Causal Insights into Speeding Crashes

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ABSTRACT

Excessive speeding poses significant risks to road safety, impacting a driver's ability to maneuver safely around obstacles and leading to longer stopping distances and delayed reactions to hazardous situations. It is a major contributor to fatal and serious road trauma, accounting for over 20% of such incidents in the US. Eliminating speeding entirely could potentially substantially reduce fatal injuries by 20% or more. This study leveraged the comprehensive National Highway Traffic Safety Administration's (NHTSA) Fatality Analysis Reporting System (FARS) data, focusing on 50,081 speed-related motor vehicle traffic fatal crashes that occurred between 2016 and 2021, and a probabilistic graphical model to investigate the causal associations between key contributing factors involved in these speeding incidents. Ultimately, this high-impact research advanced our understanding of the risks posed by speeding and impaired driving, guiding the way for evidence-based interventions and transformative policies to build safer roads and protect all road users from preventable tragedies.

INTRODUCTION

The relationship between speed and crashes in road safety is a complex interplay of multiple factors. However, it is evident that as driving speeds increase, so does the crash rate. Moreover, individual vehicles traveling at higher speeds than other traffic on the same road are at a higher risk of crashes. These crashes also lead to more severe injuries for both the driver responsible for the crash and the other party involved. Speeding, encompassing exceeding speed limits or driving too fast for prevailing conditions, ranks among the most common factors contributing to motor vehicle crashes in the United States (U.S.). Various factors, such as road type, driver age, alcohol impairment, and roadway characteristics like curvature, grade, width, and adjacent land use influence the impact of speed on crash involvement.

In contrast, the link between speed and injury severity remains consistent and direct. Higher vehicle speeds result in more significant changes in velocity during a crash, directly correlating with the severity of injuries sustained. This correlation is particularly critical for vulnerable road users, such as pedestrians, who lack the protective structures of a vehicle.

The National Highway Traffic Safety Administration (NHTSA) categorizes drivers as speeding if their vehicle's speed falls into one of four categories: exceeding the speed limit, driving too fast for conditions, racing, or speeding with specific details unknown. Speed limits established by states for various road types define the first category. In contrast, the second category is based on the basic speed law, which requires drivers to operate at a reasonable and prudent speed given the prevailing environmental conditions. Between 2016 and 2021, speeding contributed to 50,081 traffic fatalities in the U.S., with a 26% increase in fatalities related to speeding observed from 2019 to 2021. The surge in speeding-related fatalities highlights the pressing need for a comprehensive analysis of speeding-related fatal crashes in the U.S. To address this, the current study utilized a probabilistic graphical method, Bayesian networks (BNs), to explore the causal relationships among key contributing factors. The findings of this research offer valuable insights for policymakers to implement more effective speed management strategies and interventions, reducing the prevalence and impact of speeding-related crashes.

By understanding the intricate relationships between speeding and crash outcomes, policymakers can devise evidence-based measures to promote safer driving behaviors and safeguard the well-being of all road users. This research is a powerful tool to inform the development of targeted policies and initiatives, fostering a culture of responsible and safe driving to protect lives and improve road safety across the nation.

LITERATURE REVIEW

Since higher speed is one of the major factors increasing crash risk and injury severities, there has been a lot of research in assessing the relationship between speeding and crash contributing factors related to driver, vehicle, roadway, and environmental characteristics. Some of the previous investigations explored speeding-related crashes by focusing on specific vehicle types. For instance, a Das et al. (2022) used crash data from Louisiana from 2010 to 2016 to identify the patterns associated with motorcycle crashes caused by speeding. Edwards et al. (2016) conducted interviews and ride-along observations to explore speeding cultures among drivers of heavy vehicles. The study found that truck drivers tended to consider speeding as generally safe, wanted to accelerate quickly, and did so to save time and earn more money.

Prior research has focused on driver demographics (age, gender) and behavior (seatbelt use, cellphone use, alcohol involvement) in crashes caused by speeding. For example, Se et al. (2023) conducted in Thailand explored the differences in crash-contributing factors affecting the injury severity of drivers (seatbelt-restrained and unrestrained) involved in speeding-related crashes. Using cellphone-involved single-vehicle crash datasets (2004 to 2019) from Pennsylvania, Wu et al. (2022) reported that combining cellphone usage with risky driving behaviors like speeding significantly increased the injury severity of drivers. The link between young drivers and speeding has also been explored by (Breen et al. 2020; Tay, 2005). For example, Ferguson, (2013) a national US-based report focused on speeding-related fatal crashes involving teen drivers aged 16-19. According to the investigation, speeding commonly results in single-vehicle and run-off-road crashes and is more common in males, at night, and when other teen passengers are present. (Bhalla et al. 2013; Høye, 2020; Romano et al. 2021; Ajay Kumar Yadav and Velaga, 2020) explored the role of drunk driving in speeding-related crashes. The common major finding from these studies was that an increase in Blood Alcohol Concentration (BAC) increases the likelihood of speeding-related crashes.

The crash risk associated with speeding can vary spatially, so some of the previous research addressed speeding-related crashes in specific locations. Yan et al. (2022) investigated speeding-related crashes on rural roadways focused on two distinct types of crashes – a) overturned and b) hitting fixed-object. The study identified some critical factors that present relative temporal stability, such as alcohol involvement, truck, aggressive driving, vehicle age (greater than 14 years old) and posted speed limit of less than 45 mph. Jiang et al. (2017) investigated over-speeding violation behaviors of drivers on expressways recorded by a global positioning system (GPS) enabled smartphone application. Kveladze and Agerholm (2020)identified speeding patterns on arterial roadways using Geovisual Analytics (GVA).

Prior studies have explored speeding-related crashes focusing on specific vehicle types, driver demographics, and behaviors. Compared to other models, BNs stand out for their ability to effectively capture complex relationships and dependencies among variables, making it a promising approach for understanding the intricate dynamics of speeding-related crashes more comprehensively and accurately.

METHODOLOGY

Data Collection

This study acquired fatal crash data for 6 years by the different types of speeding, including too fast for conditions, exceeded the speed limit, racing, and specifics unknown. Table 1 shows that over the six years from 2016 to 2021, the total number of recorded driving incidents increased from 8,334 cases in 2016 to 9,551 cases in 2021. Among the severity categories, incidents involving specifics unknown showed the most significant rise, increasing by 76.9%. Although the number of exceeded speed limit incidents remained relatively stable, there was a slight increase of approximately 0.8% by 2021. Incidents related to racing remained low and consistent throughout the years. However, incidents attributed to too-fast-for conditions saw a notable 9.6% increase.

Table 1. Fatalities by Year by Speeding Type

Year	Too Fast for Conditions	Exceeded Speed Limit	Racing	Specifics Unknown	Yearly Total
2016	3,742	3,496	58	1,038	8,334
2017	3,520	3,253	51	1,135	7,959
2018	3,473	3,056	51	1,054	7,634
2019	3,468	2,868	48	1,176	7,560
2020	3,685	3,628	104	1,626	9,043
2021	4,102	3,524	91	1,834	9,551
Grand Total	21,990	19,825	403	7,863	50,081

Table 2 shows the distribution of different variables considering different speeding types. The most common land use for all types was rural. When the specific functional system was known, other principal arterials were the most common for the too fast for conditions, exceeding the speed limit, and specifics unknown speeding types and minor arterials were the most common for racing. Crashes typically occurred on weekdays, during the daylight, and were evenly split across all seasons. The most harmful event for too fast for conditions was a rollover or overturn, but for all other speeding types, it was motor vehicle in transport. Not collision with MVIT was the most common crash type. Drivers were usually 25 to 45 years old, not impaired by alcohol, had a valid driver's license, and were not ejected from the vehicle. Typically, no restraints were used. The roads usually had a straight alignment, a level road profile, and two lanes. Generally, the roadways were two-way undivided. The most common speed limit for too fast for conditions or specifics unknown was 50-55 MPH. For exceeding the speed limit and racing, however, the most common speed limit was 35-45 MPH. Cars were the most common body type, and usually, crashes involved single vehicles. Generally, no rollover occurred.

Table 2. Distribution of Variables Considering Different Speeding Types

Variable	Too Fast for Conditions N=21990	Exceeded Speed Limit N=19825	Racing N=403	Specifics Unknown N=7863	p-val.
rur_urb (Land Use)					.
Rural	11759 (53.5%)	8968 (45.2%)	75 (18.6%)	3155 (40.1%)	
Unknown	88 (0.40%)	62 (0.31%)	3 (0.74%)	38 (0.48%)	
Urban	10143 (46.1%)	10795 (54.5%)	325 (80.6%)	4670 (59.4%)	
func_sys (Functional System)					<0.001
Interstate	3305 (15.0%)	2085 (10.5%)	36 (8.93%)	1048 (13.3%)	
Major Collector	4028 (18.3%)	3562 (18.0%)	42 (10.4%)	1251 (15.9%)	
Minor Arterial	4138 (18.8%)	4423 (22.3%)	121 (30.0%)	1435 (18.3%)	
Other	5982 (27.2%)	5063 (25.5%)	86 (21.3%)	2233 (28.4%)	
Principal Arterial - Other	4537 (20.6%)	4692 (23.7%)	118 (29.3%)	1896 (24.1%)	
day_week (Day of the Week)					0.014
Weekday	13782 (62.7%)	12121 (61.1%)	246 (61.0%)	4865 (61.9%)	
Weekend	8208 (37.3%)	7704 (38.9%)	157 (39.0%)	2998 (38.1%)	
Season (Season)					<0.001
Autumn	5529 (25.1%)	5029 (25.4%)	97 (24.1%)	2201 (28.0%)	
Spring	5195 (23.6%)	5050 (25.5%)	118 (29.3%)	1887 (24.0%)	
Summer	5797 (26.4%)	5874 (29.6%)	118 (29.3%)	2252 (28.6%)	
Winter	5469 (24.9%)	3872 (19.5%)	70 (17.4%)	1523 (19.4%)	
lgt_cond (Lighting Condition)					<0.001
Dark - Lighted	3747 (17.0%)	4355 (22.0%)	148 (36.7%)	1980 (25.2%)	
Dark - Not Lighted	6542 (29.7%)	6237 (31.5%)	86 (21.3%)	2168 (27.6%)	
Dawn	402 (1.83%)	315 (1.59%)	1 (0.25%)	122 (1.55%)	
Daylight	10487 (47.7%)	8111 (40.9%)	145 (36.0%)	3263 (41.5%)	
Dusk	559 (2.54%)	550 (2.77%)	17 (4.22%)	210 (2.67%)	
Other	253 (1.15%)	257 (1.30%)	6 (1.49%)	120 (1.53%)	
m_harm (Most Harmful Event)					.

Fire/Explosion	417 (1.90%)	480 (2.42%)	9 (2.23%)	215 (2.73%)	
Guardrail Face	447 (2.03%)	361 (1.82%)	8 (1.99%)	181 (2.30%)	
Motor Vehicle In-Transport	6107 (27.8%)	5725 (28.9%)	155 (38.5%)	2340 (29.8%)	
Other	3573 (16.2%)	2880 (14.5%)	55 (13.6%)	1374 (17.5%)	
Parked Motor Vehicle	366 (1.66%)	249 (1.26%)	10 (2.48%)	164 (2.09%)	
Pedalcyclist	4 (0.02%)	3 (0.02%)	0 (0.00%)	1 (0.01%)	
Pedestrian	10 (0.05%)	13 (0.07%)	1 (0.25%)	29 (0.37%)	
Rollover/Overturn	6201 (28.2%)	4838 (24.4%)	66 (16.4%)	1681 (21.4%)	
Tree (Standing Only)	3906 (17.8%)	4173 (21.0%)	76 (18.9%)	1445 (18.4%)	
Utility Pole/Light Support	959 (4.36%)	1103 (5.56%)	23 (5.71%)	433 (5.51%)	
man_coll (Collision Type)					.
Angle	2512 (11.4%)	3039 (15.3%)	80 (19.9%)	1074 (13.7%)	
Front-to-Front/Rear	2977 (13.5%)	2435 (12.3%)	38 (9.43%)	1128 (14.3%)	
Not Collision with MVIT	15877 (72.2%)	13679 (69.0%)	218 (54.1%)	5360 (68.2%)	
Other	94 (0.43%)	85 (0.43%)	7 (1.74%)	49 (0.62%)	
Rear-end	49 (0.22%)	33 (0.17%)	1 (0.25%)	9 (0.11%)	
Sideswipe	481 (2.19%)	554 (2.79%)	59 (14.6%)	243 (3.09%)	
Age (Driver Age)					.
25-45 years	8819 (40.1%)	9334 (47.1%)	153 (38.0%)	3529 (44.9%)	
46-65 years	5001 (22.7%)	3238 (16.3%)	37 (9.18%)	1488 (18.9%)	
Children	370 (1.68%)	240 (1.21%)	5 (1.24%)	108 (1.37%)	
Infant	64 (0.29%)	43 (0.22%)	0 (0.00%)	16 (0.20%)	
Older than 65 years	1843 (8.38%)	723 (3.65%)	5 (1.24%)	542 (6.89%)	
Unknown	27 (0.12%)	29 (0.15%)	1 (0.25%)	18 (0.23%)	
Young	5866 (26.7%)	6218 (31.4%)	202 (50.1%)	2162 (27.5%)	
Drinking (Driver Impairment)					<0.001
No	6273 (28.5%)	5943 (30.0%)	113 (28.0%)	2020 (25.7%)	
Unknown	11133 (50.6%)	8619 (43.5%)	222 (55.1%)	4120 (52.4%)	
Yes	4584 (20.8%)	5263 (26.5%)	68 (16.9%)	1723 (21.9%)	
Ejection (Driver Ejection)					<0.001
Ejected	5464 (24.8%)	5697 (28.7%)	106 (26.3%)	1840 (23.4%)	
Not Ejected	11934 (54.3%)	9548 (48.2%)	207 (51.4%)	4186 (53.2%)	
Unknown	4592 (20.9%)	4580 (23.1%)	90 (22.3%)	1837 (23.4%)	
l_status (Driver Licensing Status)					.
Canceled or denied	62 (0.28%)	112 (0.56%)	2 (0.50%)	27 (0.34%)	
Expired	506 (2.30%)	321 (1.62%)	11 (2.73%)	193 (2.45%)	
Not licensed	1895 (8.62%)	1899 (9.58%)	73 (18.1%)	903 (11.5%)	
Revoked	401 (1.82%)	634 (3.20%)	3 (0.74%)	167 (2.12%)	
Suspended	2127 (9.67%)	2437 (12.3%)	35 (8.68%)	787 (10.0%)	

Unknown License Status	263 (1.20%)	221 (1.11%)	10 (2.48%)	137 (1.74%)	
Valid	16736 (76.1%)	14201 (71.6%)	269 (66.7%)	5649 (71.8%)	
rest_use (Restraint Usage)					.
Child Restraint	135 (0.61%)	62 (0.31%)	0 (0.00%)	21 (0.27%)	
Helmet	1505 (6.84%)	1415 (7.14%)	26 (6.45%)	447 (5.68%)	
None used	12160 (55.3%)	12438 (62.7%)	191 (47.4%)	4397 (55.9%)	
Restraint Used	6507 (29.6%)	4370 (22.0%)	109 (27.0%)	2001 (25.4%)	
Unknown	1683 (7.65%)	1540 (7.77%)	77 (19.1%)	997 (12.7%)	
Valign (Alignment)					.
Curve	10180 (46.3%)	7719 (38.9%)	108 (26.8%)	2633 (33.5%)	
Driveway Access	19 (0.09%)	7 (0.04%)	0 (0.00%)	6 (0.08%)	
Straight	11345 (51.6%)	12001 (60.5%)	286 (71.0%)	5101 (64.9%)	
Unknown	446 (2.03%)	98 (0.49%)	9 (2.23%)	123 (1.56%)	
vnum_lan (Number of Lanes)					<0.001
Five lanes	1253 (5.70%)	1045 (5.27%)	34 (8.44%)	404 (5.14%)	
Four lanes	1599 (7.27%)	1727 (8.71%)	77 (19.1%)	772 (9.82%)	
Other	1357 (6.17%)	842 (4.25%)	31 (7.69%)	415 (5.28%)	
Three lanes	1904 (8.66%)	1845 (9.31%)	69 (17.1%)	925 (11.8%)	
Two lanes	15877 (72.2%)	14366 (72.5%)	192 (47.6%)	5347 (68.0%)	
Vprofile (Road Profile)					0.000
Downhill	2190 (9.96%)	1783 (8.99%)	11 (2.73%)	299 (3.80%)	
Grade, Unknown Slope	2983 (13.6%)	2169 (10.9%)	49 (12.2%)	1128 (14.3%)	
Level	12734 (57.9%)	13499 (68.1%)	273 (67.7%)	5138 (65.3%)	
Other	1885 (8.57%)	1848 (9.32%)	25 (6.20%)	419 (5.33%)	
Unknown	2198 (10.00%)	526 (2.65%)	45 (11.2%)	879 (11.2%)	
vspd_lim (Speed Limit)					.
30 MPH and Lower	1943 (8.84%)	2840 (14.3%)	57 (14.1%)	1229 (15.6%)	
35-45 MPH	7029 (32.0%)	8414 (42.4%)	207 (51.4%)	2475 (31.5%)	
50-55 MPH	7920 (36.0%)	5918 (29.9%)	77 (19.1%)	2682 (34.1%)	
65-70 MPH	3717 (16.9%)	1931 (9.74%)	40 (9.93%)	860 (10.9%)	
75-85 MPH	732 (3.33%)	311 (1.57%)	5 (1.24%)	216 (2.75%)	
No Statutory Limit	92 (0.42%)	24 (0.12%)	2 (0.50%)	18 (0.23%)	
Unknown	557 (2.53%)	387 (1.95%)	15 (3.72%)	383 (4.87%)	
Vtrafway (Trafficway Type)					<0.001
Other	1636 (7.44%)	1181 (5.96%)	37 (9.18%)	640 (8.14%)	
Two-Way Divided Median Barrier	3005 (13.7%)	2252 (11.4%)	70 (17.4%)	1175 (14.9%)	
Two-Way Divided Unprotected Barrier	2717 (12.4%)	2888 (14.6%)	93 (23.1%)	1028 (13.1%)	
Two-Way Undivided	13724 (62.4%)	12600 (63.6%)	170 (42.2%)	4691 (59.7%)	

Two Way TWLCL	908 (4.13%)	904 (4.56%)	33 (8.19%)	329 (4.18%)	
body_typ (Vehicle Body Type)					.
ATV	369 (1.68%)	101 (0.51%)	6 (1.49%)	128 (1.63%)	
Bus	39 (0.18%)	7 (0.04%)	0 (0.00%)	3 (0.04%)	
Car	9000 (40.9%)	9344 (47.1%)	231 (57.3%)	3500 (44.5%)	
Light Truck	3347 (15.2%)	2467 (12.4%)	21 (5.21%)	877 (11.2%)	
Motorcycle	4497 (20.5%)	4481 (22.6%)	87 (21.6%)	1790 (22.8%)	
Motorhome	11 (0.05%)	2 (0.01%)	0 (0.00%)	2 (0.03%)	
Other	319 (1.45%)	114 (0.58%)	10 (2.48%)	110 (1.40%)	
Truck	665 (3.02%)	188 (0.95%)	2 (0.50%)	140 (1.78%)	
Utility	3225 (14.7%)	2778 (14.0%)	44 (10.9%)	1150 (14.6%)	
Van	518 (2.36%)	343 (1.73%)	2 (0.50%)	163 (2.07%)	
Rollover (Rollover Type)					<0.001
No Rollover	14507 (66.0%)	13034 (65.7%)	281 (69.7%)	5558 (70.7%)	
Other	646 (2.94%)	500 (2.52%)	11 (2.73%)	181 (2.30%)	
Rollover, Tripped by Object/Vehicle	5667 (25.8%)	5316 (26.8%)	99 (24.6%)	1763 (22.4%)	
Rollover	1170 (5.32%)	975 (4.92%)	12 (2.98%)	361 (4.59%)	
ve_total (Vehicles Involved)					<0.001
Multiple	7515 (34.2%)	7230 (36.5%)	214 (53.1%)	3039 (38.6%)	
Single	14475 (65.8%)	12595 (63.5%)	189 (46.9%)	4824 (61.4%)	

Bayesian Network

A Bayesian Network (BN) or belief network is a probabilistic graphical model used to represent and reason uncertain relationships between variables. It is based on Bayesian probability theory, which allows for incorporating prior knowledge and updating probabilities as new evidence is obtained. The network consists of nodes representing variables and directed edges representing probabilistic dependencies between the variables. There are several data-driven techniques available, including Naive Bayesian Networks (NBN), Augmented naive Bayesian Networks (ABN), and Tree-augmented naive Bayes Networks (TAN). TAN learning specifically constructs qualitative BNs that capture the interactive relationships among risk influential factors (RIFs). This approach proves valuable for extracting valuable insights into crucial human variables that play a role in different types of crashes, such as those related to speeding. Additionally, research by Friedman et al. (1997) highlighted that TAN outperforms NBN in terms of predictive accuracy while still maintaining computational simplicity and robustness. A study by (Howard and Matheson, 1984; Pearl, 1988) discussed an influence diagram, also known as a Bayesian belief net or decision diagram, depicts the factors that contribute to a particular conclusion or uncertainty within the context of speeding types in fatal crashes. Moreover, Shachter (2007) emphasized that the influence diagram allows for the incorporation of decisions, enabling decision-makers to comprehend how each alternative impacts the probability of a specific outcome.

RESULTS AND DISCUSSIONS

Several steps were involved in developing the BN model in this study. Firstly, Netica 6.04 (a user-friendly software specifically designed for BN applications) adopted by Norsys (2020) was used to construct a DAG representing the model. DAG is a causal network in which a node represents each variable's conditional probability distribution (CPD), and the edges show how those nodes are related to one another. To fit the network to the input-output combinations obtained from the Monte Carlo (MC) runs using the model, the Lauritzen (1995) expectation maximization (EM) technique was used. The BN model parameters (conditional probability distributions) were estimated through the learning process. These distributions provide information about the likelihood of different states within each node of the BN. Figure 1 illustrates the layout of the final BN network. The relationships between different nodes are depicted in this figure. Each node's conditional probability tables (CPTs) are represented as belief bars and reflect the probabilities associated with the various states of that node.

Figure 1 presents the initial data on different speeding types of vehicle crashes, modeled through a BN. The most frequently contributing speeding types to fatal crashes are too fast for conditions (43.9%) and exceeded speed limit (39.6%). Among fatal crashes, 51.8% occur in urban areas, with a majority on two-way undivided (62.3%) and two-lane (71.4%) roadways. The most common functional system is 'other' (26.7%) or an 'other' form of principle arterial (22.4%). Considering vehicle types and drivers' perspectives, it can be observed that drivers between 25 and 45 years old (44.1%), holding a valid driving license (73.6%), and driving a car (44.1%) tend to be involved in fatal crashes most often. Typically, no restraint is used (58.3%). Usually, drinking is either unknown (48.1%) or not involved (28.7%). These crashes predominantly occur when driving on straight (57.4%), leveled (63.2%), two-lane (71.4%), and two-way undivided (62.3%) roads in urban areas (51.8%). The most common speed limit is 35 to 45 MPH. The most common collision type is not a collision with an MVIT (70.2%). The most harmful event was often motor vehicle in transport. Usually, no rollover occurred, and the driver was generally not ejected. Usually, crashes involved a single vehicle (64.1%). These crashes often occur during the weekday (61.7%), in the daylight (43.9%), and are relatively evenly split across all seasons.

Counterfactual Scenarios

Figure 2 illustrates a counterfactual scenario considering all crashes to have been too fast for the conditions. There was an increase in crashes that occurred in rural areas (by 5.7%), making it the most dominant category. Siskind et al. (2011) study identified the over-representation of fatal crashes in rural areas where the drivers had been travelling at or below the posted speed limit, but too fast for the prevailing condition. Afghari et al. (2018) discussed the intuitive relationship between 'driving too fast for conditions' and 'curved alignment' reveals a critical safety concern in such settings. Curved roads often limit the driver's line of sight.

Figure 3 shows a counterfactual scenario considering all crashes occurred with a speeding type of exceeded the speed limit. Urban areas were again the most common location for these crashes, although it only increased by 2.7% compared to the original data. The relationship between exceeding the speed limit and urban area type is well documented in previous research (Heydari et al. 2014; Hu and Cicchino, 2020; Moradi et al. 2013; Pérez-Acebo et al. 2021; Yannis et al. 2013). Urban areas are often characterized by heavy traffic congestion, especially during peak hours. Drivers may feel rushed, impatient, or stressed due to time constraints, leading them to speed to reach their destinations faster. A 35 to 45 MPH speed limit became the dominant category, increasing by 6.2%. There was also a slight increase in crashes that occurred on level roads of 4.9%. Interestingly, there was no notable change in any of the other variables.

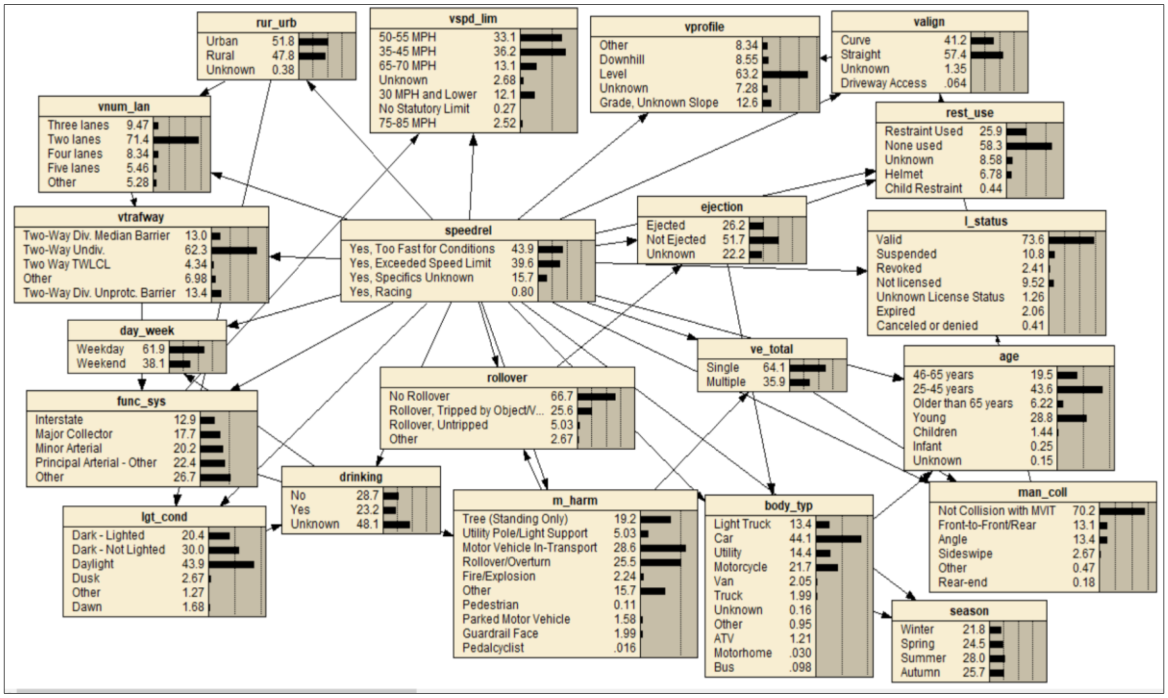

Figure 1. BN of full data

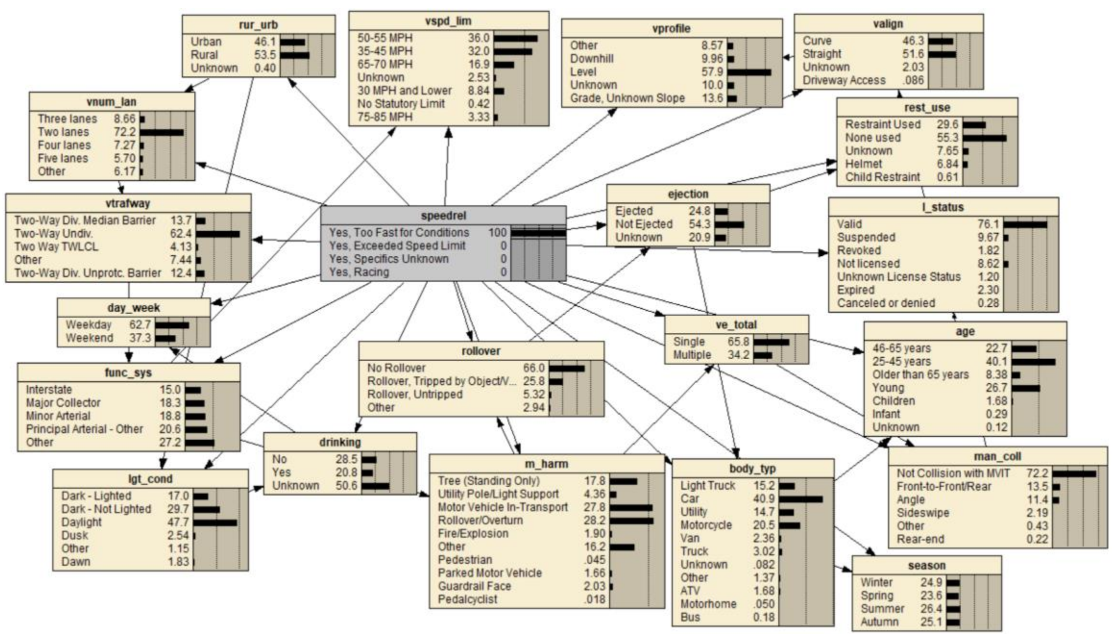

Figure 2. BN of counterfactual scenario considering all crashes occurred with the speeding type of too fast for conditions.

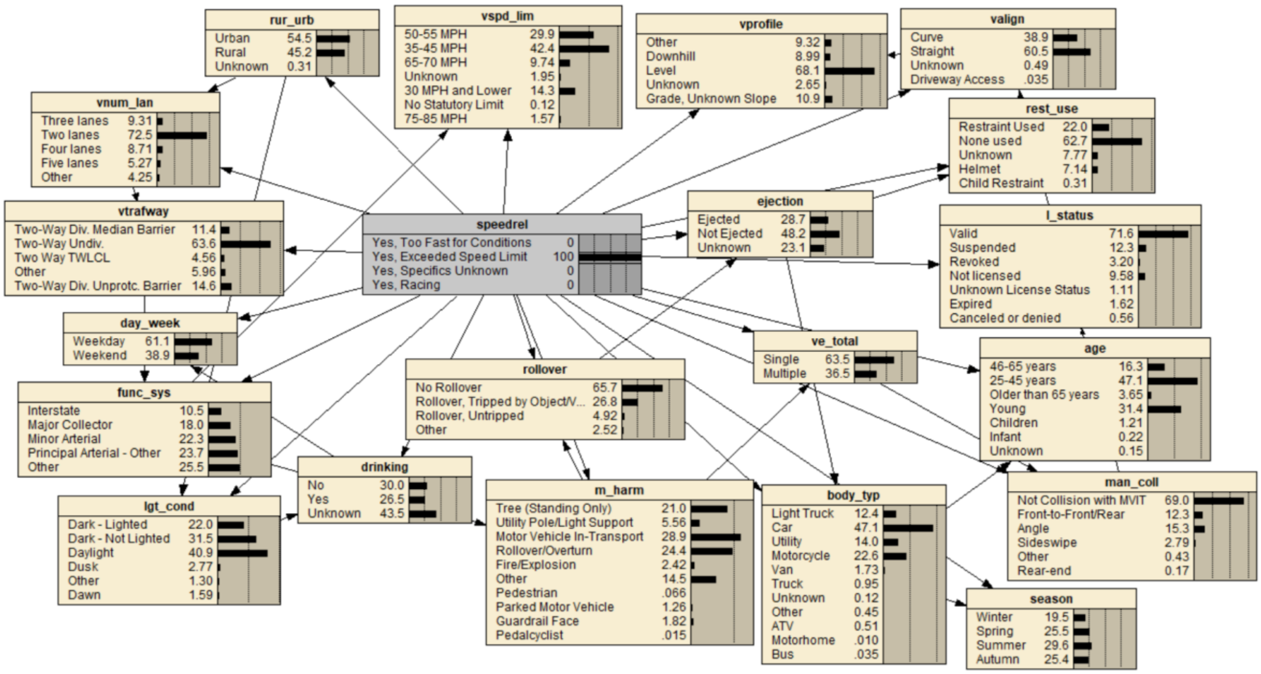

Figure 3. BN of counterfactual scenario considering all crashes occurred with a speeding type of exceeded speed limits

CONCLUSIONS

Speeding is one of the most prevalent factors in motor vehicle crashes in the United States. This study provides valuable insights into fatal crashes related to different types of speeding over six years from 2016 to 2021. A BN analysis uncovered the intricate relationships between speeding and crash outcomes. The initial data highlights that fatal crashes' most common speeding types were too fast for conditions and exceeded the speed limit. Urban areas accounted for slightly over half of fatal crashes, and drivers aged 25 to 45 with valid licenses were most involved. Counterfactual scenarios showed that altering specific variables could lead to notable shifts in crash patterns. For instance, increasing the speed limit to 35-45 MPH resulted in more urban crashes. In comparison, a speed limit of 75 to 85 MPH led to an increase in crashes involving driving too fast for conditions and a substantial increase in crashes on interstates.

The study's unique contributions involved using a BN analysis to understand the complex relationships between speeding and crash outcomes, offering insights into speeding types, road types, and driver characteristics related to fatal crashes. The research also employed counterfactual scenarios to assess the potential impact of interventions on crash patterns, aiding evidence-based policy decisions. The study findings also highlighted the need for speed management strategies, road infrastructure improvements, targeted enforcement and education, and comprehensive road safety initiatives to reduce speeding-related crashes and fatalities on U.S. roads.

The study's limitations include the focus on fatal crashes, potentially missing non-fatal incidents, and excluding combined speeding behaviors. Furthermore, improved data recording and reporting practices may influence the observed trends. BN modeling's accuracy may be impacted by changes in driving behavior or infrastructure over time. Future research should explore the effectiveness of intervention strategies and adopt a broader perspective on road safety, considering injuries and property damage. Regular updates to the model with recent data are crucial. Addressing these limitations can enhance road safety measures and guide evidence-based policy decisions.

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