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Identification of Risk Factors for Bus Operation Based on Bayesian Network

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Abstract: Public transit has been continuously developing because of advocacy for low-carbon living, and concerns about its safety have gained prominence. The various factors that constitute the bus operating environment are extremely complex. Although existing research on operational security is crucial, previous studies often fail to fully represent this complexity. In this study, a novel method was proposed to identify the risk factors for bus operations based on a Bayesian network. Our research was based on monitoring data from the public transit system. First, the Tabu Search algorithm was applied to identify the optimal structure of the Bayesian network with the Bayesian Information Criterion. Second, the network parameters were calculated using bus monitoring data based on Bayesian Parameter Estimation. Finally, reasoning was conducted through prediction and diagnosis in the network. Additionally, the most probable explanation of bus operation spatial risk was identified. The results indicated that factors such as speed, traffic volume, isolation measures, intersections, bus stops, and lanes had a significant effect on the spatial risk of bus operation. In conclusion, the study findings can help avert dangers and support decision-making for the operation and management of public transit in metropolitan areas to enhance daily public transit safety.

Keywords: urban public transit; Bayesian networks; Tabu search algorithm; risk identification

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1. Introduction

The increasing concentration of greenhouse gases (GHG) in the atmosphere is the cause of global warming. Carbon dioxide (CO_2) is the main component of GHG [1]. A recent study reported that global CO_2 emissions increased by 0.1% in 2023 compared to the previous year, resulting in 35.8 Gt of CO_2 [2]. The transport sector is considered as the second leading source of CO_2 emissions worldwide [3]. The transport sector generates 32% of CO_2 and approximately 27% of GHG emissions [4]. In addition, due to the trend of population and income growth, the demand for transport is anticipated to increase over the next few decades [5]. According to IEA data, it is expected that global transport, as measured in passenger kilometers, will double in volume.

Urban transport has played a crucial role in the proper functioning of cities, meeting the communication needs of urban residents, promoting trade development, and overall social construction. In the past few decades, the rapid development of urban areas has led to a growing demand for public transit systems [6]. High-capacity transport modes such as subways and buses have been widely applied to reduce congestion, energy consumption, and GHG emissions [7]. In developing countries, public bus transit systems are considered one of the most desirable sustainable systems [8]. The system has high capacity, less GHG emissions, and low energy consumption compared to others.

Therefore, the significant proportion of CO_2 emissions from the transport sector, the projected growth of transport demand in the future, and the unique advantages of public transport highlight the importance of developing public transportation modes to reduce carbon emissions.

Although many studies have analyzed the factors affecting traffic safety, most of them focused on accident rates and casualty rates as research objects [9–11]. This research is based on the bus alarm data. It can reveal potential safety hazards in the public transit system and reflect the spatial risk for bus operation. Bus operation spatial risk refers to the probability of aberrant behavior exhibited by drivers and buses on certain road sections or specific areas. Aberrant behavior includes drivers smoking, distracted driving, not wearing seat belts, vehicle speeding, lane departure, forward collisions, etc. Identifying risks before accidents occur and taking timely measures to prevent them from happening can greatly help reduce property damage and lower casualty rates. In addition, the incidence of public transport accidents is low, and the amount of related data is small. However, the amount of bus alarm data is large, and data richness is stronger. Compared to ultimate outcome indicators such as accident and casualty rate, bus alarm data provides more real-time and detailed information, which helps to better understand and improve traffic safety issues.

Causes of traffic accidents are complex and involve a variety of factors, including road user behaviors (e.g., driver/pedestrian behavior), vehicle condition (e.g., speed), road infrastructure (e.g., roadway surface conditions), traffic (e.g., congestion), and other environmental issues (e.g., inclement weather), etc. Acquiring knowledge of the risk factors that contribute to road crashes is vital in formulating the priorities of action plans and interventions to reduce the risks associated with those factors [12]. A cutting-edge system, known as the advanced public transport system (APTS), has been used to further improve the efficiency of public transit. The fuzzy analytic hierarchy process was utilized by Aoonrot et al. [13] to create an APTS to produce the best indicators for intelligent mobility. According to their findings, the safety dimension was ranked highest among the three major weight indicators associated with public transit, including fewer traffic accidents, density of intelligent public transit networks, and waiting duration of public transit. Using crash data from the previous five years, Kitali et al. [14] conducted an extensive investigation to assess safety. Most incidents involving pedestrians and Bus Rapid Transit (BRT) buses were caused by drivers who failed to abide by traffic control signs. Crashes involving collisions between BRT buses and non-motorized road users were more likely to be severe. Non-motorized traffic, distractions, and non-compliance with traffic control devices were the main causes of serious automobile accidents. Currently, machine learning (ML) technology can be applied to assess the safety of a bus driver's driving style. Using actual data, Luo et al. [15] employed deep and shallow learning techniques to produce precise labels for drivers in public transit.

With the development of disciplines, Bayesian Networks (BN) have been used to promote traffic safety. BN models can effectively mine complex logical relationships in road accidents and express uncertain relationships between related variables. It can not only quantitatively predict the probability of accidents occurring under specific road traffic conditions but also identify the key causes and most unfavorable combinations of accidents [16]. BNs have great advantages in solving causal inference problems such as driver behavior and accident diagnosis [17–19]. In addition, in the field of driverless, BNs can also be used to analyze the dangers encountered by autonomous vehicles during driving, such as collision, rear-end collision, etc. [20,21].

BNs can be used to discover the relationships between bus operation spatial risk and transport-related factors. The joint and conditional probability between the bus operation spatial risk and other components can be calculated by BNs. The prediction and diagnosis can be performed using a well-developed BN. Prediction examines the relationship between child and parent nodes, whereas diagnosis investigates the relationship between parent and child nodes [22]. Thus, the factors that influence the spatial risk of bus operation can be deduced from the building of BNs.

The environmental, physical, and human elements that constitute the bus operation environment are extremely complex despite the value of earlier studies on operational safety. However, previous studies have often focused on individual factors, such as the subject being the driver or the location in a tunnel [23]. The factors that affect bus operation safety have not been comprehensively considered and could not fully represent this complexity. The effect of outside variables on the operational risks associated with public transit was considered as much as possible in this study. Additionally, the alarm data used in this study were pre-event data, whereas previous studies primarily used post-accident data.

To investigate and deduce the relationship between bus operation spatial risk and different factors such as drivers, vehicles, roads, and the environment, this study aimed to build a BN. Compared to other methods, BN has advantages in handling uncertainty, model interpretability, conditional independence assumptions, reasoning ability, and decision support. First, the Bayesian Information Criterion (BIC) was used to verify the network score and identify the optimal network structure. Second, the network parameters were obtained by fitting the network to the monitoring dataset. Finally, diagnosis and prediction were used to draw conclusions.

The remainder of this paper is organized as follows. Section 2 presents the BN. Section 3 describes the case study and operational monitoring data. The BN structure and parameters, accuracy of the model, and reasoning for the bus operation spatial risk are discussed in Section 4. Finally, Section 5 summarizes the findings of the study.

2. Methodology and Dataset

2.1. Methodology

The research mainly used bus operation monitoring data to construct a BN model. The key factors affecting the bus operation spatial risk can be identified through the BN model. There are many other methods to solve this problem, such as ML and mathematical statistics.

Other ML algorithms perform excellently in handling complex nonlinear relationships, high-dimensional classification, image, and speech problems. However, compared to BNs, other ML algorithms have significant disadvantages in dealing with uncertain problems, model interpretability, conditional independence assumptions, reasoning ability, and decision support. For example, compared to Decision Trees that focus on classification rules, BNs provide richer probability information and conditional independence assumptions. Support Vector Machine is mainly used for classification tasks, distinguishing categories by finding the best boundary, while BNs focus more on probabilistic modeling and inference. Deep Learning has advantages in handling large-scale data and complex pattern recognition but often lacks clear explanatory and conditional independence assumptions. In this regard, it is inferior to BNs. BNs are suitable for scenarios that require understanding variable relationships and causal inference. It also performs better when data are noisy or missing. Overall, BNs have higher interpretability compared to the 'black box' properties of traditional ML models. Meanwhile, BNs are based on mathematical statistics and probability theory. It can perform uncertainty reasoning and statistical analysis when facing complex problems. BNs can not only answer the predicted results but also the processes involved in the prediction and provide evidence. More importantly, BNs are an improved model of Naive Bayes, which effectively solves the problem of independent variables and consistent effects on the dependent variable among Naive Bayes.

Regression analysis has been widely used to determine influencing factors. The most commonly used regression models are logistic regression and ordered probability model. However, compared with BNs, regression analysis has more obvious shortcomings in dealing with outliers, multicollinearity, complex relationships, and causal inference. By directed acyclic graphs, BNs can capture direct and indirect dependencies between variables. It is suitable for modeling complex relationships in multivariate systems. However, other statistical methods are lacking in addressing the research question. In terms of decomposition models, Poisson regression models can be used to analyze the impact of each risk factor on accident frequency [24]. The negative binomial regression model has been widely used in traffic safety analysis models [25,26]. However, the assumption that the mean of Poisson distribution equals the variance is often inconsistent with the actual situation. In the analysis of longitudinal data samples, the Poisson regression model and negative binomial regression model may result in biased estimates or even incorrect results. When the explanatory variable only takes a limited number of discrete values, the regression model established is a discrete choice model. The Logit model is the earliest discrete choice model and one of the widely used models [27,28]. For applicable statistical models, the research subjects need to be independently distributed. Although security data has a complex spatial distribution, ignoring spatial features will greatly affect the accuracy and robustness of security level estimation. In addition, for regression models, if two independent variables are correlated with each other, they cannot exist in the same model. It will result in a lack of influence between variables. Regression models can not present the effects between dependent and dependent variables, nor can they present the interactions between independent variables.

Therefore, after analyzing and comparing it with other methods, this research ultimately chooses BNs as the research method.

BN is a probabilistic graphical model that uses Bayesian inference for probability calculation. A BN was built using the concept of directed acyclic graphs in graph theory by analyzing the mutual influence between independent and dependent variables. We determined the edge probability in a directed acyclic graph by applying a Bayesian formula. The interrelationships between the variables could be abstracted using a topological framework of points and edges by building a directed acyclic graph. In a BN, the direct correlation between different variables is represented by edges, and each vertex represents a random variable. Every random variable consistently influences the dependent variable and is independent of other variables.

BN can be represented as $N = (G,\ P)$, where N represents the network, G represents the graph, and P represents the joint probability of the network. G is a graph that can be further represented by $(V,\ E)$, where V represents the set of nodes $(x_1,\ x_2,\ x_3, \ldots, x_n)$, E represents the directed edges of causal relationships between variables.

The construction of BNs usually adopts three methods: data-driven methods, knowledge-based methods, and a combination of the two methods [29]. Data-based methods use the conditional independence semantics of BN to generalize models from data. The knowledge-based approach utilizes the causal knowledge of domain experts to construct BNs. Different experts may have different opinions on the same issue, resulting in knowledge-based methods having a significant subjective component. The bus operation monitoring system is dynamically changing, while BNs based on knowledge construction are usually static. To adapt to changes, it is necessary to constantly update the model structure and parameters, which is very time-consuming and difficult in practice. With the advancement of big data technology, data-driven automatic learning methods can provide better model performance in certain scenarios. For example, ML algorithms can be used to automatically learn BNs from data.

At present, the main categories of structural learning include independence testing and score-based search. Due to the need for a large number of samples to test independence, the method of independence testing has a high time cost. Sometimes, unreliable conditional independence testing may amplify errors in the input stage and propagate them to the output stage, leading to a decrease in the accuracy of network inference results. The method of core-based search generally first selects the scoring criterion of the network structure and then searches for the network structure with the best rating. Although this type of method can search for optimal network structures, it is prone to getting stuck in local optimal structures due to the large search space and the decomposability of the scoring function for local or random searches. The search for the optimal BN structure from all possible network structure spaces has been proven to be an NP-Hard problem [30]. Therefore, score-based search methods generally adopt heuristic strategies to reduce search space.

Therefore, we need to determine a scoring criterion for BN structures and then obtain the network structure with the highest score by heuristic search methods. Common scoring criteria include BIC, BDE, MDL, etc. BIC can measure the fit between structure and data. It has penalty terms related to model complexity and is widely used as a scoring criterion in large sample data. Therefore, BIC was chosen as the scoring criterion in the research. Common heuristic algorithms include K2, hill climbing in greedy search, and tabu search (TS). However, the K2 algorithm requires a known node order, which imposes high limitations on its application. Moreover, greedy algorithms are prone to getting stuck in local optima. TS has no special requirements for the objective function. It can jump out of local optima and approach global optima based on its unique memory mechanism. And the probability of generating the optimal solution is much higher than that of other solutions. Although it cannot be guaranteed that the optimal solution will be found, practical solutions can be obtained in practice.

A flowchart of the TS algorithm is presented in Figure 1.

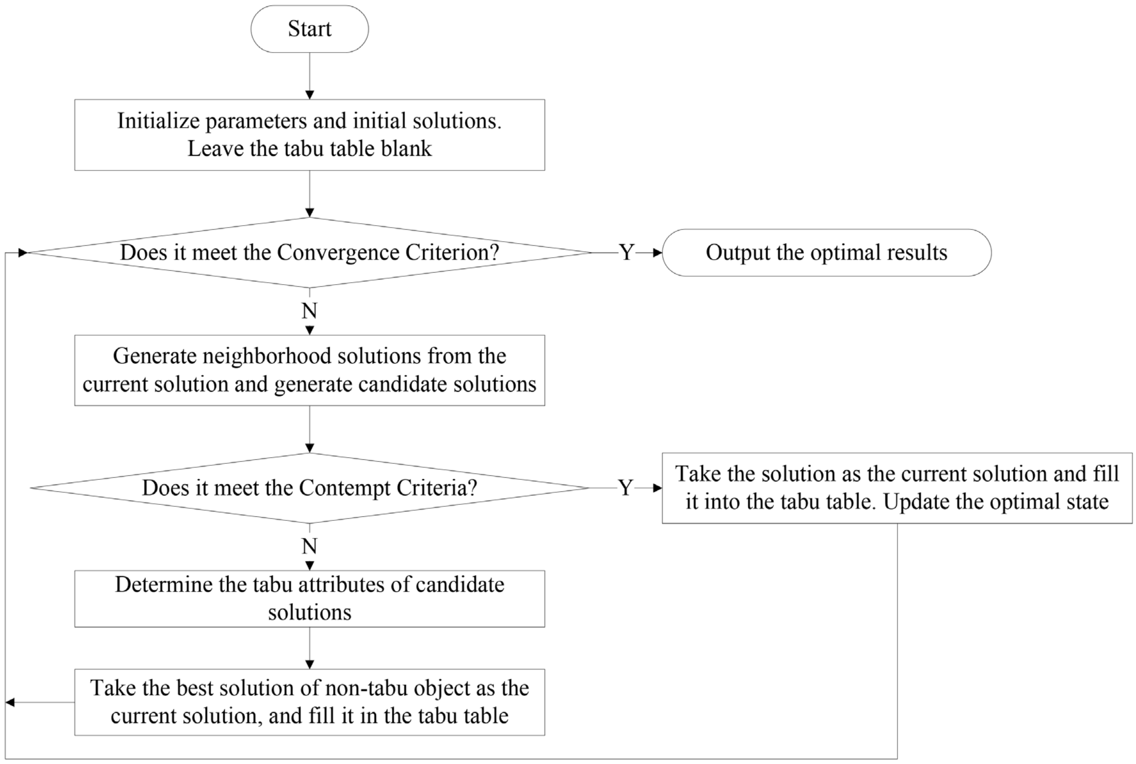

Figure 1. Tabu search algorithm flowchart.

After determining the structure of the BN, it is necessary to determine its parameters. The parameter learning of BNs is relatively easy and intuitive. Simply put, it is to determine the parameters of the BN model given the BN structure based on the observed dataset, that is, the conditional probability table (CPT) on each node. Common BN parameter learning methods include maximum likelihood estimation and Bayesian parameter estimation. Although maximum likelihood estimation is simple, intuitive, efficient, and highly consistent, it has the disadvantages of being sensitive to outliers and lacking uncertainty quantification. Bayesian parameter estimation transforms the prior probability density distribution into its posterior probability density. It uses the information from the sample data to correct the initial prior estimation of parameters. This research chose Bayesian parameter estimation as the method for determining parameters. The calculation method for the joint probability equation P of variables is shown in Theorem 1. The joint probability P is obtained by multiplying it with the corresponding local conditional probability distribution.

Theorem 1. $P(Y) = \sum_{i=1}^{n} P(X_i)P(Y|X_i)$,

The conditional probability distribution for discrete variables is expressed as a CPT. Each element in the CPT represents the probability of a given variable taking a specific value given a specific combination of its parent node values [31]. The CPT of the variable, which forms the foundation for the probability reasoning of BN, contains probability parameters.

The computation of probability values forms the foundation of BN. The set of discrete node variables is $M = \{X_1,\ X_2, \ldots,\ X_n\}$, where X_n represents the node variables of BN. The CPT of each node includes all conditional probabilities P of its internal parent node. The Bayesian formula is presented in Theorem 2.

Theorem 2. $P(X_i|Y) = \frac{P(X_i)P(Y|X_i)}{P(Y)}$,

Among them, n represents the total number of node variables. $i = 1,\ 2, \ldots,\ n$. $P(X_i)$ is a prior probability, derived from data statistics or empirical knowledge. $P(X_i|Y)$ is a posterior probability, meaning that X_i occurs at Y and $P(Y|X_i)$ is a conditional probability.

Validating the accuracy of the model after building the BN is essential. The receiver operating characteristic (ROC) curve is currently the most widely used validation indicator of accuracy. It can visualize the performance of models. The ROC curve displays the relationship between the true rate and false positive rate of the model through different thresholds. It provides an intuitive way to evaluate the classification ability of the model. By comparing the ROC curves of different models, the classification performance of different models can be evaluated at various thresholds. It helps in selecting the optimal model. In addition, the ROC curve is not affected by the proportion of sample categories. It is suitable for situations with class imbalance, which is common in many practical applications. The classifier performance was assessed by the ROC curve. The area under the curve (AUC) was lower than that of the ROC curve. AUC values range from 0 to 1, with higher values denoting superior classifier performance. AUC provides a single numerical value that can comprehensively reflect the performance of the model at different thresholds. Therefore, it is more comprehensive than individual indicators such as accuracy. When comparing models, the AUC value can be an important basis for selecting the optimal model, especially when there is little difference in model performance.

2.2. Dataset

The dataset used in this case study was obtained from the Zhenjiang Public Transport Company (Zhenjiang, Jiangsu, China). The driver smart band and bus operation monitoring records were included in this dataset. The sensors installed on buses were mainly responsible for determining, c gathering, and uploading the monitoring records of bus operation. It can collect corresponding risk information during bus operation, including aberrant states of the bus, such as sudden deceleration, forward collision, and lane departure, along with aberrant behavior of the driver, such as distraction, calling, and yawning. In addition, it can record the data, such as time, speed, specific road, driver's personal information, and license plate number of the aberrant state. Bus operation spatial risk refers to the probability of risk occurring during the operation of buses on specific road sections or within a certain range. Drivers, vehicles, roads, and the environment were the variables considered. The driver's smart band was primarily responsible for gathering and uploading wristband data. Bus driver's physiological parameters were recorded every two minutes, including heart beats and blood pressure. The road data were captured using the Amap software (v13.07.0.2160). The monthly average road condition data were used as the basis for traffic volume. The environmental data were obtained from weather websites.

The problems of the data used in this research mainly include missing and abnormal data. For missing data, we delete all alarm records where it is located. For abnormal data, we use box plots to identify outliers and delete them. We use five statistical values of the dataset, including the minimum value, first quartile (Q1), median, third quartile (Q3), and maximum value. Assuming $IQR = Q3 - Q1$, values outside of $[Q3 + 1.5\ (IQR)]$ and $[Q1 - 1.5\ (IQR)]$ are considered outliers.

The driving factors in the dataset were age, gender, blood pressure, and heartbeats. The vehicle factor included the instantaneous bus speed. The number of bus stops, lanes, intersections, isolation measures, and traffic volume were the road factors. The environmental factors included the weather. The descriptions and classifications of each factor are listed in Table 1. Each factor was modeled as a discrete variable. The data were binned for ease of modeling. The methods of data partitioning included boxplot, isometric, natural discontinuity, quantile, and standard deviation methods. The equidistant approach was used to redivide the independent variables based on the features of the data distribution.

Table 1. Dataset description.

	Independent Variable	Description	Classification
Driver	Gender	Gender of driver	Men = Men, Women = Women
	Age	Age of driver	(20, 30] = Youth, (30, 40] = Mid
	SBP	Systolic pressure of driver	(100, 115] = Low, (115, 130] = Medium, (130, 145] = High
	DBP	Diastolic pressure of driver	(63, 73] = Low, (73, 83] = Medium, (83, 93] = High
	BPM	Heart Beats per minute of driver	(59, 75] = Low, (75, 91] = Medium, (91, 107] = High
Vehicle	Speed	Instantaneous speed of bus	(30, 43] = Low, (43, 56] = Medium, (56, 69] = High
Road	Lane	Number of road lanes at the time of warning	[1, 2] = Low, (2, 4] = Medium, (4, 8] = High
	Traffic Volume	Traffic volume at the time of warning	Unblocked = Unblocked, Light congestion = LightCongestion, Jam = Jam
	Isolation Measure	Road isolation measures at the time of warning	Lineation = Lineation, Banister = Banister, Green belt = GreenBelt
	Bus stop	Number of bus stops on the road at the time of warning	[0, 18] = Low, (18, 36] = Medium, (36, 54] = High
	Intersection	Number of road intersections at the time of warning	[0, 8] = Low, (8, 15] = Medium, (15, 22] = High
Environment	Weather	Weather at the time of warning	Sunny or cloudy = ClearandCloudy, Sleet = Sleet, Rainy = Rainy

In this study, the target (dependent) variable was the spatial risk of bus operation. Gender, age, systolic pressure, diastolic pressure, heartbeat, speed, lane, traffic volume, isolation measure, bus stop, intersection, and weather were the explanatory (independent) variables.

Table 2 presents a quantitative analysis of the cleaned data. Quantitative analysis of data is beneficial for understanding the basic situation of the dataset. Statistical indicators include mean, standard deviation, maximum value, and minimum value.

Table 2. Data statistics of variables.

	Statistical Indicators	Mean	Std	Min	Max
Driver	Age (Years)	40.5	6.06	32	50
	SBP (mmHg)	118	5.73	106	149
	DBP (mmHg)	75	4.64	64	94
	BPM (Per minute)	74	7.56	57	117

Table 2. *Cont.*

	Statistical Indicators	Mean	Std	Min	Max
Vehicle	Speed (Km/h)	39.9	8.40	30	63
Road	Lane	5	1.35	1	8
	Bus stop	14	10.17	0	53
	Intersection	8	4.38	1	22

3. Results

The relationships between the variables were expressed by the network structure. BNs are essentially directed acyclic graphs. It describes the relationships between variables, including driver, vehicle, road, and environment. With the BIC value as the objective function, 70% of the dataset was used for training compared with the TS algorithm. The BIC value was increased by iteratively performing unilateral operations. The search was stopped when the optimal Bayesian model was identified, and a directed acyclic graph was created. Figure 2 shows the optimal network graph discovered after running the TS algorithm.

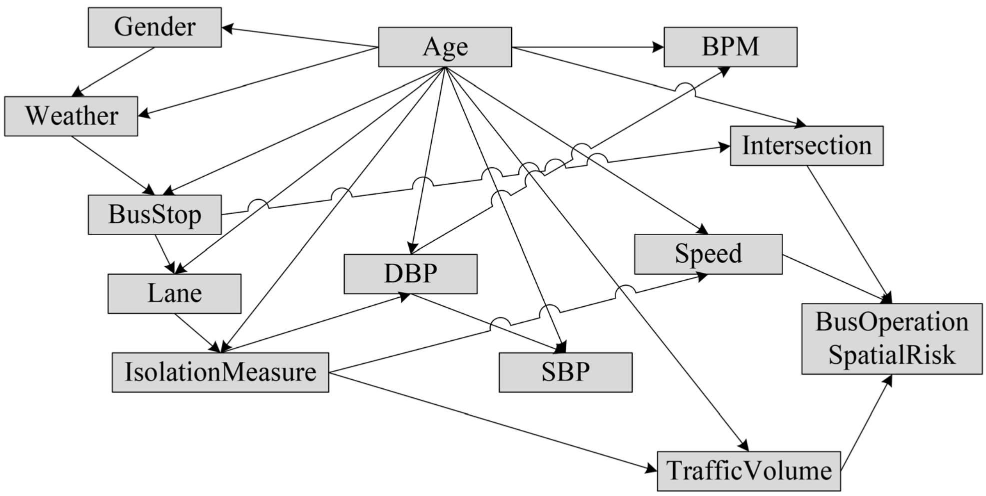

Figure 2. BN (directed acyclic graph).

We concluded that the number of intersections, speed, and traffic volume directly affected the spatial risk of bus operations. Several factors were indirectly related to bus operation spatial risk, including weather, gender, age, isolation measure, and number of bus stops and lanes. Additionally, an interaction between variables occurred. For example, isolation measures and the number of lanes were strongly correlated. Generally, roads with four or more lanes should use railing or greenbelt isolation, whereas roads with two or three lanes should use line isolation. Age and gender have certain relationships with physiological markers. In general, the heartbeats of women are higher than those of men. Blood pressure frequently increases with age.

The final parameters of the BN were ascertained by analyzing the outcomes of the structural learning section. Every node in the network had its CPT determined through parameter learning, which accounted for all potential connections between the node and its parent node. The size of node CPT depends on the number of parent nodes of the node and the available classes of the parent nodes. Therefore, the size of CPT may be very large. [32]. Taking age as the parent node and diastolic pressure as the child node as an example, Table 3 lists the probability distribution conditions of various levels of diastolic pressure for drivers under various levels of age.

Table 3. Conditional probability diagram.

	Age (Youth)	Age (Mid)
DBP (Low)	0.466	0.656
DBP (Medium)	0.477	0.219
DBP (High)	0.057	0.125

We edited the node states and parameters in the Netica software (v5.19) based on structural and parameter learning. Figure 3 shows the BN model for bus operation spatial risk.

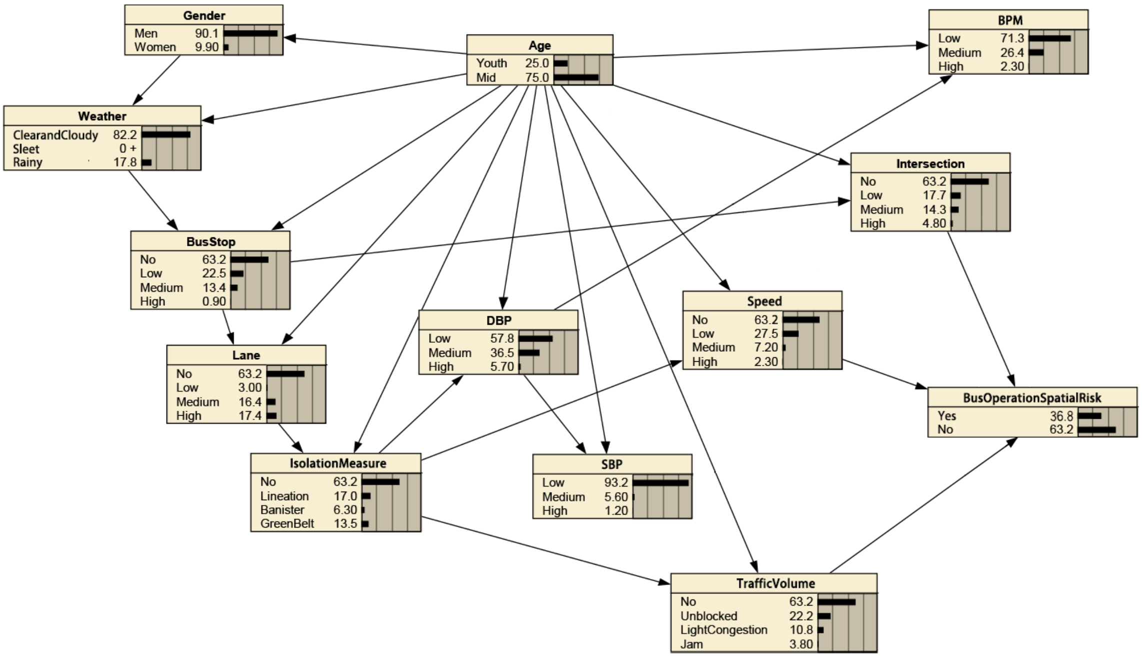

Figure 3. BN model for bus operation spatial risks.

From Figure 3, the majority of bus drivers are male. Middle-aged drivers comprised most of the sample. Drivers' SBP, DBP, and BPM was usually low. Typically, buses move slowly. Most roads with bus operation spatial risk have more lanes, fewer intersections, and fewer bus stops. The roads were unblocked, and the primary measure was line isolation. The chance of spatial risk during bus operation was 36.8%.

The known data was substituted into the joint probability Theorem 1 to obtain the complete probability of bus operation spatial risk, as shown in Equation (1).

$$P(Risk) = \sum_{X_i=1}^{12} P(X_i)P(Risk|X_i) \; = \; 36.8\% \tag{1}$$

The calculation results are consistent with the software simulation results. It indicates that Netica is reasonable for predicting the bus operation spatial risk of BN.

When the model was validated by the remaining 30% of the dataset, its accuracy was 70%. The AUC and ROC curves were used to simultaneously test the performance of the model. Ideally, the ROC curve should be close to the upper left corner. The AUC value is used to quantify the overall performance of the ROC curve. The range of AUC values is [0, 1]. AUC less than 0.5 indicates poor performance of the classifier. AUC equal to 0.5 indicates that the classifier's performance is comparable to random guessing. AUC = 1 indicates that the model is a perfect classifier. Figure 4 shows that the AUC of the model is 0.89, and the ROC curve is close to the upper left corner. This indicates that the model has good predictive performance.

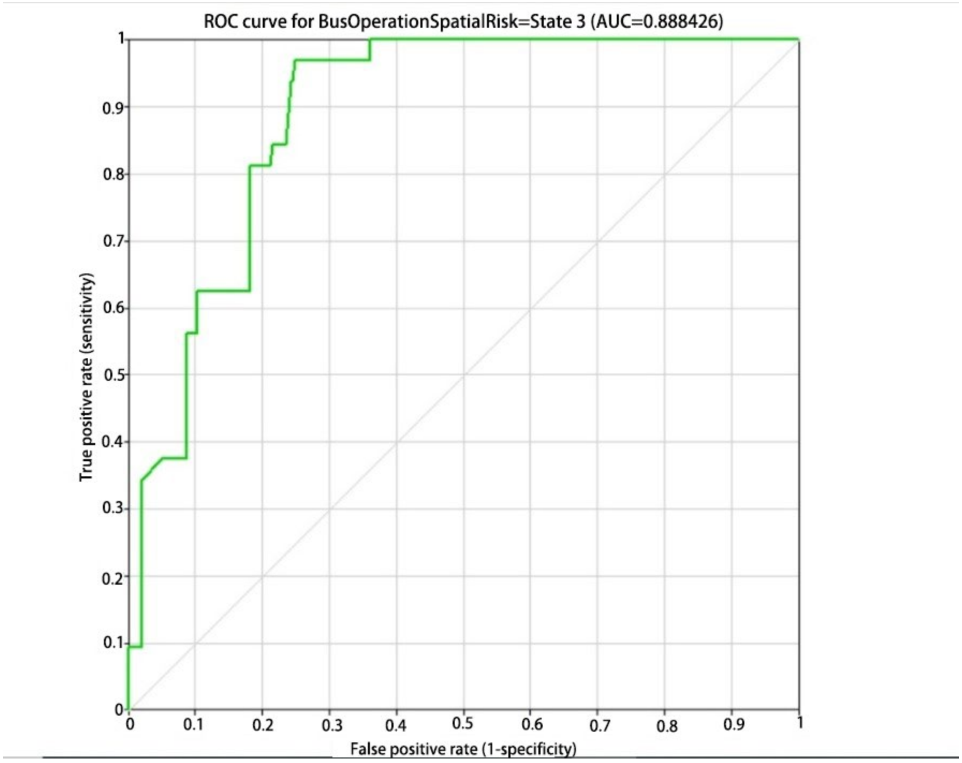

Figure 4. Model performance verification chart.

Meanwhile, we compared the effectiveness of the constructed BN horizontally by the same training dataset. We compared the BN model with two types of prediction models: Random Forest (RF) and Support Vector Machine (SVM). We used three indexes: mean square error (*MSE*), root mean square error (*RMSE*), and mean absolute error (*MAE*) to evaluate.

The equation for *MSE* is shown in Equation (2).

$$MSE = \frac{1}{n}\sum_{1}^{m} w_i (y_i - \hat{y}_i)^2 \tag{2}$$

Among them, n is the number of samples. y_i is the real data. $\hat{y}_i$ is the fitted data. The equation for *RMSE* is shown in Equation (3).

$$RMSE = \sqrt{\frac{1}{n}\sum_{1}^{m} w_i (y_i - \hat{y}_i)^2} \tag{3}$$

The equation for *MAE* is shown in Equation (4).

$$MAE = \frac{100\%}{n}\sum_{1}^{m} \left| \frac{y_i - \hat{y}_i}{\hat{y}_i} \right| \tag{4}$$

The comparison table of model results is shown in Table 4.

Table 4. Comparison of Model Results.

Model \ Index	Accuracy	MSE	RMSE	MAE
BN	70.0%	0.416	0.645	0.335
RF	68.6%	0.449	0.670	0.355
SVM	66.4%	0.557	0.746	0.409

According to Table 4, the accuracy of BN prediction is better than RF and SVM. And the three indexes of MSE, RMES and MAE are superior to the other prediction models. Overall, the BN model performs better in the research. One of the advantages of BN is the high interpretability. It can provide clear explanations of risk factors and greatly assist transit authorities in implementing management measures for public transit safety. Therefore, the BN constructed in this research basically meets the application requirements.

4. Discussion

4.1. Backward Reasoning

Given that the state of a target node already occurred, backward reasoning was the process of calculating and analyzing possible scenarios. In short, backward reasoning examines the causes of assumed outcomes that must occur. The reasoning results are shown in Figure 5. We can determine the potential causes of bus operation spatial risk by analyzing the probability changes of the other nodes. With the bus operation spatial risk set to 100%, the amplitudes of the changes in the comparison variables of each initial network model are listed in Table 5. The variables were discretized. Age and gender were divided into two levels. The SBP, DBP, BPM, and weather were divided into three levels. The remaining factors were divided into four categories. In Table 5, i is sequentially represented as table variables, and j represents the number of levels for each variable. In Table 5, m represents the level of each variable ($1 \leq m \leq 4$). A_m represents the changes in each variable probability.

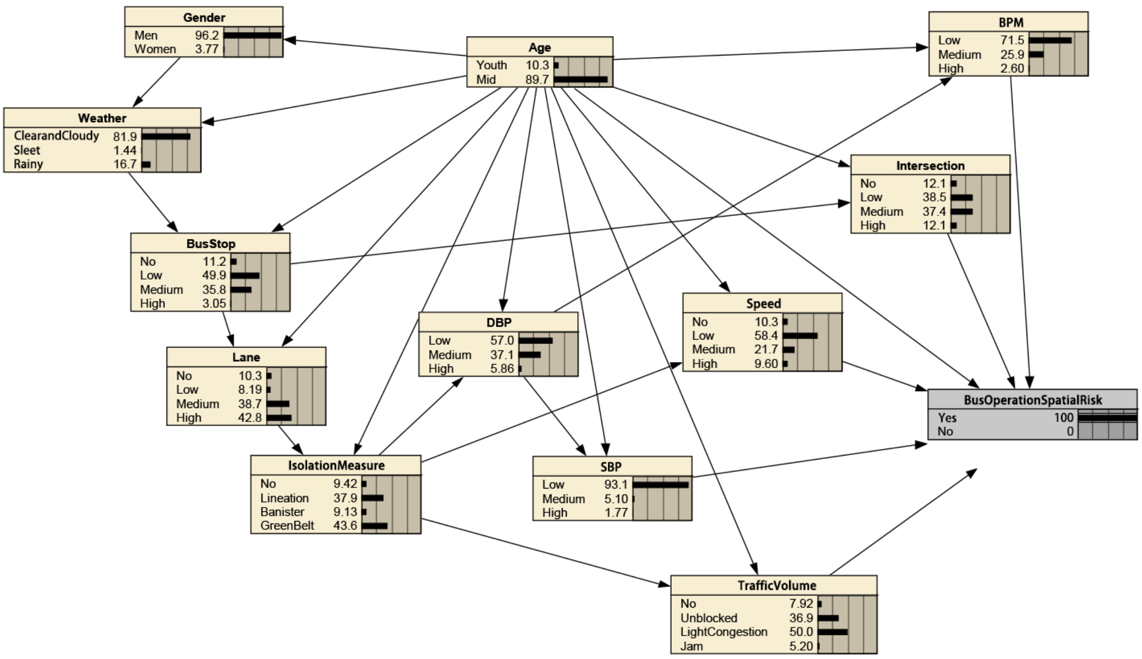

Figure 5. Backward reasoning results for bus operation spatial risk condition.

Table 5 shows that the main factors affecting the spatial risk of bus operation include number of bus stops, intersections, lanes, speed, isolation measures, and traffic volume. An unreasonable number of bus stops are set up within a specific road range, which may lead to frequent entry and exit of buses. An unreasonable number of lanes may prompt buses to change lanes frequently, thereby triggering lane departure alarms. When there are too many intersections and unreasonable isolation measures, the probability of pedestrians and non-motorized vehicles crossing the road increases. Giving way to pedestrians leads to frequent acceleration and deceleration of buses. High-speed and congested road conditions also cause frequent acceleration and deceleration of buses, resulting in forward-collision alarms.

Table 5. Changes of variable probability in scenarios under bus operation spatial risk and initial conditions.

Variable \ Level	A_1(%)	A_2(%)	A_3(%)	A_4(%)
Age	−14.7	+14.7	–	–
Gender	+6.1	−6.13	–	–
SBP	−52.7	+30.9	+14.5	+7.3
DPB	−0.1	−0.5	+0.57	–
BPM	−0.8	+0.6	+0.16	–
Speed	+0.2	−0.5	+0.3	–
Lane	−52	+27.4	+22.4	+2.15
Traffic volume	−52.9	+5.19	+22.3	+25.4
Isolation measure	−51.3	+20.8	+23.1	+7.3
Bus stop	−53.78	+20.9	+2.83	+30.1
Intersections	−55.28	+14.7	+39.2	+1.4
Weather	−0.3	+1.44	−1.1	–

After adjusting the bus operation spatial risk to 100% in the network model, Table 5 presents a comparison of the amplitudes of the changes in each variable. A bar chart comparing the variables that significantly alter bus operation spatial risk is shown in Figure 6.

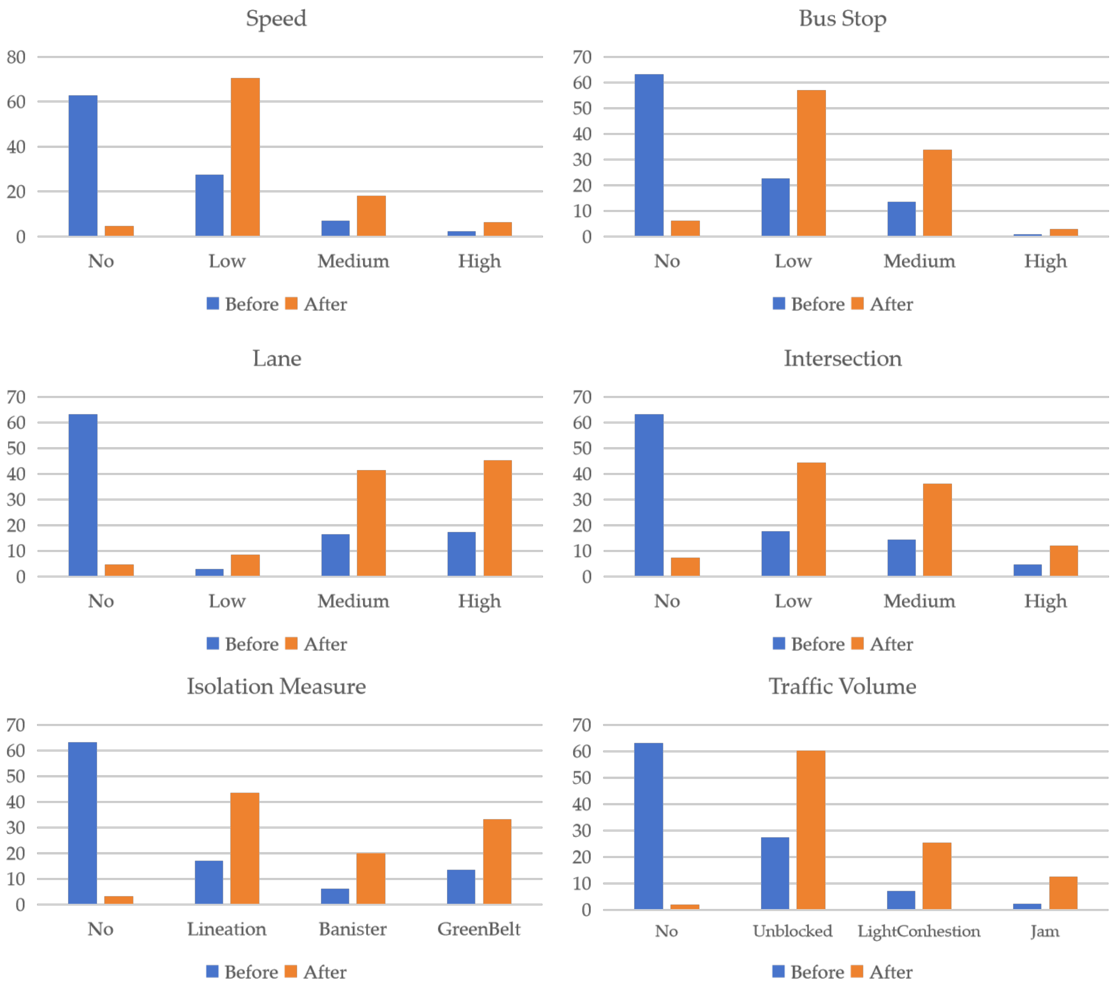

Figure 6. Probability distributions of variables in scenarios under bus operation spatial risk and initial conditions.

4.2. Most Probable Explanation

After setting the probability of the target node 'bus operation spatial risk' to 100%, we used the most probable explanation (MPE) function of Netica software to find the most probable combination that was consistent with the state of the target node. Figure 7 shows the MPE for the spatial risk of bus operation.

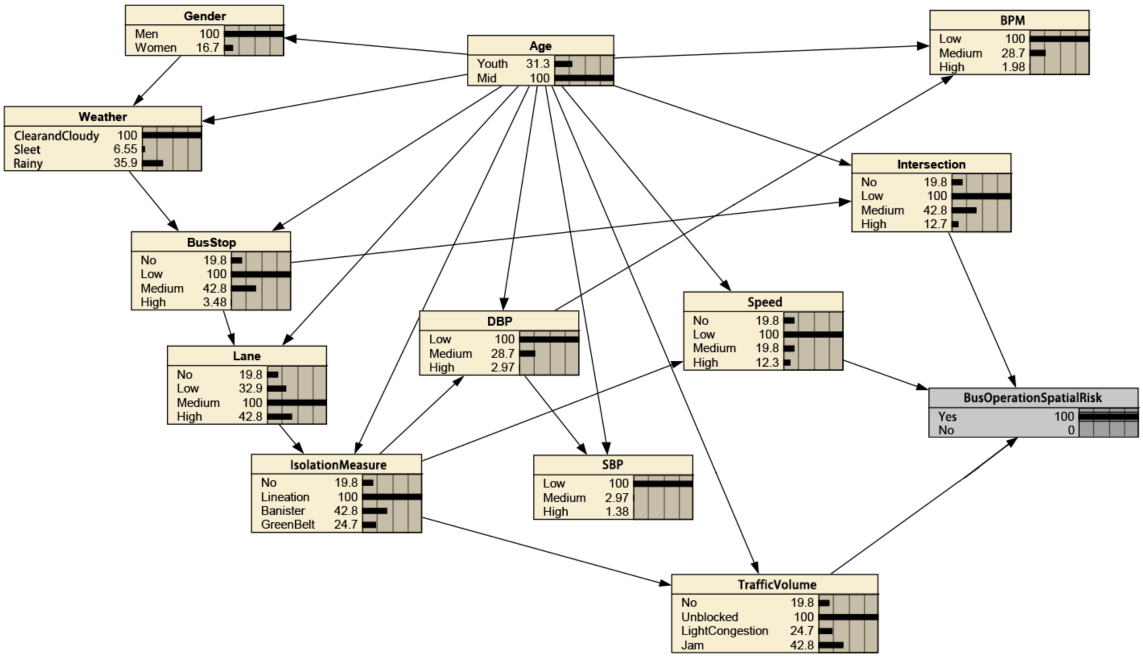

Figure 7. MPE for bus operation spatial risk condition.

From Figure 7, the probability of bus operation spatial risk is relatively high when the conditions listed in Table 6 are met. According to the probability combination, the MPE for bus operation spatial risk is when the driver is a male aged 30–40 years, with a systolic pressure of 100–115 mm Hg, diastolic pressure of 63–73 mm Hg, and heartbeats of 59–75 beats per minute. The bus speed is 30–43 km/h. The roads have 0–18 bus stops, 0–8 intersections, and 2–4 lanes. The traffic volume remains unblocked. The isolation measure is a line, and the weather is clear and cloudy.

Table 6. MPE for bus operation spatial risk condition.

Variable	MPE
Age	30–40 years
Gender	Men
SBP	100–115 mm Hg
DPB	63–73 mm Hg
BPM	59–75 beats/min
Speed	30–43 km/h
Lane	2–4
Traffic volume	Unblocked
Isolation measure	Line isolation
Bus stop	0–18
Intersection	0–8
Weather	Clear and cloudy

Studies have shown that experienced drivers have a higher risk of rear-end collisions than novice drivers [33]. After our investigation, drivers aged 30–40 had more experience than drivers aged 20–30 in this research. Although experienced drivers are usually more mature in driving skills, factors such as mentality, driving habits, and environmental complexity may work together to increase the risk of rear-end collisions in some situations. Some drivers' confidence in their driving skills may lead them to overlook certain potential risks and relax their vigilance while driving. Some drivers who have been driving for a long time may have developed certain unsafe driving habits. For example, they handle multiple tasks simultaneously. The most typical way is checking information on a phone while driving. It is worth noting that vehicle assistance systems have a negative impact on high-risk groups of skilled drivers [34]. The predictive effect of risk perception on dangerous driving behavior is more significant in women than in men [35]. In the sample we used, male drivers accounted for 92.3%, while female drivers only accounted for 7.7%. Therefore, the gender of drivers in the MPE of bus operation space risk is male.

Multiple papers have proved that the impact of speed on traffic safety is crucial [36,37]. Their viewpoint is that the average speed is directly proportional to the accident rate and severity. However, driving at low speed for a long time may increase the driver's fatigue and distraction and instead increase the probability of accidents. During peak hours, low bus speeds can reduce road capacity and cause traffic congestion. If other vehicles rush to overtake, it will increase the risk of collision or scraping accidents, especially on narrow or complex road sections. In addition, when the speed of the bus is too low, pedestrians and non-motorized vehicles may be more likely to collide with the bus.

Unreasonable infrastructure on roads can also increase the bus operation's spatial risk. Too few bus stops will reduce residents' willingness to take public buses and increase the number of private cars on the road. In order to arrive on time, drivers may exceed the speed limit on certain road sections due to excessively long station distances. An excessive number of lanes prompts buses to change lanes frequently. Very few lanes can easily lead to road congestion and reduced road capacity. When isolation measures are set unreasonably, the probability of pedestrians and non-motorized vehicles crossing the road increases. To accommodate pedestrians, frequent acceleration and deceleration of buses may occur. A low intersection density may lead to excessive traffic flow and reduce its capacity at an intersection. Although smooth road conditions do not directly affect the spatial risk of bus operation, drivers are prone to relax their vigilance. Once an unexpected situation occurs, the driver may not be able to react quickly.

Many previous studies have opined that inclement weather has a negative impact on road traffic [38,39]. Most of these studies were simulations or focused on private cars on highways and in rural areas. However, urban bus drivers are professionally trained and more cautious when driving in inclement weather. And the drivers are familiar with the routes and road conditions. They have experience in driving in inclement weather. Compared to cars, buses are less affected by external factors such as wind and rain and have stronger stability. An easily overlooked point is that there are fewer people going out in inclement weather. Compared to sunny days, the traffic flow on the road is much smaller.

4.3. Sensitivity Analysis

Sensitivity analysis is a critical component of uncertainty risk management decision analysis. It aims to demonstrate the extent of the impact of changes in sensitive factors on target nodes in the project. Target nodes may change significantly, even when certain factors only change slightly. The sensitivity analysis function provides a convenient tool in Netica software. It can be used to analyze factors that have a significant impact on the bus operation's spatial risk. It can help to evaluate the sensitivity between each factor and the alert status of bus operation spatial risk. In traffic safety management, it is possible to quickly identify the factors that have a significant impact on risk and adopt a focused monitoring approach based on the sensitivity coefficients of various factors. In addition, it is possible to eliminate factors with low sensitivity and reduce the complexity of the system. Table 7 lists the obtained data.

Table 7. Sensitivity analysis of bus operation spatial risk.

Node	Mutual Information	Percentage	Variance Credibility
Bus operation spatial risk	1.329	100	0.311
Speed	0.780	58.7	0.143
Traffic volume	0.775	58.3	0.140
Isolation measure	0.771	58	0.139
Intersection	0.769	57.9	0.139
Bus stop	0.767	57.7	0.139
Lane	0.766	57.6	0.139
SBP	0.011	0.799	0.001
DBP	0.007	0.559	0.000
BPM	0.006	0.451	0.000
Age	0.006	0.414	0.001
Weather	0.003	0.188	0.001

Mutual information can be used to determine whether two variables are related and the strength of that relationship. The larger the value, the greater the sensitivity. The sensitivity of changes in one variable to another is represented as a percentage. The variance value between two nodes is represented by variance credibility. Table 7 indicates that the number of intersections, bus stops, lanes, isolation measures, speed, and traffic volume significantly affect the bus operation spatial risk. It indicates that the bus operation spatial risk is affected more by a small change in the probability of these factors. It is consistent with the result of backward reasoning. The speed of buses during operation has the greatest influence on the spatial risk of bus operation. Therefore, in the process of road construction or renovation, key considerations should be given to road isolation measures, the number of intersections, the number of bus stops, and the number of lanes. Bus companies should closely monitor the speed of bus vehicles. It can balance traffic flow and improve road conditions by adjusting speed limits, lane arrangements, and intersection configurations.

Public transport is of great significance in many aspects, such as protecting the environment, supporting economic development, and promoting social equity. Therefore, bus safety is crucial. Through BN inference, we found that the bus operation spatial risk is sensitive to speed, isolation measures, traffic flow, and number of intersections, bus stops, and lanes. Therefore, transit authorities need to focus on the reasonable form of isolation measures and the number of intersections, bus stops, and lanes when planning traffic. Bus companies need to emphasize speed limits while driving during employee training. Understanding risk factors can drive the development and improvement of relevant policies and regulations, such as setting stricter safety standards. By analyzing key risk factors, public transport managers can rely on data to make more scientific decisions. In addition, promotional and educational activities can be targeted to convey to passengers and drivers how to avoid and respond to specific risks.

5. Limitations

Our research analyzed the main factors affecting bus operation spatial risk from the perspectives of driver, vehicle, road, and environment. The data mainly came from the operation monitoring of public transport companies in the real world. However, there is still a problem of incomplete selection of representative indicators in the research due to limited data sources. Taking vehicle factors as an example, it is often necessary to consider indicators such as speed, acceleration, braking distance, tire pressure, etc., when analyzing traffic risks. However, the types of data provided by the bus company are limited, and the only data related to vehicles is the speed at the time of warning. Meanwhile, limited data sources also affected the implementation of triangulation because the triangulation method requires comparing information collected from different sources to verify the authenticity and reliability of the research.

In addition, the data provided by the bus company has many missing or aberrant issues, resulting in low quality. Although data cleaning can improve data quality, the higher the quality of raw data, the better.

The quality and form of data are crucial for the construction and final performance of BNs. Therefore, the data used to construct BNs typically needs to meet basic requirements such as sufficiency, completeness, accuracy, and balance. In some cases, there may be class imbalance issues in the dataset. To ensure the robustness of the model, the dataset should be balanced as much as possible, or the data distribution should be adjusted through resampling techniques. Meanwhile, the data should conform to the assumptions of the model, such as conditional independence and data distribution stability. If the training and testing data come from different distributions, the performance of the model will significantly decrease. In addition, the discretization of variables, noise processing of data, and the correlation between variables are also key issues that need to be focused on when constructing BNs. For example, the number of states of discrete variables should not be too many. Otherwise, it will affect the interpretability and computational efficiency of the model.

Therefore, in future research, it is necessary to further expand data sources, strengthen data verification, and enhance the analysis of the model construction process to obtain more reasonable and reliable conclusions.

6. Conclusions

Generally, transport elements include people, vehicles, roads, and the environment. The spatial risk of bus operation involves multiple factors that are not independent but interrelated. Our research integrated various data to study the factors that affected the spatial risk of bus operation and the magnitude of their impact. BNs have considerable advantages in addressing complex risks caused by multiple factors. The BN structure was selected based on the highest BIC value obtained by the TS algorithm. The operation monitoring dataset was fitted to a BN to determine its parameters. Then, the risk factors with high sensitivity to the spatial risk of bus operation and the most probable explanation were identified. The proposed method provides a more comprehensive description of bus operation spatial risk from different dimensions. Additionally, adjusting each explanatory and objective attribute consideration class without altering the suggested framework or losing its universality is possible. Consequently, the classes considered in this study can be modified according to regional circumstances and anticipated uses in subsequent case studies.

The BN model constructed in this research has a wide range of applicability. The data we want to analyze can be directly input to determine the key risk factors. This model can be integrated with real-time monitoring systems to dynamically monitor and respond to potential risk factors. Based on risk prediction, transit authorities can develop and optimize emergency response plans for public transport systems and use models to determine the effectiveness of the plans. In addition, the analysis results of this model can be used to improve decision-making in public transport systems to ensure continuous optimization of the system.

In summary, the development of public transit is a critical step in addressing excessive carbon emissions and road congestion in the context of dual carbon emissions. The safety of urban bus systems during operation is essential for public transit. The present study can enhance the safety of urban buses during regular operations by preventing risks associated with bus operations early and precisely and serve as a reference for future studies.

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