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Identifying characteristics that impact motor carrier safety using Bayesian networks

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ABSTRACT

Problem Statement: In the U.S., a safety rating is assigned to each motor carrier based on data obtained from the Motor Carrier Management Information System (MCMIS) and an on-site investigation. While researchers have identified variables associated with the safety ratings, the specific direction of the relationships are not necessarily clear.

Objective: The objective of this study is to identify those relationships involved in the safety ratings of interstate motor carriers, the largest users of the U.S. transportation network.

Method: Bayesian networks are used to learn these relationships from data obtained from MCMIS for a 6-year period (2007–2012).

Results: Our study shows that safety rating assignment is a complex process with only a subset of the variables having statistically significant relationship with safety rating. They include driver out-of-service violations, weight violations, traffic violations, fleet size, total employed drivers, and passenger & general carrier indicators.

Application: The findings have both immediate implications and long term benefits. The immediate implications relate to better identification of unsafe motor carriers, and the long term benefits pertain to policies and crash countermeasures that can enhance carrier safety.

1. Introduction

A motor carrier safety rating is an evaluation given by the US DOT Federal Motor Carrier Safety Administration (FMCSA). The safety rating represents a motor carrier's overall crash risk and its ability to operate safely. FMCSA determines the safety rating of a motor carrier by using a two-stage system. In the first stage, unsafe motor carriers are identified using the Safety Measurement System (SMS), an automated system that assesses a motor carrier's on-road performance and compliance by filtering data from the Motor Carrier Management Information System (MCMIS) into seven Behavior Analysis and Safety Improvement Categories (BASICs): Unsafe Driving, Crash Indicator, Hours of-Service Compliance, Vehicle Maintenance, Controlled Substances/Alcohol, Hazardous Materials Compliance (HM), and Driver Fitness (FMCSA, 2017b).

In the second stage, a small portion of the identified motor carriers are selected each year for an on-site investigation, which consists of a 3–4 day examination of a motor carrier's operations. The majority of information reviewed and obtained during an on-site investigation is not included in MCMIS. At the end of an on-site investigation, one of three safety ratings is given: Satisfactory, Conditional satisfactory, or Unsatisfactory. In 2016, only 2.7% of the motor carriers were included in this second stage (FMCSA, 2018a, 2017a). For those motor carriers that do not include a second stage, their safety ratings are based on MCMIS data that is more than two years old. While there exists a plethora of variables, the best or most important predictors of safety is not clear.

The MCMIS database provides information on each carrier that includes their characteristics (names, addresses, type of organization, number of vehicles, number of commercial drivers, etc.), operation classifications (for-hire, private, etc.), cargo type, violation history, and crash history. The MCMIS variables are widely examined using regression-based techniques to examine overall motor carrier safety given the carrier characteristics (Moses and Savage, 1992, 1996; Chen, 2008; Cantor et al., 2013; Lantz, 1994). Cantor (2014) used ordinary least squares (OLS) regression models to show the impact of firm size on safety performance. More specifically, larger firms had lower violation rates than smaller firms, but larger firms also had larger crash rates. Cantor et al. (2017) also used OLS to show that carriers that participated in the new entrant program had a significantly better safety

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Table 1
Inspection, crash, and rating variables used in learning the Bayesian Network.

Name	Node name	Definition
Safety Performance Metrics		
Driver out-of-service rate	DOO	Number of driver out-of-service/ Number of inspections
Vehicle out-of-service rate	VOO	Number of vehicles out-of-service/ Number of inspections
Weight infringements	WT	Number of weight infringements/ Number of inspections
Traffic infringements	TR	Number of traffic infringements/ Number of inspections
Alcohol infringements	ALC	Number of alcohol infringements/ Number of inspections
Drug infringements	DRG	Number of drug infringements/ Number of inspections
Crash rate	CR	Number of crashes/ number of power units
Crash miles	CM	Number of crashes/ total miles driven by carrier
Fatal rate	FR	Number of crashes with fatalities/number of power units
Rating variables		
Safety Rating	SR	Federal safety rating assigned to the carrier
Safety Audit Rating	SAR	Safety audit results for the carrier

Note: All variables were given categorical values prior to use for the BN learning.

performance than carriers that did not participate. These OLS models are designed to examine each outcome or safety performance metric as separate models, rather than consider the interactions that may exist among them. The performance and interpretation of the model is impacted if any of the assumptions associated with a regression model (multicollinearity, linearity, and homoscedasticity) are violated. For example, violation variables, such as traffic violations and driver violations, are highly correlated, which makes studying these variables in unison difficult using traditional regression models. Past research in carrier safety have not accounted for the complex interactions of the safety performance metrics, but rather were constrained to examining each safety performance metric separately.

Bayesian networks (BNs) provide a framework that integrates graphical models with Bayesian inference to identify the statistically significant relationships among many variables, and they are being widely used in transportation safety research (Hossain and Muromachi, 2012; Leu and Chang, 2013; Häanninen, 2014; Mbakwe et al., 2016). Compared to other modeling techniques, BNs have the ability to handle high levels of uncertainty, learn complex and non-linear relationships among the variables, and represent these relationships in an easy to understand graphical form (Uusitalo, 2007; Chen and Pollino, 2012). For example, Lam et al. (2015) applied a BN to identify the significant interaction effects between ambulance response times for trauma incidents and patient and process-related risk factors. Rather than examining all the possible interaction terms in a multinomial logistic (MNL) regression model, only those significant interactions were used to model the likelihood of short, medium, and long ambulance response times.

Chen et al. (2015) used BN and MNL to model the relationships of driver injury severity in rear-end crashes. They first used the MNL to identify the significant variables, which were then fed into a BN to model the relationships between driver injury severity and the explanatory variables. The findings showed that the classification accuracy of driver injury severity using BNs was better than the accuracy using only traditional MNL models. BN inference was used to quantify the contributions of windy conditions, alcohol, and disabled vehicles on the likelihood of driver injuries and fatalities.

Oña et al. (2013) used BNs in conjunction with latent class clustering (LCC) to identify the factors involved in the injury severity of rural highway crashes. This study clustered the crashes into four different types (collisions with shoulder, collisions without shoulders, run-off-road crashes with shoulder, and run-off-road crashes without shoulder); and constructed BNs for each crash type as well as a complete model. The results showed that even with a sample size of 3229 crash records, the BNs were able to learn the relationships that affected the severity of each crash type. These studies demonstrate the capabilities of BNs to model and learn the relationships among variables, and how the BN structure can be learned from data without any predefined assumptions.

The goal of this study is to identify the carrier characteristics and safety performance metrics that impact motor carrier safety ratings. The motor carrier safety rating is selected as the outcome of interest as this is the metric used by FMCSA to determine the overall safety fitness of the interstate motor carriers, which constitute the largest users of the U.S. interstate network (FMCSA, 2017a). To accomplish this research goal, we identify the relationships among the variables commonly employed to examine motor carrier safety using MCMIS data and BNs. BNs allow us to learn the relationships directly from the data, and quantify the contributions of the variables on the safety rating of the motor carriers. This approach, therefore, provides a more holistic model of the variables that affect motor carrier safety rating.

2. Methods

2.1. Data

The forthcoming analysis was based on data from MCMIS, a database that contains the safety records of motor carriers. The database is maintained by the U.S. DOT – FMCSA and includes variables that describe the roadside and on-site inspections, crash characteristics, and carrier characteristics. Only motor carriers that had on-site inspections with an updated safety ratings were considered in this study. An updated safety rating would indicate that there was activity in the two years prior to the inspection. Furthermore, only interstate carriers were considered since there are regulations specific to this driver population as well as safety differences in out-of-service violations (Thakuriah et al., 2000).

The motor carrier safety rating can be one of three categories: Satisfactory (S), Conditional (C), and Unsatisfactory (U). For the purpose of this study, C & U safety ratings were grouped together given the sample size and the focus on motor carriers with a satisfactory rating. Data for a 6-year period (2007–2012) was used and any motor carrier with missing values was excluded from this study.

The variables used in the forthcoming BN are shown in Tables 1 and 2 and were calculated using data from two years prior to the initial on-site inspection date; this is the same time frame that is used by SMS. Previous research in this area have separated passenger carriers from the rest of the carriers given the differences between these two groups. Both carrier populations are included in our BN model as it should be able to learn and identify any differences between these populations. The infringements shown in Table 1 are calculated by dividing the total number of infringements by the total number of inspections. It is reasonable to use the total number of inspections as a denominator because these infringements are checked in approximately 98% of all roadside inspections from 2009 to 2013. (FMCSA, 2014, 2018b). The final dataset used for learning the BN included 27 variables aggregated at the carrier level with a total of 3640 records (see Table 3).

Table 2
List of carrier characteristics used in learning the BN.

Carrier Characteristics	Node name	Definition
New entrant program code	NEP	Identifier code of whether a carrier participated and graduated from the new entrant program
Equipment ownership ratio	OWN	Number of owned straight trucks, truck tractors, and trailers/Total number of equipment
Power units	PU	Number of power units carrier has
Total Drivers	TDR	Total number of employed drivers
Cargo: passenger	PAS	Transports predominately passengers
Cargo: household	HH	Transports household cargo
Cargo: intermodal	INT	Transports intermodal container cargo
Cargo: produce	PRD	Transports produce cargo
Cargo: building	BLD	Transports building cargo
Cargo: large	LRG	Transports large object cargo
Cargo: general	GEN	Other cargo not listed above
Miles driven per driver	MILE	Total miles driven by carrier/number of drivers
Carrier Class: for hire	FH	The carriers operating class
Carrier Class: exempt	EXM	The carriers operating class
Carrier Class: private	PRV	The carriers operating class
Number of drivers		The number of drivers employed and leased by the carrier
Commercial Driver License (CDL) ratio	CDL	Number of CDL drivers/number of drivers employed by carrier

Note: All variables were given categorical values prior to use for the BN learning.

Table 3
The safety ratings by year for the final dataset.

Year	Safety ratings		
	Satisfactory	Conditional and unsatisfactory	Total
2007	23	8	31
2008	129	27	156
2009	431	134	565
2010	535	467	1002
2011	462	724	1186
2012	246	454	700
Total	1826	1814	3640

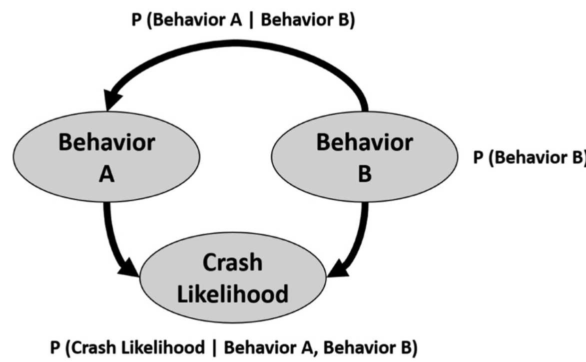


Fig. 1. An example of a simple Bayesian network (BN) using 3 nodes for Behaviors A and B, and Crash Likelihood. The relationships are captured by the directed links among the nodes.

2.2. Bayesian networks

A Bayesian network (BN) is a probabilistic graphical model that represents the joint distribution of a set of random variables compactly in the form of a directed acyclic graph (DAG). Each variable is represented as a node with directed links that form the edges (or arrows) between them, which denote conditional dependencies. Mathematically, if $S = [\{x_1, \ldots, x_n\}, n \geq 1]$ is a set of random variables, a BN over S is the set of Conditional Probability Tables (CPTs) $P_{x_i} = p(x_i|\mathrm{pa}(x_i))$, $x_i \in S$, where $pa(x_i)$ is the set of parents of x_i.

Based on the theory of BNs, the edges are interpreted as probabilistic conditional dependencies that provide information on the causal relationships among the connected nodes (Koller and Friedman, 2012). The directions of the edges (arrows) indicate the direction of the relationship between a parent node and their descendents (or child nodes). If the two nodes are connected directly, we refer to this connection as a relationship that gives insight into the direct causal relationship. If the two nodes are connected along a network path through intermediate nodes, then this connection is identified as an indirect relationship that gives insight into the indirect causal relationship.

Fig. 1 shows a simple example of a BN, where the likelihood of being involved in a crash is influenced by the driver's behavior A and B. The parent of A is B, and the parents of Crash Likelihood are A and B. Behavior B has a direct relationship on both A, $P(A|B)$, and Crash Likelihood, $P(\text{CrashLikelihood}|A, B)$, as indicated by the direction of the edges between the nodes.

The continuous variables obtained from MCMIS were further categorized into distinct values to learn the BN structure. The variables were categorized into four quartiles (0–25%, 26–50%, 51–75%, and 76–100%). Some carriers did not have any crashes or out-of-service violations during the study period. The variables associated with these carriers could be zero, and, hence, a fifth category was included to account for cases where a carrier had 0 incidents. The other four categories were determined based on the quartiles as noted earlier.

In this study, tabu search and hill-climbing algorithms, based on the scores from the Bayesian information criterion (BIC), were used to learn the BN structure (Koller and Friedman, 2012). These score-based algorithms, as compared to constraint-based algorithms, are less sensitive to errors in the individual independence tests, and allow for trade-offs between the BN structure complexity and the overall fit of the BN (Yan and Cercone, 2009).

3. Results

The analyses were carried out on a Windows 10 Operating System using the R programming language version 3.4.1. R packages, namely, bnlearn (Scutari and Ness, 2016) and caret citepcaret, were used for generating the BN models; ggplot2 (Wickham, 2009) and dplyr (Wickham et al., 2016) were used for visualizing the results.

Of the 3640 records, 2912 are used for training and 728 were used for testing. Fig. 2 shows the BN learned using both score based algorithms (tabu search and hill-climbing). To avoid physically unrealistic connections from being learned in the BN, the edges between the different motor carrier cargo types as well as those between various motor carrier operating classes are excluded from consideration. While all the variables used in learning the BN are present in the final model, two distinct BNs are observed (Fig. 2), one for safety rating and another for safety audit, indicating that these are independent processes. This

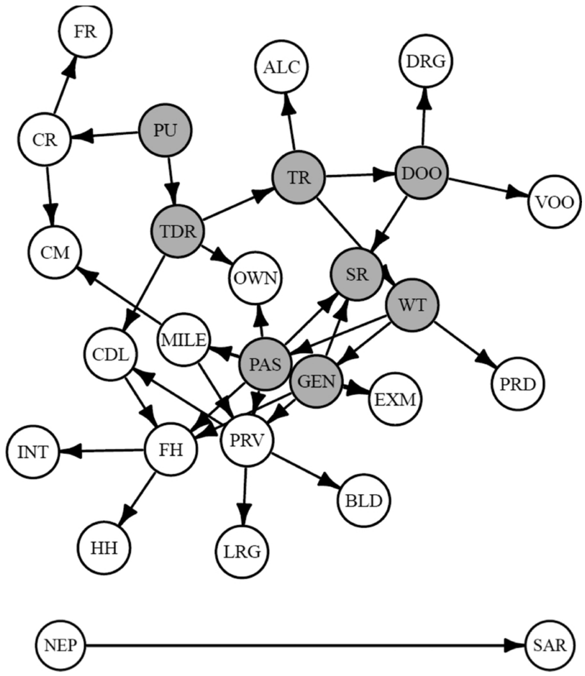
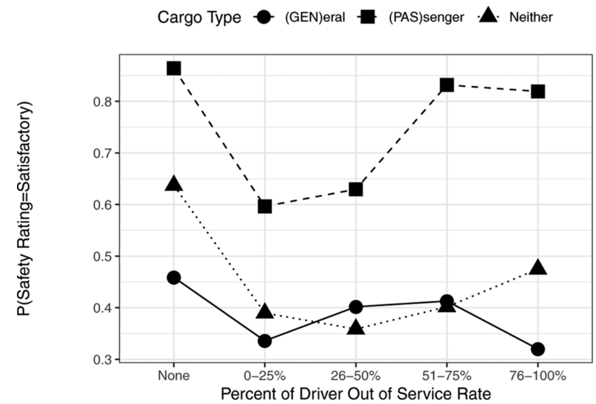


Fig. 2. The learned BNs from data using tabu search and hill-climbing algorithms. Two distinct networks are learned, one for safety rating (SR) and the other for safety audit (SA). SR and the nodes causally related to SR are highlighted in gray. NOTE: Acronyms are defined in Tables 1 and 2.

observation is consistent with FMCSA's process (FMSCA, 2007), which states that the safety audit is used for assessing only new entrant carriers (NEC). Hence, the forthcoming analysis focuses on the BN that includes the safety rating node.

The BN (Fig. 3) shows that the relationships between the variables in the sub-network are complex and non-linear. Of the 26 variables used for learning, only seven have a significant statistical relationship with the carrier's safety rating: passenger carrier, general carrier, driver out-of-service rate, weight infringement rate, traffic infringement rate, total employed drivers, and fleet size. Three of those variables have a direct relationship with safety rating (passenger carrier, general carrier,



	None	0–25%	26–50%	51–75%	76–100%
(PAS)senger	0.864	0.596	0.630	0.832	0.819
(GEN)eral	0.459	0.336	0.402	0.413	0.320
Neither	0.637	0.390	0.359	0.402	0.475

Fig. 4. Probabilities of obtaining a satisfactory safety rating for (1) general freight, (2) passenger, and (3) neither general or passenger (e.g., liquids/gases, heavy construction equipment, lumber) at different percent of driver out-of-service rate.

and driver out-of-service rate), while the remaining variables have an indirect relationship to safety rating.

For BN inference, we then examine these seven variables across the quartile levels to quantify the variable's contribution to the motor carrier safety rating. Fig. 4 shows that the probability of having a satisfactory safety rating is affected by the type of cargo the carrier delivers and the percentage of driver out-of-service rate for that carrier type. Compared to other motor carrier types, passenger carriers have a higher likelihood of receiving a satisfactory rating. The probability of having a satisfactory rating is 28.93% greater than other cargo types. On the other hand, general carriers, when compared to other cargo types, are 9.06% less likely to receive a satisfactory safety rating. When a motor carrier has no driver out-of-service violations, the probability of having a satisfactory safety rating is the highest, but when a motor carrier has even a single driver out-of-service violation, the probability of having a satisfactory safety rating drops by an average of 21.18%. As the driver out-of-service rate increases, the results show that the probability of having a satisfactory safety rating remains relatively flat

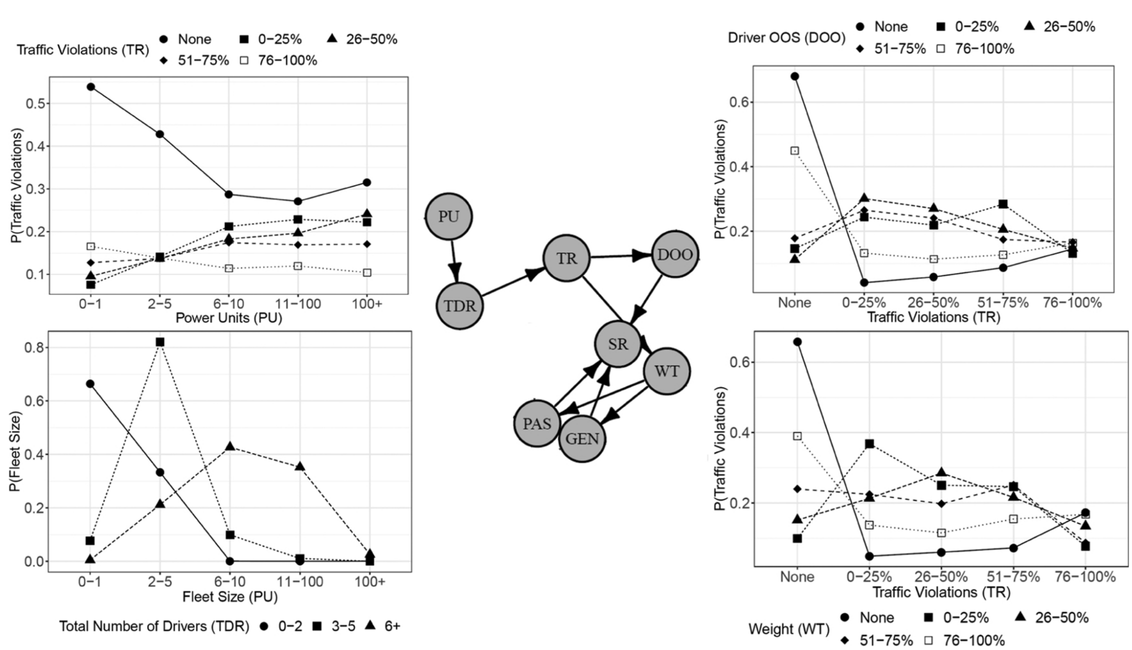


Fig. 3. The sub-network for safety rating (SR) extracted from Fig. 2 with plots depicting the indirect relationships.

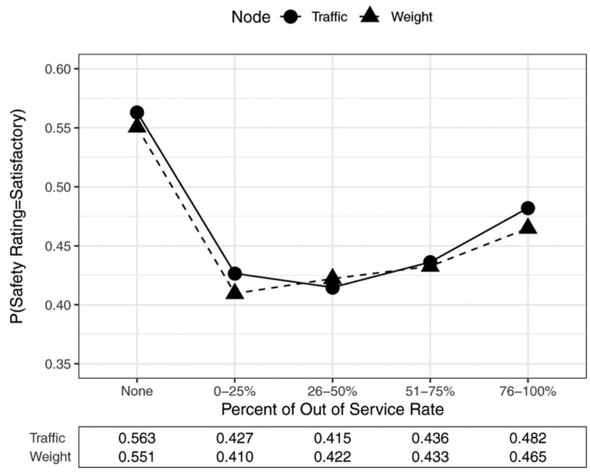


Fig. 5. Probabilities of obtaining a satisfactory safety rating for traffic (TR) and weight (WT) violations, when controlled for other variables.

for general carriers and carriers that are neither classified as general or passenger in MCMIS. For passenger carriers, there is an increasing trend in the probability of having a satisfactory safety rating as driver out-of-service rate increases.

Fig. 5 shows how the probability of having a satisfactory safety rating is affected as the indirect variables are altered (traffic violations and weight violations), while keeping the other variables constant. Similar to Fig. 4, for all the variables, there is a distinct drop in the probability as driver out-of-service rate increases from none to 1st quartile values, and then the probability remains flat until it increases sharply for the 4th quartile values. Compared to the direct variables, the indirect variables do not have as strong of an effect on the safety rating. The largest change in the probability for the indirect variables is 14.69%, whereas for the direct variables, the largest change in the probability is 30.33%.

Predictive reasoning was performed on the test set to examine how well the direct predictor variables (driver out-of-service rate, general carriers, and passenger carriers) explain the safety rating assigned to a motor carrier. The results are shown in the confusion matrix in Table 4. Even with just three predictor variables, the BN achieves an overall accuracy of 64.97%. The model achieves an accuracy of 61.15% for the Conditional (C) & Unsatisfactory (U) safety rating, and 72.54% for the Satisfactory (S) safety rating. Although the model does not have a high accuracy for predicting C & U safety ratings, it has a specificity of 81.54%, which allows it to identify the majority of unsafe carriers.

4. Discussion

This study shows that only a subset of variables have a direct or indirect effect on the safety rating of a motor carrier. These include driver out-of-service violations, weight violations, traffic violations, fleet size, total employed drivers, and passenger & general carrier indicators. No direct relationships were observed among the three crash variables (crash rate, crash miles, and fatal rate) with respect to safety rating. This was surprising as crash rates are often used as an indicator of unsafe carriers (Cantor et al., 2017). The BN shows that the paths between these crash variables and safety ratings are extensive, thereby revealing relatively weak relationships. However, the causation that is often attributed to crash rates may actually be captured in the violations. This observation is consistent with other studies which show that the violations are associated with unsafe motor carriers (Cantor et al., 2013; Lantz and Loftus, 2005).

Table 4
Confusion matrix results for predicting safety rating on the test dataset (768 observations) using the BN and the parents nodes of safety rating.

		Predicted value		
		C &U	S	Total
Observed value	C &U	296	67	363
	S	188	177	365
	Total	484	244	728

Our BN model shows that fleet size (identified using power units) and total drivers per carrier are not directly related to safety ratings. This finding is initially surprising given past studies that showed a significant difference in safety ratings across different fleet sizes and number of employed drivers (Cantor et al., 2017; Lantz, 1994; Cantor, 2014). However, these variables do have an indirect relationship and this study shows that safety ratings are based on complex interactions among many variables that do not necessarily correlate linearly. Further, while driver out-of-service is directly related to safety ratings, traffic and weight violations are only indirectly related to safety ratings. This finding may reflect the fact that 87% of crashes are associated with driver-related errors (FMCSA, 2007). Other studies have also shown that the driver has a substantial impact on overall safety (Lantz and Loftus, 2005; Cantor et al., 2013).

The dataset used for this study does not reflect policy changes or interventions after 2012. It was also not representative of all interstate motor carriers given that we only include records that had an updated safety rating based on on-site interview and no missing MCMIS data. This greatly reduced the sample size used for analyses. Hence, our model could have learned relationships that do not generalize to all motor carriers.

In this context, it is worth mentioning that one of the advantages of BNs is the lack of any minimum sample size is requirement to perform the analyses. In fact, past research has demonstrated that BNs provide good prediction accuracy even with reasonably small sample sizes (Uusitalo, 2007). Furthermore, the current SMS, which is the system used to identify unsafe motor carriers, segments the motor carrier population into two categories for identifying unsafe carriers, namely, passenger carriers and general/other carriers. Even with our relatively small dataset, the BN is able to detect these differences by learning the direct relationships between safety rating and passenger and general carrier nodes, as seen in Fig. 3.

Another potential limitation of this study is the possibility that omitted variable biases could impact the identified relationships. Given that this data is also used by FMCSA for identifying unsafe motor carriers, this limitation would also be observed in their identification. Our analysis is based on data aggregated at the carrier level as the goal is to identify the unsafe motor carriers. For larger carriers, one unsafe driver would not have as great an impact on the overall safety rating as it would for smaller carriers, which encompass a large portion of interstate carriers. Accounting for these individual differences could impact the outcomes.

Our study focused on determining the direction of the relationships among the variables that are used to predict the motor carriers safety ratings. When compared to traditional approaches such as regression modeling, Bayesian networks (BNs) are particularly useful for this purpose. Although safety rating was analyzed in this research, BNs allow us to analyze the relationships that impact any of the other safety performance metrics. The results show that not all safety performance metrics are equally important indicators of safety rating. Some of the metrics are stronger indicators (traffic violations, driver out-of-service violations, and weight violations) than others (crash indicator). And while it is not stated in the SMS methodology document (FMCSA, 2017b), there may be some inherent biases toward driver-related factors. BNs allow us to learn all the relationships in the form of a network, demonstrate how each variable impacts other variables within the network, and identify the root causes of violations and safety ratings assignments.

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