Bayesian Modeling Applied to Risk Estimation in the Road Cargo Transportation

Modelagem Bayesiana aplicada na estimativa de Riscos no Transporte Rodoviário de Cargas

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ABSTRACT

RCT is essential to the Brazilian economy, accounting for 61.1% of freight movements. Despite its importance, it faces risks such as accidents, theft, and infrastructure damage, influenced by road conditions, driver behavior, and cargo characteristics. While previous studies have examined specific risks, gaps remain in the integrated modeling of interdependent factors, especially regarding the sustainability of logistics operations (SDG 11). This study aimed to develop a probabilistic model based

on Bayesian Networks (BN) to assess risks in RCT, considering interactions among critical factors and supporting managers in mitigation strategies. The methodology combined a systematic literature review, the Delphi technique with experts to prioritize 15 risk factors (excluding "Traffic Conditions"), BN construction using MSBNx software, and validation through sensitivity analysis and simulations. Twenty simulations (10 optimistic and 10 pessimistic) and a survey with 105 experts were conducted. The results showed that "Driver Profile," "Cargo Type," and "Vehicle Conditions" were the most critical factors for accidents, while "Cargo Type" and "Driver Profile" strongly influenced theft. In pessimistic scenarios, accident probabilities reached 71–72% and theft probabilities ranged from 80–94%. In optimistic scenarios, these risks dropped to 5–7% and 13–41%. Validation achieved a 70% level of expert agreement. In conclusion, the proposed model enables dynamic risk assessment in RCT, supporting strategic decisions that enhance operational safety (SDG 9) and efficiency.
Keywords: Bayesian Networks; risk factors; road cargo transport.

RESUMO

O transporte rodoviário de cargas (TRC) é essencial para a economia brasileira, responsável por 61,1% do deslocamento de mercadorias. Apesar de sua relevância, enfrenta riscos de acidentes, furtos e danos à infraestrutura, influenciados por fatores como condições das rodovias, perfil do motorista e características das cargas. Embora existam estudos sobre riscos específicos, ainda há lacunas na modelagem integrada de fatores interdependentes, sobretudo quanto à sustentabilidade das operações logísticas (ODS 11). O objetivo deste estudo foi desenvolver um modelo probabilístico baseado em Redes Bayesianas (RB) para avaliar riscos no TRC, considerando a interação entre fatores críticos e apoiando gestores em estratégias de mitigação. A metodologia combinou revisão sistemática da literatura, aplicação da técnica Delphi com especialistas para priorizar 15 fatores de risco (excluindo "Condições de Tráfego"), construção da RB com o software MSBNx e validação por análise de sensibilidade e simulações. Foram realizadas 20 simulações (10 otimistas e 10 pessimistas) e pesquisa com 105 especialistas. Os resultados apontaram "Perfil do Motorista", "Tipo de Mercadoria" e "Condições do Veículo" como fatores críticos para acidentes, enquanto "Tipo de Mercadoria" e "Perfil do Motorista" influenciaram diretamente roubos. Nos cenários pessimistas, a probabilidade de acidentes chegou a 71-72% e de furtos a 80-94%. Já em cenários otimistas, esses riscos caíram para 5-7% e 13-41%. A validação obteve 70% de concordância. Conclui-se que o modelo permite avaliar riscos de forma dinâmica, apoiando decisões estratégicas que fortalecem a segurança operacional (ODS 9) e promovem eficiência no TRC.
Palavras-chave: Redes Bayesianas; fatores de risco; transporte rodoviário de cargas.

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1 INTRODUCTION

Road transport plays a vital role globally, serving as a primary means for cargo movement. In Brazil, road cargo transport (RCT) is particularly significant: according to the 2024 CNT Roadways Survey, 111,853 km of paved roads were assessed across federal and state networks. Only about 32.5% of those roads were rated "good" or "excellent," while 67.5% were in "regular," "poor," or "very poor" condition. Additionally, 65% of domestic cargo continues to rely heavily on roadways, reflecting the dominance of RCT (CNT, 2024; UFF, 2024). These updated statistics supplement earlier figures of 61.1% cargo share and ~1,720,700 km of road network. Earlier estimates remain informative, but the 2024 data convey more recent conditions and challenges.

Despite its economic importance, RCT exposes both drivers and cargo to multiple risks, such as mechanical failures, accidents, theft, and robberies. These threats not only endanger human safety but also cause significant operational disruptions and financial losses. Risk exposure varies across regions: while the Southeast suffers from high cargo theft rates, the North is more affected by poor infrastructure and lack of maintenance (Overhaul, 2024; CNT, 2024).

In this context, risk management becomes crucial, therefore requiring precise methodologies to assess threats in an integrated way. Recent studies emphasize the need for quantitative models that account for interdependent factors, going beyond traditional analyses restricted to hazardous materials or isolated accident types (Newnam *et al*., 2022; Sun *et al*., 2024).

To address this gap, the present study proposes a probabilistic model based on Bayesian Networks (BNs). By integrating empirical data and expert insights, the model identifies and simulates critical risk scenarios, providing managers and policymakers with a robust decision-making tool. This approach enhances mitigation strategies, improves safety, and strengthens operational efficiency in RCT.

2 THEORETICAL BACKGROUND

The development of a robust analytical framework for assessing risks in RCT begins with a systematic literature review, conducted under the PRISMA protocol to ensure methodological rigor and evidence-based consistency. This review identified recurring risk factors in RCT and examined the approaches commonly employed to evaluate them (Cassia *et al*., 2020). Building on these findings, the section explores essential principles of risk management, with an emphasis on quantitative analysis techniques widely used in logistics and transportation. Special attention is given to BNs), presented as a probabilistic modeling tool grounded in Bayes' theorem. The explanation covers their core elements - nodes, arcs, conditional probability tables, and inference mechanisms - demonstrating how they operate in practice. The rationale for employing BNs in RCT risk modeling lies in their ability to represent causal relationships, handle uncertainty effectively, and dynamically update probability estimates as new data emerges, making them particularly suitable for transportation risk contexts.

2.1 Risk Factors for Road Cargo Transport

The systematic review of the literature identified several risk factors associated with RCT activity, and the respective methodologies employed by researchers to evaluate these factors (Lakehal; Tachi, 2018). These factors include theft and robbery of various types of products and goods (Ekwall; Lantz, 2015), road conditions (Yang *et al.,* 2018), types of merchandise being transported (Ekwall; Lantz, 2013), driver behavior (Wedagma; Wishart, 2018), vehicle conditions (Dong *et al.,* 2017), and weather conditions (Wang; Yang, 2018).

In China, between 2000 and 2008, studies revealed a total of 322 accidents involving the road transport of hazardous materials. The most frequent types of accidents reported were leaks (84.5%), followed by gas clouds (13.0%), fires (10.2%), and explosions (5.9%) (Classification and Code of Dangerous Goods, 2005).

By conducting a systematic review following the PRISMA model, this study ensures a comprehensive analysis of the literature, identifying and categorizing the recurring risk factors in RCT. These findings contribute to the understanding and assessment of risks in the field of cargo transport.

For the development of this study, five pairs of keywords were defined: (i) *Road Transport* and *Risk Factors*, (ii) *Road Transport* and *Risk Assessment*, (iii) *Road Transport* and *Risk Evaluation*, (iv) *Road Transport* and *Risk Estimation*, and (v) *Transport* and *BN*. An analysis of these keyword combinations revealed a substantial number of studies focused on the investigation of risk factors in road freight transport.

The literature review was conducted using these five keywords sets across several academic databases, including Wiley, Science Direct, Scopus, Emerald, SciELO, Taylor & Francis, CAPES, EBSCO, and ProQuest. This search process initially identified 680 articles; of these, 279 were excluded due to duplication, and 371 were eliminated for falling outside the research scope. Consequently, 30 articles were selected to compose the systematic review on the topic.

Within the 30 articles analyzed, a total of 743 risk factors were identified. When considering only the five keyword sets applied to the Scopus CAPES and Science Direct databases, a total of 569 articles related to the topic were initially retrieved.

All selected articles presented a diverse range of risk factors associated with RCT, many of which appeared recurrently across different studies. This repetition suggests the consolidation of certain factors as critical elements in the specialized literature, reinforcing their relevance and the need for ongoing attention in risk assessment practices within the sector. Accordingly, the most frequently cited risk factors were used to model the risks associated with road cargo transport.

2.2 Risk Calculation in the RCT

Different techniques were applied to calculate the risk in the RCT activity, as well as in other transport modes. The transport of hazardous materials has been extensively studied to identify the recurring risk factors in RCT activity (Oggero *et al.,* 2006). Various aspects are considered during the analysis, such as the type of substance being transported, the availability of an emergency plan for accidents, and the potential environmental damage caused by leaks, fires, and explosions (Wedagama; Wishart, 2017).

Several studies have applied database analysis as a methodological approach to organize and interpret large sets of information in different contexts (Friedman, 2001; Friedman; Meuman, 2003; Ekwall; Lantz, 2013; Tubis; Wojciechowska, 2017; Tubis, 2017; Lisa; Lyndal; Elias, 2009; Bouamrane; Hamdadou; Yachba, 2012). This technique has been widely used to support systematic data exploration, improve the reliability of findings, and facilitate decision-making processes. In addition, Wedagama and Wishart (2018) extended its application to the study of network structures, illustrating the versatility of database analysis in examining both individual datasets and interconnected systems.

The Monte Carlo method (MMC) has also been utilized to calculate risk factors in RCT (Urciuoli, 2008; Bouamrane *et al.,* 2012). Additionally, authors have employed models such as Multinomial Logit (MNL) and Negative Binomial to identify and calculate risk factors (Dong *et al.,* 2017).

BNs have been applied to risk assessment across different modes of transport, including maritime (Bandeira; Correia; Martins, 2017), air (Zhao; Wu; Xu, 2009), water (Wang; Yang, 2018), and RCT (Akhtar; Utne, 2015; Zhao; Wang; Qin, 2011). Previous studies have examined factors such as accidents, driver behavior, inappropriate transport conditions, and vulnerability of transport systems (Akhtar; Utne, 2015; Bandeira; Correia; Chabchoub, 2012; Waal; Joubert, 2022). While research such as Wang and Yang (2018) incorporate multiple variables - road conditions, traffic, weather, vehicle and driver characteristics, and hazardous materials - it still lacks a systematic analysis of recurring factors.

Overall, the literature shows that although BNs are recognized as valuable for modeling risks, there is still a limited number of studies applying them to systemically examine recurrent variables in road cargo transport. This study therefore proposes a more comprehensive approach, jointly analyzing the most recurrent risk factors in RCT through the application of BNs.

2.3 Bayesian Theorem

Bayesian theory, originally formulated by Thomas Bayes in the 18th century and subsequently refined by Pierre-Simon Laplace, offers a rigorous mathematical framework for updating the probabilities of hypotheses considering new empirical evidence.

The enduring relevance of Bayesian theory lies in its remarkable capacity to manage uncertainty and systematically integrate prior knowledge with observed data (Lee, 2012). Its applications span a diverse range of fields, including medicine, artificial intelligence, engineering, and decision-making processes that can be expressed as follows:

$$P(A|B) = \frac{P(B|A) \times P(A)}{P(B)}$$ Equation (1)

Where:

- $P(A/B)$ denotes the posterior probability of event A given that event B has occurred;
- $P(B/A)$ represents the likelihood, that is, the probability of observing event B given that A is true;
- $P(A)$ is the prior probability of event A, reflecting the belief about A before observing B;
- $P(B)$ is the marginal probability of event B, serving as a normalization factor to ensure the result is a valid probability.

By applying Bayes' Theorem, BNs enable the estimation and dynamic updating of probabilities based on newly observed evidence or information. They provide a structured framework for reasoning under uncertainty, supporting more robust and informed decision-making processes. Through this formulation, Bayesian inference systematically revises prior beliefs considering new data, generating posterior probabilities that coherently integrate empirical observations with previously established knowledge.

2.4 Bayesian Networks

BNs, also known as belief or causal networks, are probabilistic models grounded in Bayes' Theorem, which formalizes how probabilities are updated as new evidence becomes available. By enabling probabilistic inference, BNs model dependencies among variables and have been applied to diverse domains such as diagnosis, classification, failure prediction, and risk analysis (Jones *et al*., 2010; Sun *et al*., 2024).

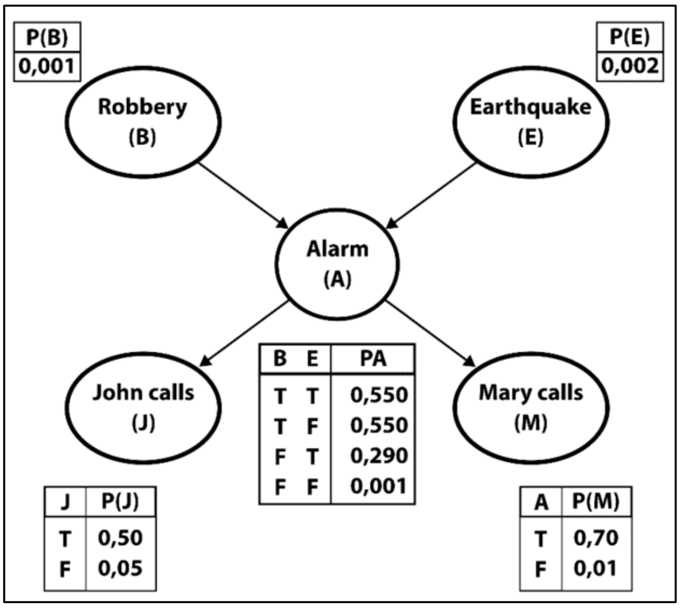
BNs were initially employed in medicine, where they integrated prior knowledge with observed data, achieving significant results in diagnostic systems. Their use has since expanded to transportation, finance, supply chains, and cybersecurity, reflecting their adaptability to complex and uncertain environments (Kinjo *et al*., 2023). In fault diagnosis, BNs efficiently model causal relationships between symptoms and underlying causes. In service quality assessment and supply chain risk analysis, they capture interdependencies among variables and support predictive risk modeling (Lockamy, 2012; Badurdeen *et al*., 2014; Ding *et al*., 2018; Librantz *et al*., 2020).

The main advantage of BNs is their ability to represent causal relationships graphically while processing uncertain information in a transparent and intuitive way, even for non-experts (Damien, 2015). Their construction requires the definition of variables, dependencies, and conditional probability distributions, while inference relies on Bayesian updating to revise probabilities as new data emerges. This makes BNs a powerful decision-support tool for complex scenarios where uncertainty and causal interdependence are significant. A BN is typically composed of the following elements:

- A set of variables: These variables represent the relevant factors or entities within the problem domain.
- Arcs connecting the variables: The arcs represent causal or probabilistic relationships between the variables.
- Directed Acyclic Graph (DAG): The variables and arcs in a BN form a directed graph without cycles, known as a DAG.

Figure 1 illustrates a commonly used model to depict BNs, visually representing the variables and their interdependence.

Figure 1 – Bayesian Networks diagram.



Source: Marques; Dutra (2002, p. 8).

The joint probability distribution of a Bayesian Network with n calculated equations X_1, X_2, X_3,..., X_n is given by Equation 2:

$$P(X_1, X_2, \ldots, X_n) = \prod_{i=1}^{n} P(X_i \mid \mathrm{Pa}(X_i))$$ Equation (2)

where:

- $P(X_1,X_2,\ldots,X_n)$ denotes the joint probability distribution over all variables in the network;
- $P(Xi \mid Pa(Xi))$ represents the conditional probability of variable X_i given its parent nodes $Pa(X_i)$;
- $\prod_{i=1}^{n}$ indicates that the overall joint probability is obtained by multiplying the conditional probabilities for each node i.

This factorization exploits the conditional independence properties encoded in the network's directed acyclic graph (DAG), thereby reducing the complexity of modeling the joint distribution of multiple interdependent variables, as illustrated in Figure 1.

3 METHODOLOGY

This study adopts a confirmatory research design using a mixed-methods approach, which is recommended when the knowledge of a phenomenon has been articulated in a theoretical way, using well-defined concepts, models, and propositions (Forza, 2002). The study comprises the following steps:

3.1 Identification of the risk factors (Step 1)

Several researchers have systematically investigated and characterized the primary risk factors associated with road cargo transport, notably Yang *et al*. (2010), Ekwall and Lantz (2015), Wedagama and Wishart (2018), and Wang and Yang (2018). These factors are widely known as critical contributors to adverse transport events, particularly accidents and cargo theft. Their analyses underscore the complex interplay between multiple dimensions of risk, including driver behavior, vehicle maintenance, road infrastructure quality, cargo vulnerability, weather conditions, and deficiencies in transport security systems.

A rigorous compilation was conducted to identify the most important variables influencing risk in road cargo operations, considering the consistent recurrence of these factors across the literature. This process culminated in the selection of sixteen risk factors most frequently cited by previous studies, forming the empirical basis for the modeling and risk assessment framework developed in the present research.

3.2 Assigning the Importance degree of the Risk Factors (Step 2)

To assess the significance of the identified risk factors (Table 1), six experts were carefully selected from among professionals in the field of road cargo transportation risk management in Brazil. Each possessed over a decade of professional experience, held senior managerial or strategic positions in leading companies, and was recognized as an opinion leader in the cargo insurance and risk consulting markets. Although the number of participants was relatively small, the selection criteria were highly rigorous, ensuring that the results would be both reliable and valid. In Delphi-based studies, reliability depends less on the number of respondents and more on the depth and relevance of their expertise. As noted by Forza (2002) and Starkweather *et al.* (1975), small panels composed of highly qualified specialists can yield robust and meaningful results, particularly when the research scope is narrowly defined.

Table 1 – Importance degree of the Risk Factors

RISK FACTORS (MACRO)	**CONCEPTS**	**EXAMPLES**	**EXP 1**	**EXP 2**	**EXP 3**
Characteristics Inappropriate for Transport	Among all modes of transport, the road is the most suitable for the transport of goods, whether internationally in export or import, whether in national transport, as well as in short and medium distance journeys. Road transport is highly recommended for the transport of high-value-added or perishable goods.	Time-consuming loading and unloading, packing characteristics, Improper loading, Damaged container, Overloading, and Loading above the permissible level.	3	2	2
Highway Conditions	Unsafe, highly congested roads and in many parts deteriorated. This reality of Brazilian highways hinders the distribution flow and causes problems with delays. However, setbacks on the roads result in non-compliance with the delivery deadline, one of the factors that, together with breakdowns, are sources of inconvenience and complaints from customers.	Roads with potholes, steeply sloping, with sharp turns, lacking structure, monotonous, heavily trafficked, unfamiliar, tolled, demonstration, under maintenance, blocked, Two-way, One-way, Inappropriate emergency service, Fixed object on track, unexpected object on track, Animal on track, Pedestrian.	2	3	3
Driver Behavior	Behavior is defined as the set of reactions of a dynamic system in the face of interactions and renewal provided by the environment in which it is involved. Examples of behavior are social behavior, human behavior, informational behavior (what the individual does with information), etc.	Alcohol consumption, Drug use, Driving after taking stimulants, Fatigue, Stress, Panic, Recklessness, Error, excessive hours behind the wheel, Excessive kilometers traveled during the year, Excessive work after loading, Lack of attention, Poor sleep, Not following traffic rules, Using a cell phone, Dangerous or irregular overtaking, Lack of safe distance between vehicles, Loss of steering control, Short space of the vehicle ahead, Failed to check the rearview mirror.	3	3	3
Luminosity Conditions	It implies the condition of viewing during the trip, as well as it can interfere with issues related to sleep and/or tiredness, as well as the degree of visibility of an object and/or environment.	Driving at night, at dusk, in the early afternoon, in the late afternoon, at dawn.	2	2	3
Weather Conditions	It is based on data from different areas such as sky visualization, analysis of cloud formation, observed temperature, and atmospheric pressure.	Rain, Fog, Storm.	1	2	2
Traffic Conditions	the use of roads by motorized vehicles, non-motorized vehicles, pedestrians, and draft animals, for circulation, passing stops, or parking.	slow	1	1	1
Vehicle Conditions	It is a very important factor to be considered in the occurrence of accidents, and the conditions of the vehicle are responsible for a huge number of accidents that occur in traffic, normally involving other vehicles, pedestrians, animals, and public property.	Poorly designed cabins, Bad cabins, Poor conservation conditions, long manufacturing time (old models), Lack of maintenance, equipment failures, Tire burst, Wheel problems, Vehicle size, Vehicle type, Heavy vehicle, No ventilation or refrigeration, Defective tank valves, Damaged tanks, Technology.	2	2	1

The Delphi technique (Machado *et al.*, 2024) was implemented using a three-point Likert scale - low importance (1), medium importance (2), and high importance (3) - to classify each risk factor (Table 1). Conducted in a single round, the procedure reflected a substantial initial consensus among experts, quantitatively validated by Kendall’s concordance coefficient (≈0.9), which confirmed the reliability of the evaluations. Following established recommendations for Delphi studies in technical domains (Forza, 2002; Synowiec; Synowiec, 1990), no additional rounds were required.

Based on the experts' assessments, the risk factor "Traffic Conditions" received the lowest score (7 points) and was excluded from further analysis. The remaining fifteen risk factors were used in BN modeling. These factors will undergo further analysis and evaluation in the subsequent stages of the study. The Delphi procedure and its outcomes are summarized in Table 2.

Table 2. The Delphi procedure adopted in this study is summarized

Step	Description	Details
1. Selection of Experts	Identification and invitation of specialists in road cargo risk management.	6 experts selected; each with over 10 years of experience and occupying senior management or strategic positions.
2. Definition of Evaluation Scale	Establishment of importance levels for risk factors.	Scale: 1 = Low importance; 2 = Medium importance; 3 = High importance.
3. First Round of Delphi	Collection of expert evaluations on the identified risk factors.	Experts individually assigned importance scores to each of the 16 initial risk factors.
4. Aggregation of Scores	Calculation of total weights for each risk factor based on expert responses.	Total weight = Sum of individual expert scores for each factor.
5. Analysis of Consensus	Evaluation of the need for additional Delphi rounds.	High convergence observed; no significant divergences detected; second round deemed unnecessary.
6. Exclusion of Low-Importance Factor	Removal of the least relevant factor based on aggregated scores.	"Traffic Conditions" identified as least relevant (lowest total score) and excluded.
7. Validation of Final Factors	Expert confirmation of the selected set of risk factors.	15 risk factors validated for BN modeling.

3.3 Grouping and Validation of Risk Factors (Step 3)

To simplify the model, a logical grouping process was carried out in which risk factors were consolidated based on their semantic similarity, functional interrelation, and relevance to the overall dynamics of road cargo transport, while preserving the causal dependence relationships among variables. Although statistical clustering methods, such as factor analysis, were considered, the semantic-functional approach was deemed more appropriate given the exploratory-confirmatory nature of this study and the relatively limited number of variables.

This methodological choice ensured the interpretability and causal consistency of the model, both of which are critical for practical applications in risk management. The grouping process was conducted in close collaboration with the same six qualified domain experts (3.2), who thoroughly reviewed and validated the proposed classifications. Their evaluation confirmed the logical coherence of the groupings and ensured that the aggregation of related factors did not undermine the distinctiveness of key risk elements.

As a result, the original fifteen risk factors were consolidated into nine aggregated categories, as illustrated in Figure 2. These categories capture the interrelated dimensions of operational, environmental, and human-related risks and serve as the structural foundation for the Bayesian modeling developed in this study.

Figure 2 – Grouping of the Risk Factors proposal

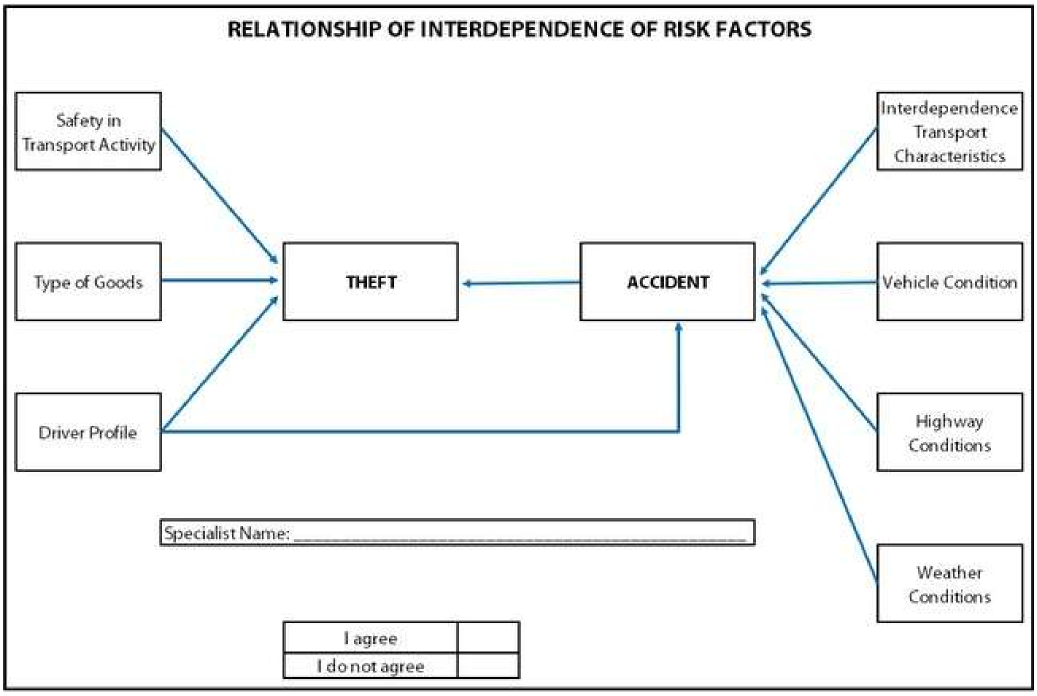
Grouping of Risk Factors

Original Risk Factors	Examples	Grouped Risk Factor
Behavioral Attitudes of Drivers	Alcohol consumption, Drug use, Driving after taking stimulants, Fatigue, Stress, Panic, Recklessness, Error, Excessive hours behind the wheel, Excessive kilometers traveled during the year, Excessive work after loading, Lack of attention, Poor sleep, Not following traffic rules.	**Driver Profile**
Drivers Profile	Age, Family problems, Emotional problems, Psychological problems, Health problems, Social status, Training level, Capacity level, Poor diet.	
Type of Good	Food, Cigarettes, Metals, Electronics, Pharmaceuticals, Beverages, Footwear, Ore, Household utensils, and Clothing.	**Type of Good**
Hazardous Goods	Fuels, Paints, Solvents, Varnishes, Ammonia, LPG, Chlorine, and Agricultural Chemicals.	
Robbery	Cargo, Truck, Container, Driver Kidnapping, Pallets, Trailer Detachment, Cargo Looting, Homicide, and Physical Assault.	**Theft**
Theft	Partial or Total Loss of Goods, Cargo Diversion, Misappropriation, and Loss of Goods.	

3.4 Interdependence of the Risk Factors (Step 4)

After defining the nine risk factors, the factors were positioned in a manner that clearly represented their interdependence. This positioning allowed the experts to evaluate and express their agreement or disagreement with the model, as depicted in Figure 3.

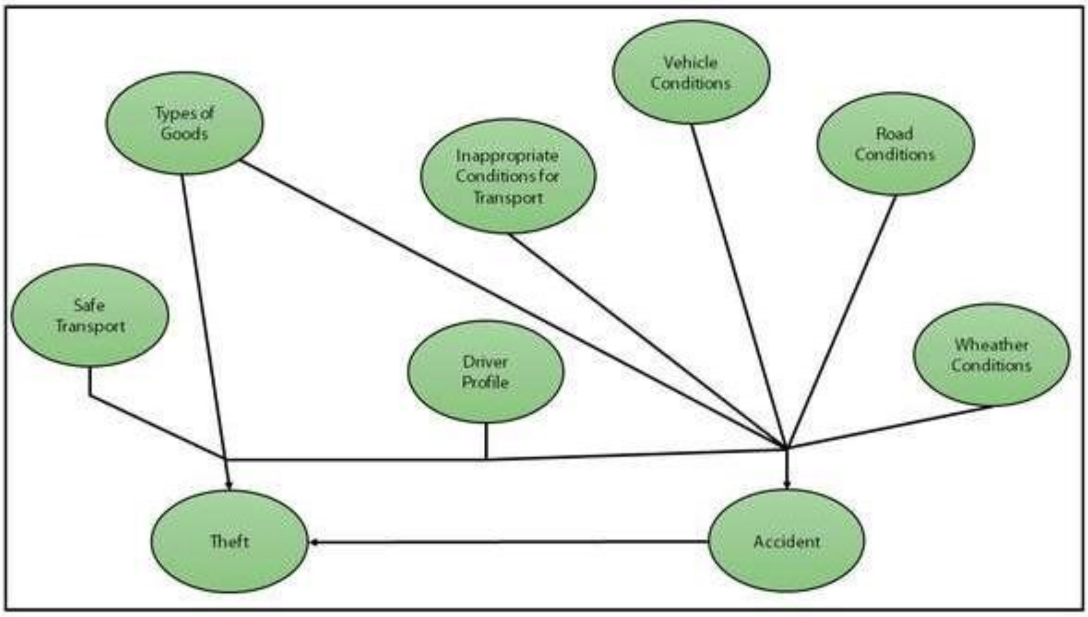
Figure 3 – Relationship of Interdependence of Risk Factors in the RCT



3.5 Bayesian Network Modelling (Step 5)

To develop the BN model, the gathered risk factors and their interdependencies need to be represented as nodes and arcs in the graphical model. Thus, MSBNx® software was used to model the interdependence of risk factors in road cargo transport, as shown in Figure 4. Once the Bayesian Network model is constructed, it can be used for various purposes, such as probabilistic inference, sensitivity analysis, and risk assessment.

Figure 4 – Interdependence of the Risk Factors in the RCT



3.6 Prior probability assignment (Step 6)

To calculate the prior probability P in the Bayesian Network model based on the experts' knowledge and experience, the geometric mean is calculated, according to the following Equation 3.

The equation should describe the geometric mean, which is defined as the n-*th* root of the product of n positive numbers a_1, a_2, ..., a_n.

$$\left(\prod_{i=1}^{n} a_i\right)^{\frac{1}{n}} = \sqrt[n]{a_1 a_2 \ldots a_n} \qquad \text{Equation (3)}$$

where:

- a_i represents each individual value within the dataset;
- n denotes the total number of values being considered.

3.7 Model validation (Step 7)

Validation is a critical step in ensuring the performance and reliability of the Bayesian Network model (Jones *et al.*, 2010; Yang; Bonsall; Wang, 2008). In this study, the process was conducted in collaboration with the same six domain experts in RCT and risk management, whose contributions enhanced both methodological rigor and practical relevance.

However, given the exploratory nature of the study, the absence of comprehensive real-world data for cross-validation, and the primary goal of constructing an expert-driven model, an internal validation approach based on established axioms was adopted.

Specifically, the model was partially validated using the axiomatic criteria proposed by Yang, Bonsall, and Wang (2008) and Jones *et al*. (2010). The following two axioms were applied:

Axiom 1: A slight increase or decrease in the prior probabilities of each parent node should proportionally increase or decrease the posterior probabilities of the child node.

Axiom 2: The total influence magnitude of the combination of x attributes should always be greater than the influence resulting from any subset of x − y attributes.

Using Microsoft BN Tools for .NET (MSBNx®) (MICROSOFT RESEARCH, 2005), 20 risk scenarios were simulated by combining seven primary risk factors - Inappropriate Transport Characteristics, Lack of Safety, Driver Profile, Type of Goods, Road Conditions, Weather Conditions, and Vehicle Conditions - each influencing the probabilities of Accident and Theft.

To explore the model's probabilistic behavior, ten scenarios were defined under best-case conditions (all factors favorable) and ten under worst-case conditions (all factors unfavorable). This structure enabled experts to verify the model's consistency across contrasting operational contexts.

3.8 Conducting the Survey (Step 8)

The survey method is a widely used research approach for collecting information from individuals or organizations. It involves the use of questionnaires, interviews, or other data collection instruments to gather data (Forza, 2002). In this case, the survey was conducted using Google Docs and distributed to a Risk Management Forum (RM) consisting of 140 risk experts.

This forum has been established in Brazil since 2017 and brings together professionals active in the road cargo transportation market through companies associated with: insurance companies, brokerage firms, transportation risk management companies, risk management consulting firms, and security companies. A total of 105 responses were obtained, corresponding to 75% of the population surveyed, with an estimated sampling error of approximately 4.8%.

3.9 Sensitivity Analysis (Step 9)

Sensitivity analysis is a technique to determine how variations in independent variables or model parameters affect the outcomes of a dependent variable. It helps to assess the responsiveness of a model to changes in inputs and underlying assumptions. The analysis involves the gradual variation of input parameters, which may increase or decrease probability values or model outputs, allowing the identification of the most influential factors (Change *et al.,* 2007; Syamsuddin, 2013).

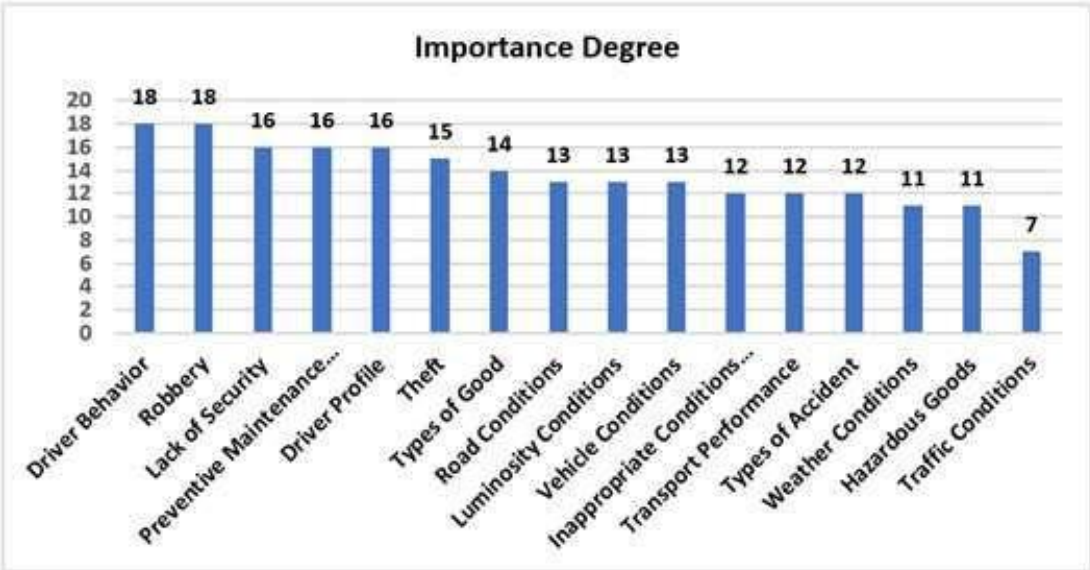
By systematically varying the values of the independent variables within a specified range, sensitivity analysis allows researchers to observe the corresponding changes in the dependent variable or the model's output. This analysis helps in identifying which variables or parameters have the most significant influence on the results and allows for the examination of different scenarios and their potential impacts.

4 RESULTS AND DISCUSSION

4.1 Application of the DELPHI Technique

Based on the experts' assessments, the risk factor "Traffic Conditions" received a total score of seven points, indicating that it was considered less relevant. As a result, this risk factor was disregarded in the analysis, resulting in a final set of 15 most relevant risk factors for cargo transport. The importance of each risk factor was determined based on the scores assigned by the experts, with values of 1 for low importance, 2 for medium importance, and 3 for high importance. Figure 5 presents all risk factors along with their respective final weights.

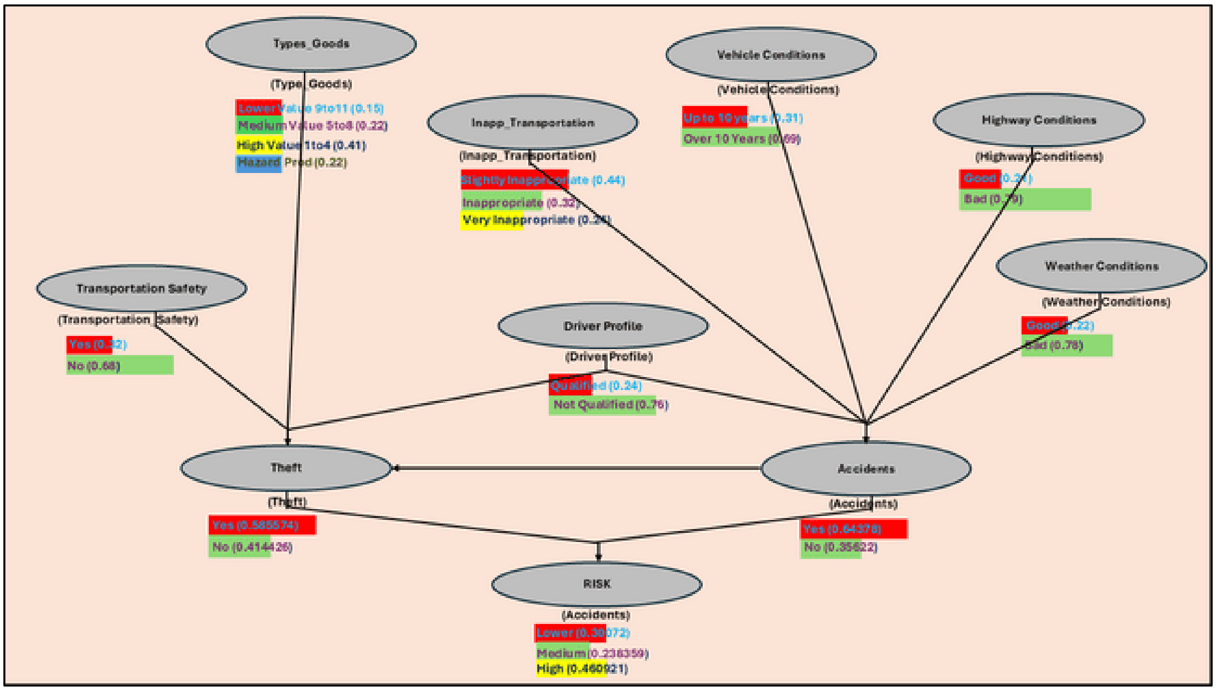
Figure 5 – Weights of the risk factors.



4.2 Prior probability definition

The prior probabilities for each of the risk factors were assigned by the six experts based on their assessments. To calculate these prior probabilities, a geometric mean was applied to the percentage weights provided by the experts for each risk factor. The resulting values obtained from the geometric mean serve as necessary information for completing the Conditional Probability Table (CPT) for each of the factors. The CPTs represent the conditional probabilities of each risk factor given the states of its parent nodes in the BN. Figure 6 depicts the Bayesian Belief Network (BBN) model used for risk assessment in transportation.

Figure 6 – BN model



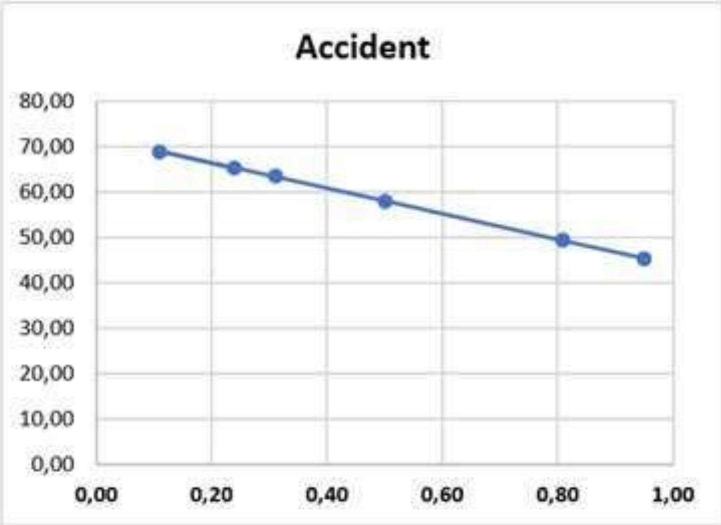
Each node contains probability distributions for its possible states. For example, the node "Weather Conditions" has two states - are good (0.22) and bad (0.78), while the node "Risk" shows probabilities for low (0.309), medium (0.239), and high (0.461) levels.

4.3 BBN Model validation based on the axioms

In the first validation experiment, the ACCIDENT risk factor varies according to its Parent Node. As illustrated in Figure 7, when the prior probabilities of the parent nodes influencing the ACCIDENT node are increased by 10%, 20%, 30%, 50%, 70%, and 100%, the probability of the accident risk also increases. Conversely, when the prior probabilities of these parent risk factors decrease, the probability of the ACCIDENT node likewise decreases.

Similarly, the SSCR node varies according to its parent nodes. For example, when the prior probability associated with the "Participants" node increases by 10% and 20%, the probability of SSCR also increases. Conversely, when this prior probability decreases, the probability of SSCR decreases accordingly, as shown in Figure 7.

Figure 7 – Experiment 1 for model validation



Moreover, other variables were kept constant, as the changes must occur only for the directly connected variables, as listed in Table 3.

Table 3 – First experiment for the model validation

Experiment	Type of Good	Transp. Charac. Inap.	Vehicle Condition	Route Conditions	Weather Conditions	Driver Qualified	Accident	Variation
Prior	0.22	0.44	0.31	0.21	0.22	0.24	65.30	0
1	0.22	0.44	0.31	0.21	0.22	0.11	69.00	1.06
2	0.22	0.44	0.31	0.21	0.22	0.31	63.50	0.97
3	0.22	0.44	0.31	0.21	0.22	0.50	58.10	0.89
4	0.22	0.44	0.31	0.21	0.22	0.81	49.40	0.76
5	0.22	0.44	0.31	0.21	0.22	0.95	45.30	0.69

These results are in good agreement with Axiom 1. Table 4 presents another example of model validation. The table shows that when the Merchandise Type risk factor is set to 100%, the ACCIDENT risk factor exhibits a negative variance of 0.15%. However, when the ACCIDENT node is associated with an additional risk factor (Transp. Charact Inaprop) the variation in the Accident risk factor increases substantially, reaching 17.79%. As this analytical process continues, the probability indices of the ACCIDENT risk factor vary progressively as additional risk factors are incorporated into the model, as shown in Table 4.

Table 4 – Second experiment for the model validation 2

SENSITIVY ANALYSIS	ACCIDENT	VARIATION (%)
Prior	65.30	0
Type of Good	65.20	0.10
Type of Good: Transp. Charact Inaprop.	76.80	17.79
Type of Good: Transp. Charact Inaprop.: Vehicle Conditions	82.70	7.68

Type of Good: Transp. Charact Inaprop.: Vehicle Conditions: Route Conditions	83.00	0.36
Type of Good: Transp. Charact Inaprop.: Vehicle Conditions: Route Conditions: Weather Conditions	84.70	2.05
Type of Good: Transp. Charact Inaprop.: Vehicle Conditions: Route Conditions: Weather Conditions: Driver Qualified	95.00	12.16

This result is in good agreement with Axiom 2 described in the validation step (Materials and Methods section), thereby contributing to the partial validation of the model. As previously indicated, these experiments constitute partial validation, as complete validation would require historical data on RCT accidents and incidents (SSC), which would be exceedingly difficult to obtain.

Overall, the experiments conducted confirmed that the BN model satisfies both Axiom 1 and Axiom 2, as proposed for internal validation. These results demonstrate that the model behaves consistently with logical probabilistic principles, ensuring its internal coherence and robustness. Therefore, although external empirical validation remains a future research opportunity, the present validation process supports the internal consistency and reliability of the proposed Bayesian model for the intended application in RCT risk assessment.

4.4 Sensitivity Analysis

A one-way sensitivity analysis was conducted to assess how variations in the probabilities of individual risk factors influenced the output variables - accident and theft probabilities. By adjusting each input variable independently while holding the others constant, the analysis revealed the isolated effect of each factor on the model’s predictions.

The results, summarized in Table 5, demonstrate that some risk factors exert a significantly greater influence, underscoring their critical role in shaping overall outcomes. This finding emphasizes the need to prioritize control actions on the most impactful variables, thereby strengthening risk management strategies in road cargo transport.

Table 5 – Sensitivity analysis for the risk factors Accident and theft.

Sensitivity Analysis	**ACCIDENTS**
Prior	65.3 %
Inappropriate Conditions for Transport	75.7%
Driver Profile	72.1%
Vehicle Maintenance Conditions	71.2%
Weather Conditions	65.9%
Road Conditions	65.6%
Type of Good/ Dangerous products	65.2%

Sensitivity Analysis	**THEFT**
Prior	58.5%
Type of Good	82.9%
Driver Profile	64.4%
Transport security	53.1%

The results indicate that the most critical risk factors for the Accident are Inappropriate Transport Characteristics, Driver Profile, and Vehicle Conditions. These factors have a significant impact on the probability of accidents in RCT suggesting that effective management and mitigation of these elements can substantially reduce accident occurrence. With respect to theft risk, the most critical factors are Goods Type and Driver Profile. These variables play a crucial role in the likelihood of theft incidents in road cargo transport, indicating that the nature of the goods being transported and driver-related characteristics have a substantial influence on theft occurrence.

4.5 Simulation for Five Representative Risk Scenarios

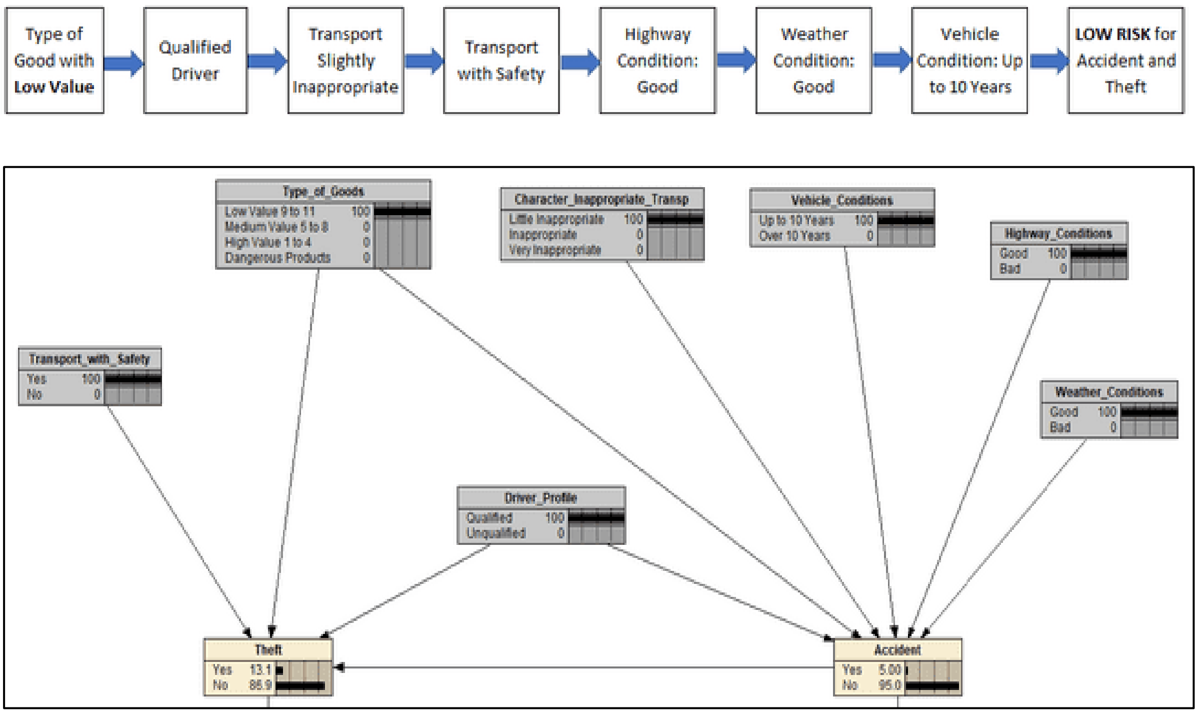
At this stage, 20 risk scenarios were simulated using MSBNx® and later NETICA® software to examine the probabilistic behavior of a BN model under different operational conditions. The model incorporated seven primary risk factors - Inappropriate Transport Characteristics, Lack of Safety, Driver Profile, Type of Goods, Road Conditions, Weather Conditions, and Vehicle Conditions - which served as parent nodes influencing the probabilities of Accident and Theft.

While simulations initially covered both optimistic (best-case) and critical (worst-case) conditions, the study strategically focused on five representative scenarios for detailed analysis. These scenarios captured a range of operational contexts, from low risk to high-risk configurations, enabling a comparative assessment of accident and theft probabilities. Rather than a statistical evaluation with confidence intervals, this approach emphasized the exploratory-confirmatory nature of the study and the expert-driven modeling process.

4.6 First Most Optimistic Risk (Scenario 1):

In this scenario, the primary risk factors are assigned values that reflect more favorable conditions, leading to lower estimated probabilities of accident and theft occurrence. The results indicate a low risk of accident (5.0%) and low risk of theft (13.1%), as shown in Figure 8.

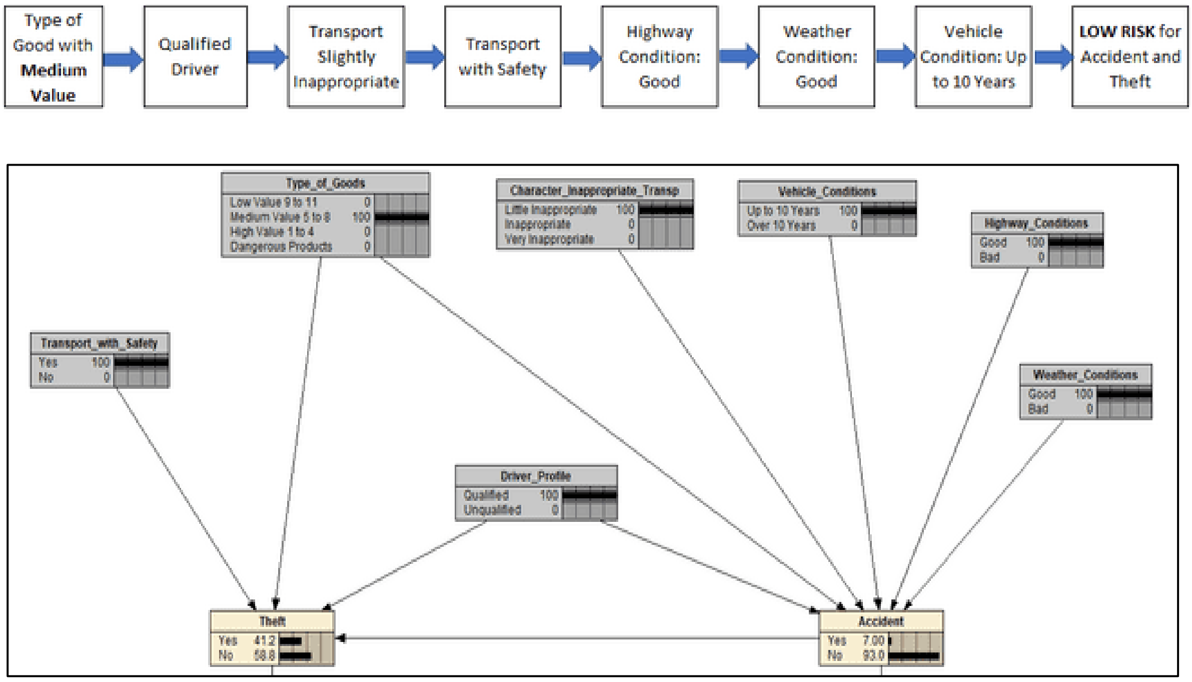
Figure 8 – First most optimistic scenario



4.7 Second Most Optimistic Risk (Scenario 2)

Similarly, this scenario assumes optimistic settings for the risk factors, again resulting in reduced probabilities of adverse events. The results indicate a low risk of accident (7.0%) and a low risk of theft (41.2%), as shown in Figure 9.

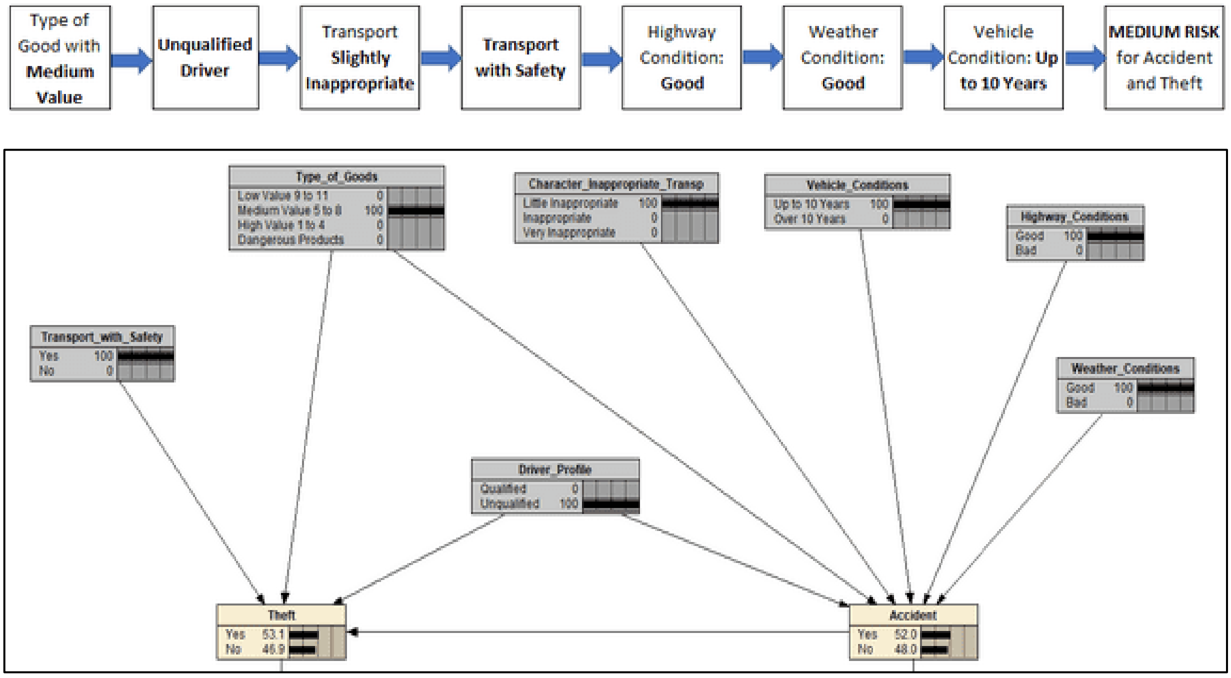
Figure 9 – Second most optimistic scenario



4.8 Medium Risk (Scenario 3)

In this case, the risk factors are configured at moderate-medium levels, indicating an intermediate probability of accidents and theft relative to the more optimistic and more critical scenarios. The results indicate a medium risk of accident (52.0%) and medium risk of theft (53.1%), as shown in Figure 10.

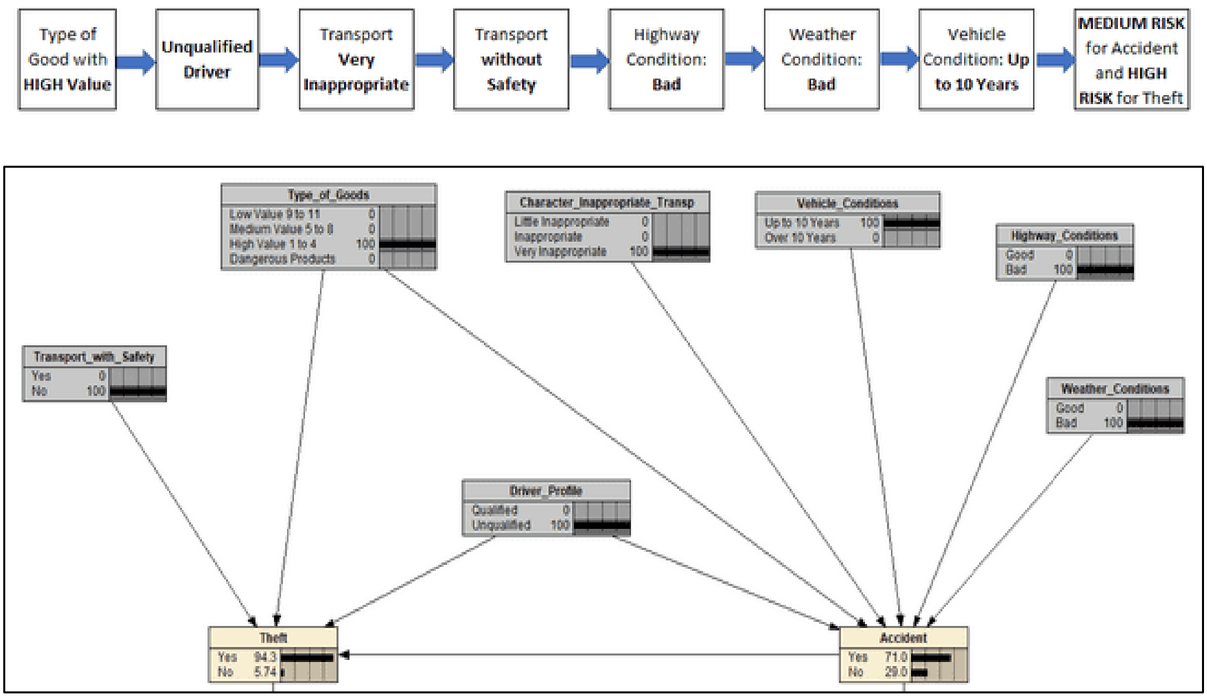
Figure 10 – Medium risk scenario



4.9 Higher Risk (Scenario 4)

Here, the risk factors are set to more unfavorable values, increasing the probabilities of both accident and theft occurrences. The result indicates a high risk of accident (71.0%) and a high risk of theft (94.3%), as shown in Figure 11.

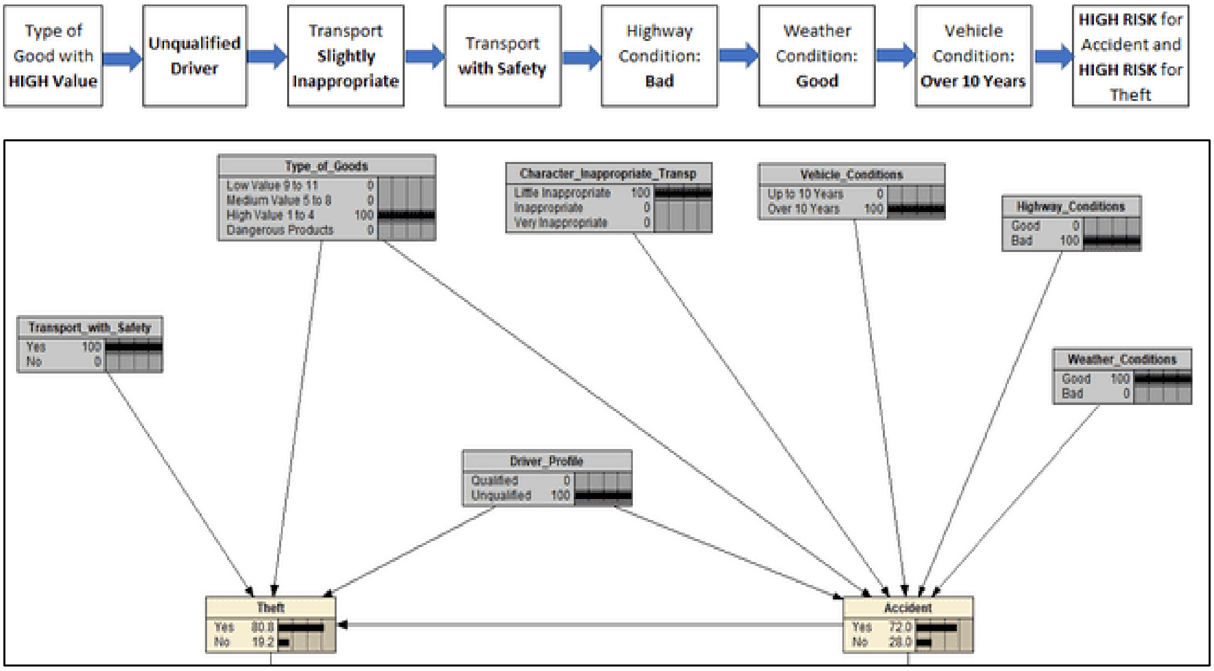
Figure 11 – Higher Risk scenario.



4.10 Worst Risk Values (Scenario 5)

This scenario also assumes the worst-case configuration for the risk factors, leading to high-risk outcomes like those observed in Scenario 4. The result points to a high risk of accidents (72.0%) and high risk of theft (80.8%), as shown in Figure 12.

Figure 12 – Worst Risk Values.



The analysis of five representative scenarios enabled the study to explore operational contexts ranging from favorable to highly adverse conditions, thus reinforcing a more comprehensive and informed risk assessment process.

In the two optimistic scenarios, probabilities of accidents and theft remained low, with values ranging from 5.0% to 7.0% for accidents and 13.1% to 41.2% for theft. The intermediate scenario, characterized by an unqualified driver and moderately risky goods, yielded medium probability for both accidents (52.0%) and theft (53.1%). Finally, the two critical scenarios, defined by unfavorable configurations of goods, driver, vehicle, and road conditions, showed markedly higher risks, with accidents reaching 71.0% - 72.0% and theft 80.8% - 94.3%.

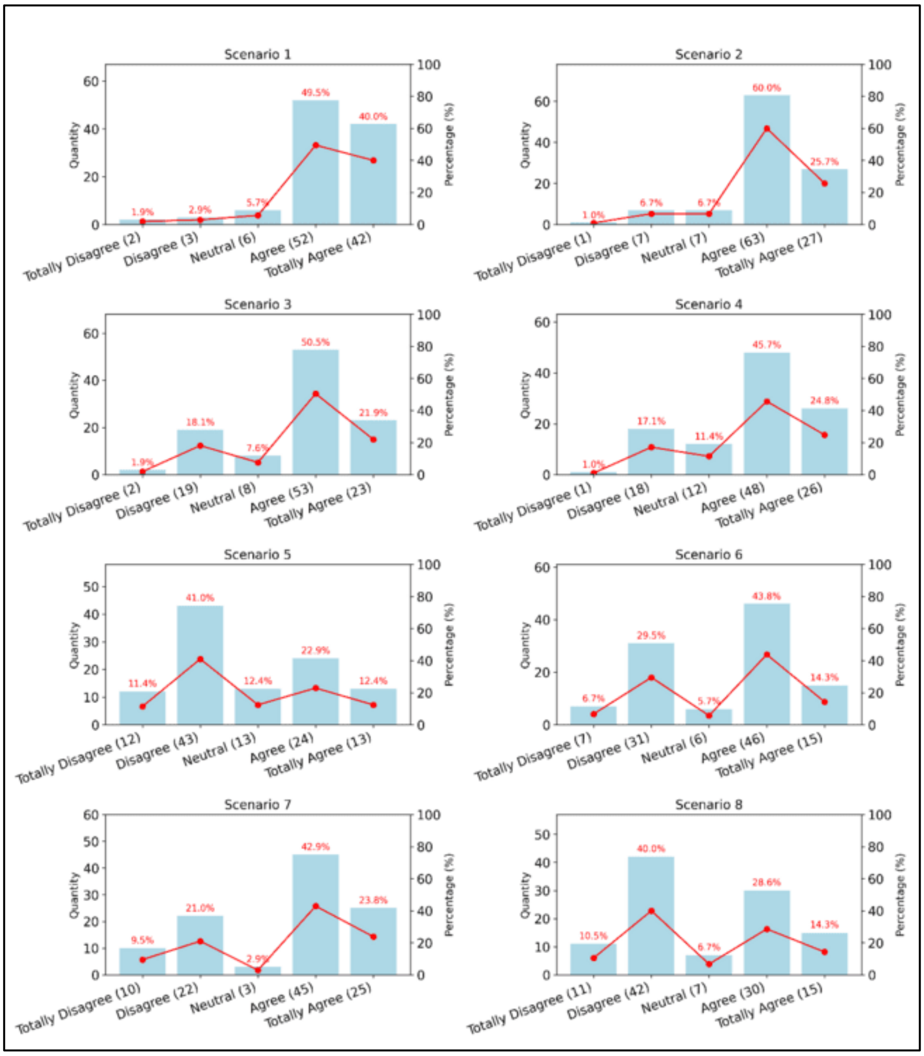
These results highlight how different combinations and severity levels of risk factors directly influence the probabilities of adverse outcomes in road cargo transport, validating the use of BNs for scenario-based risk modeling.

4.11 Model validation by the experts

For this validation, a survey presenting the results from 20 risk scenarios was administered using Google Docs and distributed to a Risk Management Forum (RM) comprising 140 risk experts. A total of 105 responses were obtained, corresponding to 75% of the surveyed population and resulting in an estimated sampling error of approximately 4.8%. Although the full text of the validation questionnaire is not presented in the document, the survey methodology is adequately described.

The responses were collected using a five-point Likert scale, ranging from "Strongly Disagree" to "Strongly Agree," to assess the perception of professionals regarding different risk scenarios modeled in the BN. Accordingly, although the individual survey questions are not fully detailed, the response quantification method and thematic focus are clearly outlined. The input from these experts were depicted in Figure 13.

Figure 13 – Results of the survey



By analyzing the responses from the Risk Management Forum, it is possible to capture a more nuanced understanding of the experts' perspectives regarding the identified risks and their likelihoods. The results across the eight simulated scenarios reveal some variation in opinions, with responses distributed among the full range of the Likert scale - from "totally disagree" to "totally agree." Nevertheless, the overall trend demonstrates a strong predominance of agreement, as most scenarios concentrated responses in the categories "agree" and "totally agree." This outcome indicates that, despite minor divergences in specific contexts, the proposed model was largely validated by the specialists.

Such a pattern reinforces both the credibility and robustness of the research findings, showing that the model can represent real-world risks in RCT and generating meaningful insights into the likelihood of accidents and thefts under different operational conditions. This expert-based validation strengthens confidence in the BN approach adopted, not only for interpreting risk dynamics but also for supporting decision-making in freight transport management.

In this way, the study highlights that risk calculation, when supported by mathematical and statistical techniques such as BN modeling and scenario simulation, becomes an effective alternative for navigating increasingly complex business environments. Risk management in freight transportation inherently involves decision-making under uncertainty, but through structured modeling and systematic analysis, managers are better equipped to enhance the likelihood of successful and safer operations (Bouamrane, 2012; De La Torre, 2013; Badurdeen, 2018).

5 CONCLUSIONS

This study presents a comprehensive risk assessment framework for RCT through the development and validation of a BN model that integrates interdependent risk factors. By synthesizing expert insights, a systematic literature review, and probabilistic modeling, the research addresses critical gaps in existing methodologies, which have historically treated risk factors in isolation. The proposed model identifies and quantifies probabilistic relationships among 15 key risk factors - including driver behavior, cargo type, vehicle conditions, and road infrastructure - while enabling dynamic risk assessment across diverse operational scenarios.

The BN framework represents the first integrated effort to model the interdependencies between risk factors in RCT. By incorporating expert-driven validation (via the Delphi technique and surveys of 105 specialists), the model ensures practical relevance and robustness. The exclusion of non-critical factors (e.g., "Traffic Conditions") and prioritization of factors like "Driver Profile" and "Type of Goods" underscore its evidence-based rigor.

Through 20 simulated scenarios (optimistic, pessimistic, and intermediate), the model demonstrated its predictive power. For instance, in worst-case scenarios, the probability of accidents reached 71-72%, while theft probabilities soared to 80-94%, whereas optimal conditions reduced these risks to 5-7% and 13-41%, respectively. Sensitivity analysis further revealed that "Inappropriate Transport Characteristics," "Driver Profile," and "Vehicle Conditions" are the most critical factors for accident mitigation, while "Type of Goods" and "Driver Profile" dominate theft risks. This aligns with expert validation, where 70% of respondents strongly agreed with the model’s outcomes.

The BN model serves as a transformative decision-support tool for RCT managers, enabling proactive risk mitigation through scenario-based planning. For example, prioritizing driver training, cargo security measures, and vehicle maintenance substantially reduce accident probabilities. Similarly, transporting high-value or hazardous goods under control minimizes theft risks. The model’s flexibility allows real-time adjustments to operational strategies, enhancing both safety and efficiency in logistics operations.

The Delphi technique and systematic literature review ensured a rigorous prioritization of risk factors, aligning academic insights with practitioner expertise. The model’s compliance with Bayesian axioms (proportional probability changes and combined influence) and its validation by industry experts establish its logical coherence and real-world applicability.

The BN framework can be extended to other transportation modes or tailored to specific regional challenges, such as Brazil’s infrastructure disparities between the Southeast and Northern regions.

Finally, the BN model developed in this study redefines risk assessment in RCT by bridging theoretical rigor and practical utility. It not only identifies critical risk factors but also provides a transparent, probabilistic framework for decision-making under uncertainty - a necessity in an industry where operational disruptions and safety failures have severe economic and human costs. By prioritizing actionable insights, this research empowers stakeholders to transform reactive risk management into a strategic, data-driven process, ultimately advancing the safety, efficiency, and resilience of global logistics systems.

For future research, additional impacts on risk calculation may be incorporated based on this model, with the aim of further improving risk assessment and management in road cargo transport. Potential extensions include external validation, dynamic model updates, multimodal transportation applications, and integration with public policy frameworks.

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