover more variables and develop effective policies and countermeasures to mitigate non-motorist crashes.

METHODOLOGY

Data Collection

This study acquired fatal crash data from FARS for 2020-2021. According to the 2021 FARS/CRSS Coding and Validation Manual, the non-motorist on personal conveyance data includes crash data regarding roller skates, in-line skates, skateboards, skates, scooters, motorized skateboard and others (2023). Table 1 shows a 43% increase in no intersection crashes and a 26% increase in four-way intersection crashes from 2020 to 2021. Conversely, T-intersection and 'others' crashes decreased by 12% and 50%, respectively, while the overall number of crashes rose by 25%.

Table 1. Non-motorists Fatal Crashes by Intersection Type

Year	Not an Intersection	Four-Way Intersection	T-Intersection	Others	Grand Total
2020	42	27	17	2	88
2021	60	34	15	1	110
Grand Total	102	61	32	3	198

Bayesian Network

A Bayesian Network (BN) determines a joint probability distribution over a set of random variables U, which is an annotated directed acyclic graph (DAG). Consider, $U = \{A_1, \dots A_n, C\}$ where n stands for the number of RIFs, the variables $A_1, \dots A_n$ are the RIFs, and C is the class variable (for example, frontage road related injury types). Consider a graph structure where the class variable is the root, that is, $\prod C = \emptyset$($\prod C$ denotes the set of parents of C in U) and each RIF has the class variable as its unique parent, *i.e.*, $\prod A_i = \{C\}$ for $1 \leq i \leq n$. A BN defines a unique joint probability distribution over U given by

$$P(A_1, \dots A_n, C) = P(C). \prod_{i=1}^{n} P(A_i|C) \tag{1}$$

The DAG on $\{A_1, \dots A_n\}$ is a tree if $\prod A_i$ contains only one parent for all A_i, except for one variable without parents (referred as the root). If, function π can define a tree over $A_1, \dots A_n$ if there is exactly one i such that $\pi(i) = 0$ (i.e. the root of the tree), and there is no sequence $i_1, \dots i_k$ such that $\pi(ij) = i_{j+1}$ for $i \leq j < k$ and $\pi(i_k) = i_1$ (i.e., no cycles). Such a function defines a tree network where $\prod A_i = \{C, \dots A_{\pi(i)}\}$ if $\pi(i) > 0$ and $\prod A_i = \{C\}$ if $\pi(i)$ >0, and $\prod A_i$ ={C} if $\pi(i) = 0$.

A Bayesian belief net or a decision diagram is a graphical representation of factors contributing to a conclusion or uncertainty (Howard and Matheson, 1984; Pearl, 1988). This diagram calculates the likelihood of the outcome given all the model's factors. Conditional probabilities establish a relationship between the inputs and the result. Decisions can be incorporated into the influence diagram so that the decision-maker can understand how each alternative impacts the probability of a result (Shachter, 2007).

RESULTS AND DISCUSSIONS

A comprehensive BN model was developed in this study by using Netica's advanced Expectation Maximization (EM) technique. EM was employed to fit the network to the input-output combinations obtained from the Monte Carlo runs (Lauritzen, 1995). The BN model parameters, also called conditional probability distributions, were estimated through the learning process. These distributions offer information about the likelihood of different states within each node of the BN. Figure 1 illustrates the final BN network layout, depicting the relationships between different nodes. Each node's conditional probability tables (CPTs, represented as belief bars) demonstrate the probabilities associated with the node's various states. These CPTs capture the relationships and dependencies between the variables within the BN, permitting probabilistic inference and analysis. The model's structure and conditional probability distributions obtained through the learning process are powerful tools for investigating the relationships and dependencies between variables related to non-motorist crashes.

Figure 1 also shows the initial data of non-motorist collisions modeled through a BN, focused on different intersection types. Most crashes occurred not at an intersection (51.5%) at a four-way intersection (30.8%). Most crashes occurred at an urban location (93.9%). The most common season for crashes was Autumn (36.4%) followed by Summer (32.3%), and most crashes occurred in the daylight (46.0%). Weekdays were the most common days for crashes to occur (79.8%). The most common sex was male (78.8%), and the most common age group was 45 to 65 years old (36.4%), followed by older than 65 years old (33.8%). In cases where drug use and drinking were known, most crashes did not involve drugs (37.4%) or drinking (42.9%). Most crashes were single-vehicle crashes (94.4%) and were often not a collision with a motor vehicle in transit (98.5%). These crashes at the intersections may occur due to collisions with properties or pedestrians based on different intersection types.

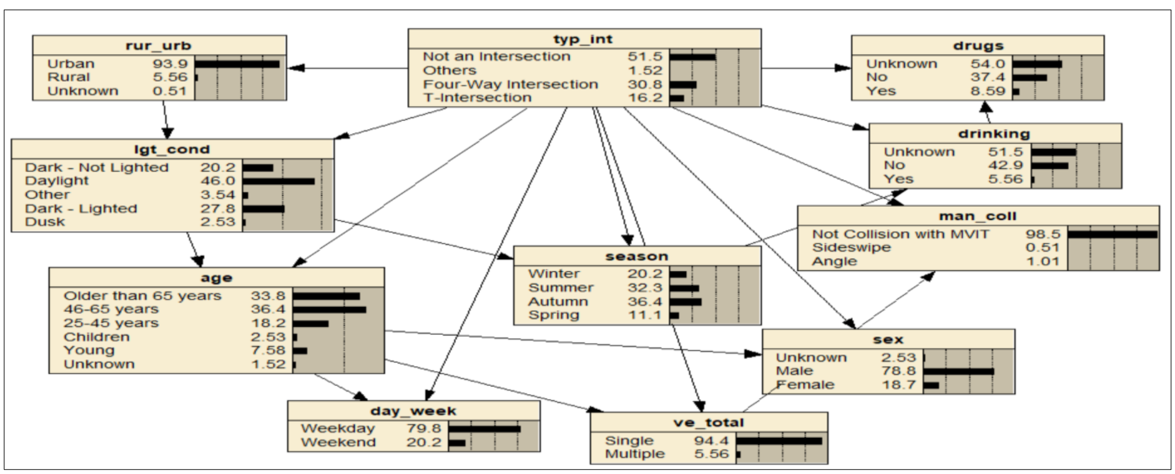

Figure 1. BN of full data

Table 2 shows the conditional probability chart for intersection types by lighting condition and age. Higher scores are displayed in dark green, and lower in lighter green to almost yellow. One of the highest probability scores occurs in the age group of 46 to 65 years old, at dusk, and not at an intersection (1.000). Probability scores of 1.000 also occur with an age group of older than 65 years old, with dusk lighting, and at a four-way intersection, with an age group young, at dusk, and at a T-intersection, with an age group of 25 to 45 years old, other lighting conditions, and a T-intersection, and with an age group of 25-45 years old, in the dark but with lighting, and at other intersection types. Overall, the highest probability scores occur between 25 to 45 years old and 46 to 65 years old.

Table 2. Conditional Probability Table for Intersection Type by Lighting Condition and Age

Intersection Type	Lighting	Children	Young	25-45 years	46-65 years	Older than 65 years	Unknown
Not an Intersection	Daylight	0.022	0.065	0.065	0.348	0.478	0.022
Not an Intersection	Dark - Not Lighted	0.037	0.148	0.259	0.444	0.111	0.000
Not an Intersection	Dark - Lighted	0.000	0.080	0.280	0.520	0.120	0.000
Not an Intersection	Dusk	0.000	0.000	0.000	1.000	0.000	0.000
Not an Intersection	Other	0.000	0.000	0.500	0.500	0.000	0.000
Four-Way Intersection	Daylight	0.115	0.000	0.115	0.308	0.462	0.000
Four-Way Intersection	Dark - Not Lighted	0.000	0.000	0.667	0.167	0.000	0.167
Four-Way Intersection	Dark - Lighted	0.000	0.080	0.320	0.320	0.240	0.040
Four-Way Intersection	Dusk	0.000	0.000	0.000	0.000	1.000	0.000
Four-Way Intersection	Other	0.000	0.000	0.500	0.500	0.000	0.000
T-Intersection	Daylight	0.000	0.053	0.000	0.263	0.684	0.000
T-Intersection	Dark - Not Lighted	0.000	0.143	0.000	0.286	0.571	0.000
T-Intersection	Dark - Lighted	0.000	0.250	0.000	0.750	0.000	0.000
T-Intersection	Dusk	0.000	1.000	0.000	0.000	0.000	0.000
T-Intersection	Other	0.000	0.000	1.000	0.000	0.000	0.000
Others	Daylight	0.167	0.167	0.167	0.167	0.167	0.167
Others	Dark - Not Lighted	0.167	0.167	0.167	0.167	0.167	0.167
Others	Dark - Lighted	0.000	0.000	1.000	0.000	0.000	0.000
Others	Dusk	0.167	0.167	0.167	0.167	0.167	0.167
Others	Other	0.167	0.167	0.167	0.167	0.167	0.167

Table 3 shows the conditional probability scores for intersection types by different lighting conditions and seasons. Probability scores of 1.000 occurred during the winter, with other lighting conditions, and not at an intersection. During the autumn, at dusk, and at a T-intersection, in the spring, with other lighting conditions, and a T-intersection, and during autumn, with other lighting conditions, and at 'other' intersection type. The only season with no conditional probability scores of 1.000 was the summer.

Table 3. Conditional Probability Table for Intersection Type by Lighting Condition by Season

Intersection Type	Lighting	Winter	Summer	Autumn	Spring
Not an Intersection	Daylight	0.174	0.391	0.326	0.109
Not an Intersection	Dark - Not Lighted	0.185	0.444	0.333	0.037
Not an Intersection	Dark - Lighted	0.120	0.240	0.520	0.120
Not an Intersection	Dusk	0.000	0.500	0.500	0.000
Not an Intersection	Other	1.000	0.000	0.000	0.000
Four-Way Intersection	Daylight	0.231	0.269	0.423	0.077
Four-Way Intersection	Dark - Not Lighted	0.167	0.833	0.000	0.000
Four-Way Intersection	Dark - Lighted	0.120	0.280	0.400	0.200
Four-Way Intersection	Dusk	0.500	0.000	0.500	0.000
Four-Way Intersection	Other	0.000	0.500	0.500	0.000
T-Intersection	Daylight	0.211	0.263	0.263	0.263
T-Intersection	Dark - Not Lighted	0.714	0.000	0.286	0.000
T-Intersection	Dark - Lighted	0.500	0.000	0.500	0.000
T-Intersection	Dusk	0.000	0.000	1.000	0.000
T-Intersection	Other	0.000	0.000	0.000	1.000
Others	Daylight	0.250	0.250	0.250	0.250
Others	Dark - Not Lighted	0.250	0.250	0.250	0.250
Others	Dark - Lighted	0.000	0.000	1.000	0.000
Others	Dusk	0.250	0.250	0.250	0.250
Others	Other	0.250	0.250	0.250	0.250

Table 4 shows the conditional probability scores for intersection types by rider age and the number of vehicles. Overall, higher probability scores occurred when there was a single-vehicle collision. For single-vehicle crashes, when not at an intersection, the rider ages of children, young, and unknown all had probability scores 1.000. At a four-way intersection, the riders ages of children, young, and 25 to 45 years old had probability scores of 1.000. When at a T-intersection, the rider age group of 25 to 46 had a probability score of 1.000. At ‘other’ type of intersection, the rider age group of 25 to 46 years old had a probability score of 1.000.

Counterfactual Scenarios

Netica facilitates the creation and analysis of models like Bayesian Networks (BNs) and Markov networks. Applied in AI, machine learning, decision analysis, and data mining, Netica utilizes counting-learning for parameter learning in Conditional Probability Tables (CPTs) within TAN models. It then computes posterior probabilities, providing valuable insights for safety enhancement and crash prevention. The insights gained from Netica's analysis have great potential for informing proactive measures and strategies to mitigate risks and promote a safer environment.

Figure 2 shows the BN of the counterfactual population considering all crashes occurred not at an intersection. There was a 6.3% increase in crashes that occurred in dark but not light conditions and a 6.7% increase in drivers aged 46 to 65 years. Interestingly, the other variables in this counterfactual did not see any significant changes.

Table 4. Conditional Probability Table for Rider Age and Number of Vehicles

Intersection Type	Rider Age	Single	Multiple
Not an Intersection	Children	1.000	0.000
Not an Intersection	Young	1.000	0.000
Not an Intersection	25-45 years	0.889	0.111
Not an Intersection	46-65 years	0.977	0.023
Not an Intersection	Older than 65 years	0.964	0.036
Not an Intersection	Unknown	1.000	0.000
Four-Way Intersection	Children	1.000	0.000
Four-Way Intersection	Young	1.000	0.000
Four-Way Intersection	25-45 years	1.000	0.000
Four-Way Intersection	46-65 years	0.889	0.111
Four-Way Intersection	Older than 65 years	0.950	0.050
Four-Way Intersection	Unknown	0.500	0.500
T-Intersection	Children	0.500	0.500
T-Intersection	Young	0.750	0.250
T-Intersection	25-45 years	1.000	0.000
T-Intersection	46-65 years	0.900	0.100
T-Intersection	Older than 65 years	0.941	0.059
T-Intersection	Unknown	0.500	0.500
Others	Children	0.500	0.500
Others	Young	0.500	0.500
Others	25-45 years	1.000	0.000
Others	46-65 years	0.500	0.500
Others	Older than 65 years	0.500	0.500
Others	Unknown	0.500	0.500

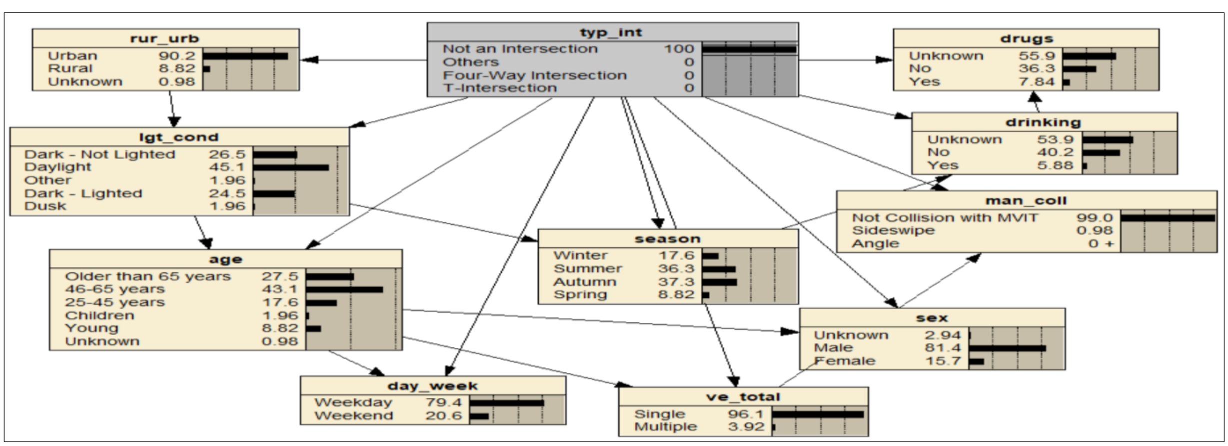

Figure 2. BN of counterfactual scenario considering all crashes occurred not at an intersection

Figure 3 illustrates a counterfactual scenario for a four-way intersection crashes. Regarding land use type, urban areas encountered a 6.1% increase. Collisions that resulted in a sideswipe decreased by 0.51%, while angle collisions increased by 1.64%. Regarding lighting conditions, there was a 10.36% decrease in dark and not lighted conditions, and a 13.2% increase in dark but lighted conditions. The recorded number of drivers using alcohol and drugs increased by 3.91% overall. In terms of driver age, the 25 to 45 years category increased by 8%, while the 46 to 65 years category decreased by 6.9%. Additionally, on weekdays there was a 5.4% increase, while on the weekends, there was a 5.4% decrease. Other variables did not show significant changes in this counterfactual scenario.

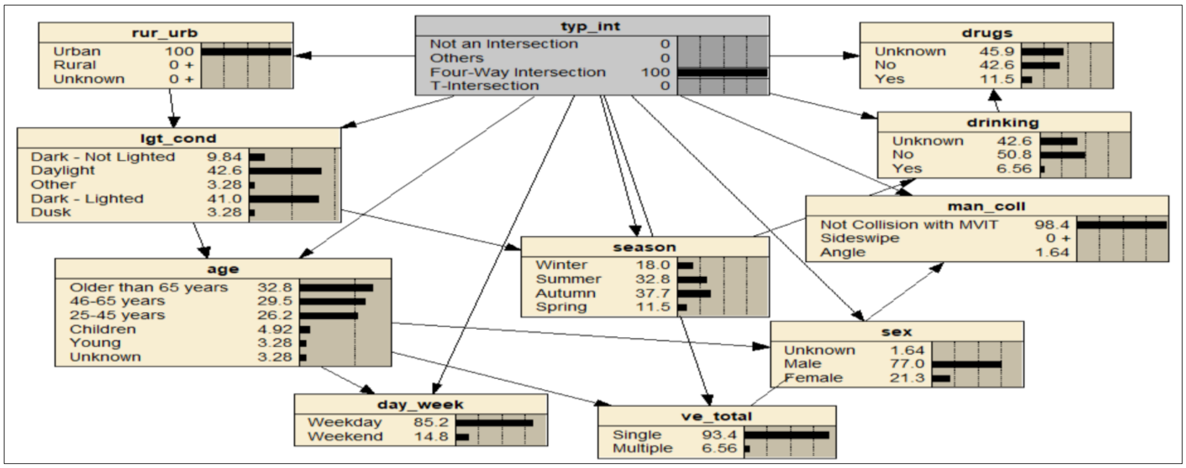

Figure 3. BN of counterfactual scenario considering all crashes occurred at a four-way intersection

Figure 4 presents the results of analyzing a counterfactual scenario where all crashes occurred at a T-intersection. There was a 2.12% increase in angle collisions in these crash incidents. The recorded number of drivers using alcohol and drugs decreased by 4.77% overall. The category of drivers aged 25 to 45 decreased by 15.07%, while those aged 65 and older increased by 16.7%. Regarding lighting conditions, there was a 13.4% increase in daylight and a 15.3% decrease in dark but lighted conditions. There was a 14.2% and 7.7% increase, respectively, in the winter season and spring seasons, while on the other hand, there was a 16.7% and 5.2% decrease, respectively, in the summer and autumn seasons. Additionally, on weekdays there was a 4.8% decrease, while on the weekends, there was a 4.8% increase. Other factors did not show significant changes in this counterfactual scenario.

The findings of this study provide comprehensive insights into non-motorist collisions using a BN model. The initial data analysis indicates that most crashes occur not at an intersection, with urban areas being the most common location. Crashes are more frequent during autumn and summer, in daylight, and on weekdays. The majority of those involved in crashes are males aged between 45 to 65 years, and alcohol and drug involvement in crashes is relatively low. Conditional probability tables also revealed crashes are more likely for ages 25 to 45 and 46 to 65, particularly during dusk and not at intersections. During the winter, crashes not at an intersection with other lighting conditions are most likely, while the summer has lower probabilities. Counterfactual scenarios showed how crash-related variables such as lighting conditions, demographics, and seasonal characteristics differ between crashes at different intersections.

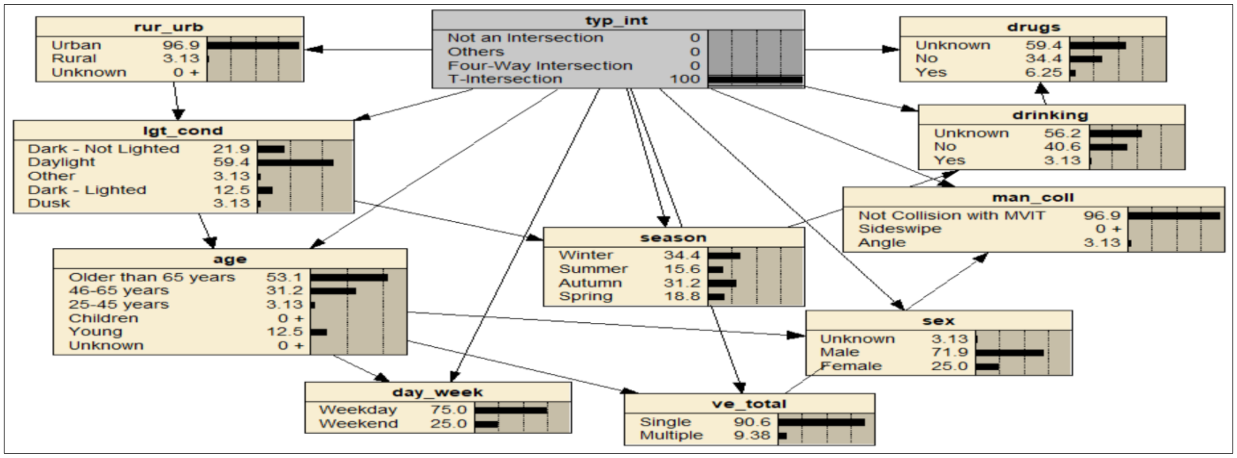

Figure 4. BN of counterfactual scenario considering all crashes occurred at a T-intersection

Based on the results, several policy-related guidelines can be recommended to improve road safety. Measures such as clear signage, designated pedestrian crossings, and advanced traffic signals can be introduced for tackling the 6.1% rise in urban crashes. Angle collision can be reduced by improving visibility at T-intersection. Increased law enforcement during high risk hours can be introduced. Targeted campaigns to reduce alcohol and drug use among drivers, especially in urban areas and on weekends can be implemented. Additionally, better street lighting should be installed, particularly at T-intersections, to address the 15.3% decrease in dark but lighted conditions. Implementation of traffic calming measurers and increased police at non-intersection zones can resolve the 4.8% increase in weekend crashes. During the summer season, intensified safety campaigns can be held and increased law enforcement efforts can be made to tackle the 12.1% rise in incidents related to summer risks.

CONCLUSIONS

This study explored the contributing factors of non-motorists on personal conveyance related fatal crashes in the U.S. by utilizing data from the 2020-2021 FARS crash database. By developing a BN model, the study successfully uncovered relationships and dependencies between variables related to non-motorist crashes, such as temporal, demographic, and locational characteristics. Additionally, CPTs for different intersections involved in non-motorist collisions were displayed based on various factors such as age groups, seasons, and number of vehicles involved. The probabilities derived from this analysis offer valuable information for understanding the likelihood of non-motorist collisions at different intersections. Furthermore, the study conducted counterfactual analyses to assess the potential impact of considering all crashes occurring at different intersections type. These analyses demonstrate the changes in various factors under these counterfactual scenarios, such as lighting conditions, demographics, and seasonal characteristics.

The study unveiled nuanced patterns, revealing peak vulnerability times, high-risk demographics, and crash-prone locations. These insights provide a basis for targeted interventions in non-motorist safety. Additionally, the research dissected interactions between non-motorists and road users, identifying conflict points and risky pedestrian behaviors, emphasizing the importance of policy interventions and awareness campaigns. Leveraging Bayesian Network analysis, the study proposed evidence-based policy interventions, recommending specific intersection designs, dedicated pedestrian crossings, bike lanes, and improved street lighting to enhance visibility, particularly at night.

Despite the valuable contributions of this study, it is crucial to acknowledge and address its limitations for future research improvement. Reliance on FARS data poses a risk of unreported incidents, limiting generalizability to the U.S. and a two-year period. Future studies could enhance data analysis by including more years and global trends, employing advanced statistical techniques and experimental designs for causal insights. Expanding variables, including weather and rider behavior, can lead to a more comprehensive understanding of non-motorist safety.

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