A Comparison of Bayesian and Frequentist Approaches for the Case of Accident and Safety Analysis, as a Precept for All AI Expert Models

Moldir Zholdasbayeva and Vasilios Zarikas
Department of Mechanical and Aerospace Engineering, Nazarbayev University, Nur-Sultan, Kazakhstan

Keywords: Artificial Intelligence with Uncertainty, Bayesian Networks, Supervised Learning, Regression Method, Frequentist Statistics, Causal Analysis, Elevator Accidents, Safety Rules.

Abstract: Statistical modelling techniques are widely used in accident studies. It is a well-known fact that frequentist statistical approach includes hypothesis testing, correlations, and probabilistic inferences. Bayesian networks, which belong to the set of advanced AI techniques, perform advanced calculations related to diagnostics, prediction and causal inference. The aim of the current work is to present a comparison of Bayesian and Regression approaches for safety analysis. For this, both advantages and disadvantages of two modelling approaches were studied. The results indicated that the precision of Bayesian network was higher than that of the ordinal regression model. However, regression analysis can also provide understanding of the information hidden in data. The two approaches may suggest different significant explanatory factors/causes, and this always should be taken into consideration. The obtained outcomes from this analysis will contribute to the existing literature on safety science and accident analysis.

1 INTRODUCTION

The choice of a modelling approach remains one of the main issues in accident studies (Alkheder, Alrukaibi, & Aiash, 2020; Mujalli, Calvo, & O, 2011; Zong, Xu, & Zhang, 2013; Gregoriades and Christodoulides, 2017). For these studies, the severity of accident or injury is often chosen as a key dependent/target variable (Eboli et al., 2020; Fountas, Ch, & Mannering, 2018; Michalaki & Quddus, 2015). By expert judgement, several factors, which affect the severity of accident or injury, can be found. In recent years, researchers elaborate on studying the causes of the occurrence of various accidents by running a concrete diagnostics and making predictions using modern statistical and Artificial Intelligent (AI) methods.

A frequentist statistical approach allows an expert to infer associations between factors (i.e. the characteristics of injured people: age and gender, the description of accidents, etc.). It evaluates the likelihood of previous and current events, therefore making it possible to prevent fatal accidents from its occurrence. Studying the causation of events (i.e. a causal approach) may be a dynamical case. Hence, it can be beneficial to find the causes of this event and predict the effect based on a dynamic change of evidences. It can be implemented efficiently with Bayesian Networks (BNs) that have learning capabilities. However, modern implementations of regression algorithms can also be updated as far as the conditions of the experiment remain the same. BNs are more robust regarding a more general type of updating with the cost of the decision/prediction dependency on the values of priors.

In accident studies, accident involvement is a dependent/target variable, whereas accident causes affect the frequency occurrence of accident results/outcomes. As this type of the analysis is statistical, the explanatory variables/causes and other characteristics of this accident may be correlated. This particular analysis regarding accidents is helpful to have "a first look" on data (Cummings, Mcknight, & Weiss, 2003; Zarikas et al., 2013).

One of the well-known statistical approaches is regression models. The regression model has been widely used in various fields, particularly in research studies on medical issues or traffic accident severity (Mujalli et al., 2011; Zong et al., 2016). Logistic and ordered probit statistical methods are used in traffic

Zholdasbayeva, M. and Zarikas, V.
A Comparison of Bayesian and Frequentist Approaches for the Case of Accident and Safety Analysis, as a Precept for All AI Expert Models.
DOI: 10.5220/0010315810541065
In *Proceedings of the 13th International Conference on Agents and Artificial Intelligence (ICAART 2021) - Volume 2*, pages 1054-1065
ISBN: 978-989-758-484-8

studies (Fountas et al., 2018). The utilization of regression models comes with model assumptions and the underlying relationships (e.g. the linear relationships between dependent and independent variables). If any violation takes place, then likelihood of the severity of accident or injury may not be estimated (Zong et al., 2016). In medical sciences, the sample size and missing values may cause problems with inconsistencies while updating (Ducher et al., 2013).

From the point of using conventional frequentist statistics, before executing the regression model it may be of some importance to study the frequency, correlation and variance analysis of explanatory variables (e.g. accident type, severity of accident, month&day&time of accident and province). It can provide information about the nature of fatalities (Shao, Hu, Liu, Chen, & He, 2019). In the work of Shao, the frequency analysis was executed to find inconsistencies in data. The correlation analysis was held to get causal relationships between factors. The collected data can be distributed uniformly (Chen, Chou, & Lu, 2013). Thus, the probabilities are calculated.

Expert judgment can provide an initial identification of explanatory variables/causes of accident and target variables. Next, the correlation analysis can be executed. The chi-square test can be completed to test the strength of relationships (i.e. or how statistically significant the observed data vs the expected one). The goodness-of-fit test can be used to test how well data fits for the used distribution type (Ugurlu et al., 2020).

On the other hand, Bayesian networks are an alternative AI technique, which are used for investigating causal relationships between variables and, therefore, predicting outcomes or effects depending on the number of observations (Conrady, Jouffe, & Elwert, 2014). In addition, Bayesian networks have been applied in in environmental, agricultural, risk management, safety and reliability (Amrin, Zarikas, & Spitas, 2018; Zarikas et al., 2015; Zarikas, 2007; Gerstenberger, Christophersen, Buxton, & Nicol, 2015; Kabir & Papadopoulos, 2019; Marcos, Wijesiri, Vergotti, & Glória, 2018; Martos, Pacheco-torres, Ordóñez, & Jadraque-gago, 2016; Mukashema, Veldkamp, & Vrieling, 2014; Ropero, Renooij, & Gaag, 2018; Tang, Yi, Yang, & Sun, 2016). It can be used for prognostics and conducting diagnostics (Amrin et al., 2018; Bapin & Zarikas, 2014; Conrady et al., 2014). Therefore, BNs can be applied under uncertainty. This distinctive feature differs Bayesian networks from other statistical methods (Iqbal, Yin, Hao, Ilyas, & Ali, 2015; Nannapaneni, Mahadevan, & Rachuri, 2016).

Bayesian networks are utilized for calculating the posterior probabilities of events A or B. It is based on building direct acyclic graphs, which in turn allow studying causal relationships rather than just finding the associations between variables.

However, “Any complication that creates problems for one method of inference creates problems for all alternative methods of generating inference, just in different ways" – Don Rubin (interview, April 15, 2014). There are the usual problems of hidden variables, common factors/causes influencing explanatory variables and target variables or weakly identifiable parameters, sensitivity to priors and the outcome etc.

Nevertheless, the advances of BNs include (i) inference of individual causal effects, (ii) integration with decision theory, (iii) suitability for post-treatment variables, sequential treatments and spatial and temporal data, (iv) modern BNs include learning and Conditional Probability Tables (CPTs) are filled automatically from data.

For building the Bayesian network from data, the nodes and edges are created, whereas nodes represent variables and edges show the relationships between these nodes. Let P(A) be the prior probability distribution of a random variable A and assume that P(B) is the prior probability distribution of a set of random variables or a dataset B. Based on the Bayesian theorem, the posterior probability is calculated by this formula:

$$P(A|B) = P(B|A) \cdot P(A)/P(B) \quad (1)$$

If the value of $P(A|B)$ is maximized by the model structure, then the relative Bayesian structure is chosen. Bayesian networks allow choosing the structure from two learning techniques (i.e. unsupervised and supervised). The unsupervised learning method has no target variable, whereas with the supervised learning method it is important to choose a target variable. For this, a target variable is a parent node, whereas child nodes are connected with “causal” relationships. Further, the supervised learning procedure can be used by creating naïve model (Figure 1(a)). Another model is called augmented naïve model (Figure 1(b)), which can be applied to a small set of data. The higher precision and accuracy are added by creating new causal relationships (Montgomery & Runger, 2014).

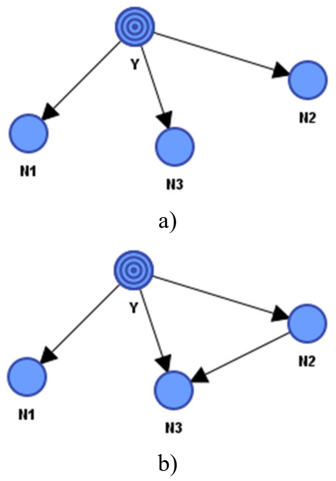

Figure 1: A simplistic naïve and augmented naïve models (Y – target node; N1, N2, N3 – child nodes): a) naïve model; b) augmented naïve model.

Bayesian networks provide pre-assumptions (Ducher et al., 2013; Zong et al., 2016). It means that the prediction is based on preliminarily provided evidence. Another issue with missing data can be solved by an automatic imputation in the network. For a missing value, implemented modern BNs use an estimated probability of having this missing datum according to other factors, which depend on it. The data is updated, which in turn means that the calculated coefficients in the network are not frozen (Ducher et al., 2013). It could be also be stated that new probabilities of the event depending on evidences are also calculated. As an example for traffic accident severity, Bayesian networks can be used to identify factors associated with the severity of injury (i.e. killed or seriously injured) by inference (Mujalli et al., 2011).

1.1 Accidents Example

Vertical transportation devices are widely used both for personal and professional purposes. Accidents may happen by violating safety rules. Accidents regarding cranes (Im & Park, 2020; Mccann, 2003; Raviv, Fishbain, & Shapira, 2017; Shin, 2015; Swuste, 2013; Swuste et al., 2020) or escalators (Almeida, Hirzel, Patrão, Fong, & Dütschke, 2012; Chi, Chang, & Tsou, 2006; Neil, Steele, Huisingh, & Smith, 2008; Xing, Dissanayake, Lu, Long, & Lou, 2019) are vastly discussed. However, there is a limited number of research works regarding elevator accidents. Elevator accidents take place during the installation or operation stages (Göksenli & Eryürek, 2009; Zarikas et al., 2013). For that, the EU has published EN 81-80 issuing 74 dangerous occasions and prevention proactive measures with elevator fatalities (Zarikas et al., 2013). Nevertheless, these safety rules may be ignored. It is vital, therefore, to investigate the causality and reasons behind elevator accidents. More than 160 thousand people died from accidents around the world in 2016, from which France took an all high of 4.6 percent. One example of these heavy accidents that occurred was in Paris:

- An elevator accident happened in 2011 during the maintenance job in an apartment block. An elevator fell down to workers. Three people were injured and another worker was dead (Warren, 2011).

In current studies, elevator accidents in France, Zarikas, 2020, ("Elevator accidents France", Mendeley Data, V1, doi: 10.17632/sstxdjj32h.1) will be studied and investigated to find causal relationships between factors (i.e. explanatory factors such as the characteristics of an injured person or the date and place of an accident). The violation of safety rules based on EN 80-81 will be also studied by the execution of two modelling techniques: the ordinal regression and supervised learning methods.

In further sections, data collection method and data arrangement will be represented. Two statistical models will be shortly presented. The use of the ordinal regression model will be discussed shortly for reasons behind its application. The prediction model based on Bayesian networks will also discussed regarding the use of supervised learning. In sections 3 and 4, results and discussion of results will be presented and discussed. In section 5, conclusions and recommendations will be given at the end based on the analysis of using both statistical methods to prevent elevator accidents.

2 METHODOLOGY

At an initial stage, a considerable amount of time was spent to collect data regarding elevator accidents from hospitals, health and safety organizations. The provided data from these organizations was not fully representative for elevator accidents. Due to this fact, most data provided by governmental data sources, for several reasons, was insufficient for current data analysis:

- Reporting system was only valuable to provide information on all accident types for categories such as "falls", "slips" and etc.;
- Data regarding elevator accidents was lack of information such as the characteristics of injured people or accident type;

- Information on accidents for each year was insufficient due to the gap in data collection (i.e. only officially registered cases were in the system).

Consequently, data concerning elevator accidents was extracted from EU Open Data Portal. It has been proven that it was a reliable source for several research works (Ugurlu et al., 2020; Gutierrez-osorio & Pedraza, 2019; Juana-espinosa & Luj, 2020). For France, data was collected for the period of 18th February, 2003 to 17th December, 2009. As a case, only accidents related for the last 6 years were studied in the current analysis due to fact that:

- most data regarding the earlier years was found to be unreliable and incomplete;
- most data regarding recent years was not collected due to the lack of resources for the reasons stated previously.

Regardless of the limited resources in current data collection, more than 200 cases were collected in Excel sheet including the information on date and places of an accident, the characteristics of an elevator accident (accident type, the type of fault), details about injured people (the severity of an injury, gender and age), the description of violated rules for each accident. It should be noted that an individual information on each accident type and of an injured person was collected with an overall number of violated safety rules separately. The sample size was considered to be sufficient for the purpose of the current research (Haghighattalab, Chen, Fan, & Mohammadi, 2019; Zarikas et al., 2013).

2.1 Data Arrangement

Table 1 shows the representation of data regarding elevator accident in France for 2003-2009. The resulting table has provided information on characteristics of an injured person including the ones with the unknown gender and age of certain injured group of people:

- Date (year and month);
- Place;
- Sum of injured;
- Gender and age of an injured person (i.e. including unknown people);
- Accident type;
- Fault type;
- Severity of injury;
- Safety rules/regulations violated (i.e. an overall summary and a separate file with rules).

Table 1: Parameters and their possible states.

Parameter	Possible states
Date	Year and month of elevator accidents: 2003 - 2009
Place	i.e. 28 cities: Angres, Avignon, Bordeaux, Brest, Dijon, Dunkirk, Grinoble, Le Havre, Lille, Limoges, Lyon, Marseille, Metz, Mulhouse, Nancy, Nanterre, Nantes, Nice, Paris, Reims, Rennes, Roubaix, Saint-Dennis, Saint-Pierre, Strasbourge, Toulon, Toulouse, Versailles
Sum of injured	The overall number of injured people
Gender	The gender of an injured person: Female: F Male: M Unknown: U (i.e. for a group of people)
Age	The gender of an injured person: Young aged (1-12): C12 Teenagers (13-18): Ad18 Middle aged (19-59): A59 Seniors (aged) (60-85): SA60 Unknown aged: UNV
Accident type	Professional: PRO Private: PRI
Fault type	Types of elevator faulties: doors, electrocution, falls, fire, floor, general, landing, machinery, power, repair, speeding, sudden stops, vandalism
Severity of injury	Light: 1 or A Heavy: 2 or B Fatal: 3 or C Light/Heavy:4 or AB Light/Fatal: 5 or AC Heavy/Fatal: 6 or BC
Safety rules	Rules related to installing, repairing, modernizing and maintaining lifts: IRMM Rules related to risks and hazardous situations: RHS Rules related to safety tips for passengers: STP

2.2 A Statistical Approach

The main objective of the current work is to investigate the possible links between factors presented in Table 1 using two statistical approaches and, as a case, identify those variables, which contribute most to the violation of safety rules. For this, two models were constructed for carrying out the statistical analysis in IBM SPSS Statistics 23 and BayesiaLab 2020. For model A, an ordinal regression model was used. Model B was constructed by following the rules of supervised learning.

The descriptive statistics was executed to obtain the first summary on the data set checking the distributions (Perez & Exposito, 2009). Frequency and correlation tables were built for variables in Table 1 to have a preliminary look on data and draw conclusions based on this information. Some of those results will be presented on the next section.

Model A was constructed to identify associations between one dependent and several independent variables. The first step was to choose a certain variable, which should be ordinal in nature. In fact, the severity of injury was labelled as a dependent variable to investigate on the effect of other variables contributing to it. Next, several predictors, which contributed to the location of the model, were selected. It is worth noting that for this type of the analysis it is uncertain what predictors should be considered first. For the start, all possible contributors were added into the model and, if not useful, then they were excluded and the model was estimated again. For this, all independent variables or, differently, predictors, were included such as gender, age, accident type, rules violated, fault type. An initial analysis was implemented without covariates to see if the location-only model was sufficient to draw conclusions. For many cases, the location-only model is adequate. However, scale variables (e.g. year and month of an accident) could also be included, if summary data is inadequate from the location-only model. It was decided to add a scale variable (i.e. individually) such as year and month or sum of injured to investigate possible associations. The basic approach was to include all of those variables and subtract from the analysis, if no correlation was found related to dependent variables. The next step was to choose the link function between complementary log-log or Cauchit or even logit based on graphical representation of the dependent variable. For this, complementary log-log and logit functions are mostly similar. The choice of the link function for elevator accidents in France will be explained in further sections.

The next step was to evaluate the model itself and, furthermore, to describe the statistics. Model fitting information was constructed, whereas the log-likelihoods could be interpreted as chi-square statistics. Finally, it gives information if the presented model gives a significant improvement over the intercept model. The significance level should be less than 0.05. Therefore, chi-square-based statistics shows how strong these relationships could be between factors (Wood, 2005). It is very useful type of statistics for the analysis of very few categorical variables. Next, pseudo R-squared statistics was implemented by measures such of Cox&Snell, Nagelkerke and McFadden, which represented how good the model fits based on the proportion of the variance. Based on this, if R-squared is high, then the appropriate measure should be chosen. In the final step, parameter estimates were obtained for the dependent variable versus predictors. Results and conclusions on ordinal regression model for each country will be presented in sections 3 and 4.

For model B a prediction model was built using supervised learning. Causal relationships or possible associations between a target variable and independent variables was found by building Bayesian networks using supervised learning. A supervised learning technique was used in order to find relationships between the severity of injury as a target variable and the rest of predictors. For this purpose, a target variable was chosen as discrete. In order to define the learning set, no test set has been considered because the presented data was sufficient for the preliminary analysis. All variables have been defined as discrete except the sum of injured which was stated as continuous. Next, the discretization method was chosen to be “Tree” for a continuous variable. After, mutual information of arcs was analyzed between a target variable and each predictor in order to find which nodes added most information to the presented model. The main objective of such an analysis was to decide on a final network structure, so that Naïve and Augmented Naïve models were constructed. Network performance based on a target analysis was investigated to calculate the precision and reliability of each model. The next step was to run the structural coefficient analysis and, if it was necessary, to adjust the structural coefficient and rerun the model. The last step was to identify causal relationships by finding the inference between a target variable and predictors. For that, an adaptive questionnaire was also included into the model. The chosen model and results related to this from supervised learning will be presented in next sections.

3 RESULTS

In this section, models A and B were built separately due to the difference in associations between explanatory factors. Only the selected results from the number of derived ones will be presented in order to concentrate on important outcomes.

3.1 Model A Outcomes

Firstly, a quick statistical analysis has been executed related to elevator accidents consisting of 205 cases in France. Therefore, Tables 2 – 10 represent preliminary obtained results from descriptive statistics based on frequencies regarding data with categories on the overall number of injured people and relevant safety rules, which have been violated. Based on this statistical analysis, several outcomes are as follows:

- Related to Table 2, the highest number of elevator accidents took place in 2007, 2008 and 2006 (with 36, 35 and 30 cases respectively).
- In Table 3, from the distribution it can be said that accidents happened frequently in January with 23 cases. The most frequent accidents occurred in June with 25 cases. Also, 20 cases took place in February and September.
- As for Table 4, it can be seen that mostly elevator accidents have occurred in Dunkirk with 12 cases, Angres, Marseille and Toulouse with 11 cases and, lastly, Versailles with 10 cases.
- More females (i.e. appx. 42 percent) have been injured than males (i.e. almost 35 percent) based on Table 5.
- Regarding the accident distribution over age categories in Table 6, mostly adults from 19 to 59 or A59 have been injured (i.e. 42 percent), whereas the least percentage was noticed in the case of young adults from 12 to 18 and the undefined age group.
- In Table 7, injuries from the private use were prevalent (53.7 percent) than the ones used for professional purposes (46.3 percent).
- As for the severity of injury in Table 8, fatal injuries defined as “C” were likely to happen (with 41.5 percent) compared to light or heavy injuries. However, it is worth noting that heavy injuries have taken 35.1 percent.
- Related to fault types as shown in Table 9, unexpected accidents related to elevators occurred with floor leveling problems (i.e. 13.2 percent) or with doors openings (i.e. 11.2 percent) and lift speeding (10.7 percent) based on Table 9.
- As for the violated rules in Table 10, safety measures have been violated regarding the cases of IRMM and IRMM/RHS with 30.2 percent each.

Table 2: The distribution over year of the accident.

Year	Frequency	Percent	Cumulative percent
2003	28	13.7	13.7
2004	21	10.2	23.9
2005	27	13.2	37.1
2006	30	14.6	51.7
2007	36	17.6	69.3
2008	35	17.1	86.3
2009	28	13.7	100.0
Total	205	100.0	

Table 3: The distribution over month of the accident.

Month	Frequency	Percent	Cumulative percent
January	23	11.2	11.2
February	20	9.8	21.0
March	19	9.3	30.2
April	15	7.3	37.6
May	16	7.8	45.4
June	25	12.2	57.6
July	13	6.3	63.9
August	12	5.9	69.8
September	20	9.8	79.5
October	15	7.3	86.8
November	12	5.9	92.7
December	15	7.3	100.0
Total	205	100.0	

Table 4: The distribution over place of the accident.

Place	Frequency	Percent	Cumulative percent
Angres	11	5.4	5.4
Avignon	7	3.4	8.8
Bordeaux	9	4.4	13.2
Brest	7	3.4	16.6
Dijon	4	2.0	18.5
Dunkirk	12	5.9	24.4
Grenoble	6	2.9	27.3
Le Havre	8	3.9	31.2
Lille	4	2.0	33.2
Limoges	6	2.9	36.1
Lyon	7	3.4	39.5
Marseille	11	5.4	44.9
Metz	6	2.9	47.8
Mulhouse	7	3.4	51.2
Nancy	8	3.9	55.1
Nanterre	8	3.9	59.0
Nantes	6	2.9	62.0
Nice	3	1.5	63.4
Paris	8	3.9	67.3
Reims	5	2.4	69.8
Rennes	8	3.9	73.7

Table 4: The distribution over place of the accident (cont.).

Place	Frequency	Percent	Cumulative percent
Roubaix	7	3.4	77.1
Saint-Denis	9	4.4	81.5
Saint-Pierre	4	2.0	83.4
Strasbourge	7	3.4	86.8
Toulon	6	2.9	89.8
Toulouse	11	5.4	95.1
Versailles	10	4.9	100.0
Total	205	100.0	

Table 5: The distribution over gender of an injured person.

Gender	Frequency	Percent	Cumulative percent
F	87	42.4	42.4
M	71	34.6	77.1
U	47	22.9	100.0
Total	205	100.0	

Table 6: The distribution over age of the accident.

Age	Frequency	Percent	Cumulative percent
A59	86	42.0	42.0
Ad18	11	5.4	47.3
C12	12	5.9	53.2
SA60	45	22.0	75.1
UNV	51	24.9	100.0
Total	205	100.0	

Table 7: The distribution over the type of the accident.

Accident type	Frequency	Percent	Cumulative percent
PRI	110	53.7	53.7
PRO	95	46.3	100.0
Total	205	100.0	

Table 8: The distribution over the severity of an injury.

Severity of injury	Frequency	Percent	Cumulative percent
AB	22	10.7	10.7
ABC	2	1.0	11.7
AC	24	11.7	23.4
B	72	35.1	58.5
C	85	41.5	100.0
Total	205	100.0	

Next, Tables 11 - 13 represent the outcomes from the execution of an ordinal regression model.
Regarding model A, the best model has been found to be with “severity of injury” as a dependent variable, “sum of injured people” as a scale covariate and predictor variables such as “gender” and “age”.

Table 9: The distribution over the type of fault.

Fault type	Frequency	Percent	Cumulative percent
Doors	23	11.2	11.2
Electro-cution	10	4.9	16.1
Falls	16	7.8	23.9
Fire	14	6.8	30.7
Floor	27	13.2	43.9
General	18	8.8	52.7
Landing	10	4.9	57.6
Machinery	14	6.8	64.4
Power	13	6.3	70.7
Repair	19	9.3	80.0
Speeding	22	10.7	90.7
Steps	7	3.4	94.1
Sudden stops	6	2.9	97.1
Vandalism	6	2.9	100.0
Total	205	100.0	

Table 10: The distribution over safety rules.

Safety rules	Frequency	Percent	Cumulative percent
IRMM	62	30.2	30.2
IRMM/RHS	62	30.2	60.5
IRMM/STP	31	15.1	75.6
RHS	28	13.7	89.3
RHS/STP	9	4.4	93.7
STP	13	6.3	100.0
Total	205	100.0	

Accident type has no effect on the dependent variable, assuming that only two categories exist. No missing data has been detected. The choice of a link function - logit (i.e. it is similar to log-log function).

Firstly, from the Goodness-of-Fit model it is concluded that the presented data is consistent. As in Table 11, it is shown from the model fitting information that the final model outperforms the intercept-only model (i.e. a significance level is less than 0.05). The next step was to verify if the chosen link functions was reliable. In Table 12, three pseudo R-squared values have been represented, whereas Nagelkerke’s is the best with the value of 0.643. The test of parallel lines shows that our model rejects the null hypothesis (i.e. a significance level is higher than 0.05).

Returning to parameter estimates in Table 13, it is seen that a significance level is high for [SOI = 2] with the negative estimate and [SOI = 6] with the positive estimate in relation with the severity of injury. A significance level for [SOI=4] is equal to 0.023, which states that it is lower than 0.05 contributing to the model. [SOI=3] has no effect on the model, which exceeds 0.05. As for the location, [Gender.category = F] is in the higher position of severity of injury with respect to the reference category [Gender.category = U]. The category [Gender.category = M] is in the lower position of severity of injury with respect to the reference category [Gender.category = U].

As for age categories, [Age.category = A59] has a negative associations with the severity of injury with the highest significance level. As for [Age.category = SA60], it is located in the lower position compared to [Age.category = C12], however showing the highest association with the dependent variable with respect to the reference category [Age.category = UNV]. [Age.category = A18] has the lowest level of association regarding the severity of injury with respect to the reference category [Age.category = UNV]. Sum of injured is a covariate.

Table 11: Model A fitting information.

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	275.942			
Final	92.237	183.705	7	.000

Link function: Logit.

Table 12: Model A pseudo R-squared.

Cox and Snell	.592
Nagelkerke	.643
McFadden	.353

Link function: Logit.

Table 13: Model A parameter estimates.

	Estimate	Sig.
Threshold		
[SOI.cat = 2]	-4.640	.000
[SOI.cat = 3]	-.358	.705
[SOI.cat = 4]	2.097	.023
[SOI.cat = 6]	5.596	.000
Location		
SumofInjured	.892	.012
[Gender.category=F]	-2.245	.010
	Estimate	Sig.
[Gender.category=M]	-2.110	.013
[Gender.category=U]	0^a	.
[Age.category=A59]	-3.286	.001
[Age.category=Ad18]	-2.355	.028
[Age.category=C12]	-3.040	.006
[Age.category=SA60]	-3.286	.001
[Age.category=UNV]	0^a	.

Link function: Logit.
a. This parameter is set to zero because it is redundant.

3.2 Model B Outcomes

For model B, the Bayesian network was constructed. To investigate causal relationships between the severity of injury and other predictors, a simple statistical model was built using the supervised learning method. As it has been noted down before, supervised learning methods need a target variable. For the current analysis, it is important to find factors which affect most to the severity of injury and which rules are mostly violated depending on those factors.

Before the start of the initial analysis a dataset with variables (i.e. a .csv file) was imported to the Bayesian network. All variables were considered to be continuous. The variable “Month” in Table 2 has not been used due to the insufficient input to the overall model. The violation of rules IRMM, RHS and STP has been included from the separate file.

The first step was to identify causal relationships between variables. Figure 2(a,b) illustrates naïve and augmented naïve models in case of elevator accidents in France. It can be noted that the violated rules were presented separately and derived from the overall rule types of IRMM, RHS and STP. From Figure 2(b), it is seen that new causal relationships have occurred between categories:

- “1,4,2i” and “Gender.category”;
- “1,1,3” and “Age.category”;
- “Fault.category” and “Accident.category”;
- “Accident.category” and several violated rules of “1,1,2”, “1,3,1h”, “1,4,1a”, “1,4,1c”, “1,4,2d”, “1,4,2h”, “1,5,3”, “2,4,4” and “3,5,1”.

The next step was to choose the model type. The final model choice was augmented naïve model explained by higher precision and accuracy (Table 14). Through running the structural coefficient analysis, the value of 0.1 was chosen to increase the precision of the presented model. The most reliable network was augmented naïve model with structural coefficient with the value of 0.1. From Table 14, it is clear that the precision has increased from approximately 87 percent using naïve model to almost 95 percent using augmented naïve model. Overall log –loss value is equal to 0.1282 with R of 0.9652, which indicates a higher accuracy regarding the future validation of the model.

After choosing the right network, inferential analysis has been implemented. In Figure 3, mutual information with the severity of injury as a target node is presented. From the initial investigation, it is clear that the sum of injured has the strongest effect on the severity of injury with the amount of mutual information of 0.7552. Certain variables have the amount of mutual information higher than 0.5 such as “Age.category” and “Gender.category”, which have higher contribution to the model. Next, the mutual information shared with a target node between the values of 0.2 to 0.5 is identified by categorical variables such as “Fault.category” with the value of 0.1550 and “Place.category” with the value of 0.4092. The contribution to the model with the value of 0.02 to 0.10 is added by the main predictor “Year” and violated rules such as “1,3,2”, “1,1,1c” and “1,4,2g” as shown in Figure 4.

Table 14: Precision of the model.

Model:	Naïve (SC=1)	Augmented Naïve (SC=0.1)
Overall Precision	86.8293%	95.1220%
Mean Precision	93.0098%	97.4771%
Overall Reliability	86.7843%	95.1296%
Mean Reliability	92.4860%	96.7967%
Overall Relative Gini Index	91.1203%	98.9249%
Mean Relative Gini Index	95.2681%	99.3890%
Overall Relative Lift Index	96.1551%	99.5718%
Mean Relative Lift Index	97.9070%	99.7768%
Overall ROC Index	95.5679%	99.4702%
Mean ROC Index	97.6655%	99.7259%
Overall Calibration Index	83.3532%	78.7967%
Mean Calibration Index	77.7412%	84.9008%
Overall Log-Loss	0.3357	0.1282
Mean Binary Log-Loss	0.1343	0.0513
R	0.9426	0.9652
R2	0.8886	0.9315

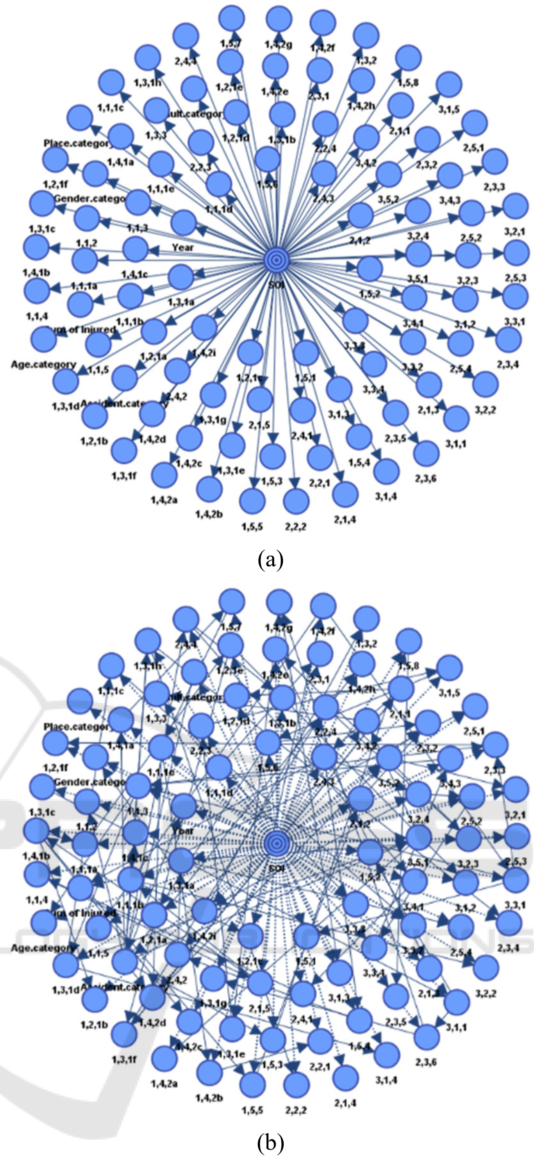

Figure 2: Naïve and augmented naïve models for elevator accidents in France: a) SC = 1 and b) SC = 0.1.

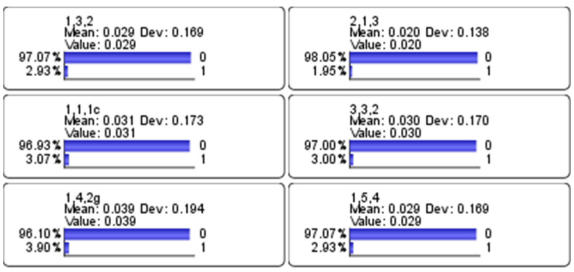

Figure 3: Mutual information with the target node for elevator accidents in France.

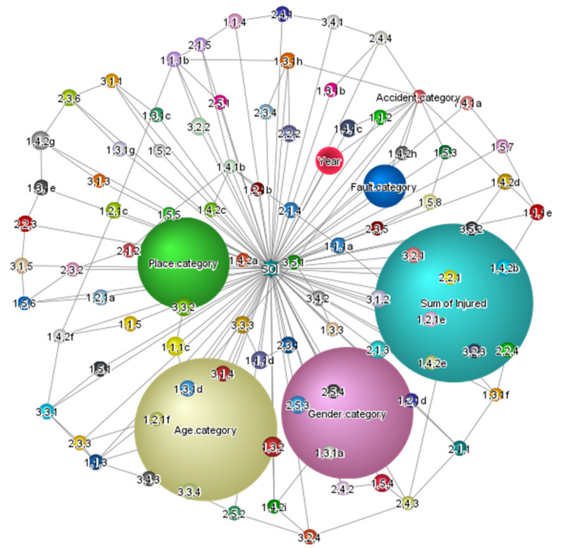

Figure 4: Prior probabilities based on target correlations with an adaptive questionnaire.

4 DISCUSSIONS

Based on the implementation of both statistical and graphical approaches, the current study has concentrated on finding the causal relationships between variables. These outcomes are based on a limited set of data. It is explained by the fact that reports for occupational injuries are rarely submitted. Preliminarily, the severity of injury was chosen as a target variable. Descriptive statistics has given initial insight on the frequency of data, which was found to be important to study the inconsistencies. An ordinal regression model was used to study the likelihood of the event.

From those results, elevators accidents in France may have an upward trend. Nevertheless, the limitation of this trend is that provided data concerns only a limited number of reports. As the case, those injured people from elevator accidents, presumably, tend to ignore providing reports for light or heavy injuries. Further, elevator accidents took place in summer and winter periods in France. The safety rules were violated due to low technical support and maintenance measures. Elevator accidents occurred in well-known cities such as Marseille, Toulouse and Versailles. As for the characteristics of an injured person, more female users were injured than male users. It can be explained by the fact that most injuries were due to: problems with floor leveling or elevator doors. Further, mostly adults were injured in elevator accidents. By building Bayesian network model based on a supervised learning, it has been found that mostly safety rules in Figure 3 have been broken related to

- providing lift workers with necessary safety information;
- the working process with the machinery;
- providing technicians with safety rules in the machine room.

The outcomes from model A using an ordinal regression model have shown a high precision based on the test of parallel lines and goodness-of-fit in Table 11. Strong correlations have been found between gender and age of an injured person. The only limitation of an ordinal regression model was that the range (i.e. size) of data and the missing values in data could affect the outcomes of the accident analysis (Eboli et al., 2020; Ropero et al., 2018; Wu, Hou, Wen, Liu, & Wu, 2019). It is also explained by the fact that more independent variables related to the type of accident should have been included to the model in order to find the relationships between the severity of injury and the number of violated safety rules.

Model B has outperformed the regression model for several reasons: pre-assumptions are not necessary, an automatic missing data imputation is available and new evidences can be included during execution. Bayesian network model is valuable to study both quantitative and qualitative data (Ugurlu et al., 2020; Juned & Bouwer, 2014; Zhou, Diew, Shan, & Fai, 2018). It can also be noted that the missing values can be handled by the missing value imputation during the analysis (Ducher et al., 2013). By building Bayesian network model, it is possible to study data with adding new cases and calculating further probabilities. It is done by providing new evidences to data and the dependency on the severity of injury will be shown regarding the strength of mutual information shared between variables. These characteristics differ Bayesian network from other statistical models (Zong et al., 2016). However, the limitation is that a sufficient amount of data should be added in order to spot the inconsistencies in data and study the reasons for unforeseen accidents behind its occurrence.

5 CONCLUSIONS

In this study, two modelling approaches have been used. The above-presented outcomes have brought important insights on elevator accidents. The chosen explanatory factors that affect the severity of injury have been studied. The Bayesian network model has been found to be useful for studying accident data for making predictions. The precision of utilizing Bayesian network is higher than that of the ordinal regression model. The conventional statistics is a valuable tool to observe the correlations between factors. Further, these results could be useful at the beginning of building the efficient strategy to prevent accidents. The limitation of current studies is the lack of explanatory variables. Further studies are suggested to them into the model to study the effect of these factors on injury severity.

In summary, this work epitomizes a good practise of use for safety analysis. It is not correct to rely on a single tool for causal analysis (Pearl, 2019). Anyway, causal analysis still needs further theoretical development and integration of a combination of experimental as well observational data together with a stronger mathematical framework, which is still under investigation. A framework, that as Judea Pearl says, should mathematically encapsulate the fact that symptoms are not causes of diseases. If data via different methods can derive similar "causal" effects from different sets of assumptions, then this is very encouraging and supportive. However, if results from different methodologies contradict each other, this is useful also to know. The usage of background expert knowledge is necessary in this case to disentangle the discrepancies. This is a precept for everyone wants to design a meaningful AI expert model.

As a future work we need to improve these preliminarily results taking into account a larger dataset and utilizing Rubin's causal model called the Potential Outcomes Framework, (Rubin, 2005) to verify inferences.

REFERENCES

Alkheder, S., Alrukaibi, F., & Aiash, A., 2020. Risk analysis of traffic accidents' severities: An application of three data mining models. *ISA Transactions*, ARTICLE IN PRESS.

Almeida, A. De, Hirzel, S., Patrão, C., Fong, J., & Dütschke, E., 2012. Energy-efficient elevators and escalators in Europe: An analysis of energy efficiency potentials and policy measures. *Energy & Buildings*, *47*, 151–158.

Amrin, A., Zarikas, V., & Spitas, C., 2018. Reliability analysis and functional design using Bayesian networks generated automatically by an "Idea Algebra" framework. *Reliability Engineering and System Safety*, *180* (July), 211–225.

Bapin, Y., & Zarikas, V., 2014. Probabilistic Method for Estimation of Spinning Reserves in Multi-connected Power Systems with Bayesian Network-based Rescheduling Algorithm, *ICAART 2019,* 840–849.

Chen, F., Chou, S., & Lu, T., 2013. Scenario analysis of the new energy policy for Taiwan's electricity sector until 2025. *Energy Policy*, *61*, 162–171.

Chi, C., Chang, T., & Tsou, C., 2006. In-depth investigation of escalator riding accidents in heavy capacity MRT stations. *Accident Analysis and Prevention, 38*, 662–670.

Conrady, S., Jouffe, L., & Elwert, F., 2014. *Causality for Policy Assessment and Impact Analysis - Directed Acyclic Graphs and Bayesian Networks for Causal Identification and Estimation*.

Cummings, P., Mcknight, B., & Weiss, N. S., 2003. Matched-pair cohort methods in traffic crash research. *Accident Analysis and Prevention, 35*, 131–141.

Person-interviewed, Don Rubin (2014, April 15). Retrieved from https://rb.gy/bhm0wl

Ducher, M., Kalbacher, E., Combarnous, F., Vilaine, J. F. De, Mcgregor, B., Fouque, D., & Fauvel, J. P., 2013. Comparison of a Bayesian Network with a Logistic Regression Model to Forecast IgA Nephropathy. *BioMed Research International, 2013.*

Eboli, L., Forciniti, C., Mazzulla, G., 2020. Factors influencing accident severity: an analysis by road accident type. *Transportation Research Procedia*, *47*, 449–456.

Fountas, G., Ch, P., & Mannering, F. L., 2018. Analytic Methods in Accident Research Analysis of vehicle accident-injury severities: A comparison of segment-versus accident-based latent class ordered probit models with class-probability functions. *Analytic Methods in Accident Research*, *18*, 15–32.

Gerstenberger, M. C., Christophersen, A., Buxton, R., & Nicol, A., 2015. Bi-directional risk assessment in carbon capture and storage with Bayesian Networks. *International Journal of Greenhouse Gas Control*, *35*, 150–159.

Göksenli, A., & Eryürek, I. B., 2009. Failure analysis of an elevator drive shaft. *Engineering Failure Analysis*, *16*(4), 1011–1019.

Gregoriades A. and Christodoulides A. (2017). Traffic Accidents Analysis using Self-Organizing Maps. *19th International Conference on Enterprise Information Systems* - Volume 1: pages 452-459.

Gutierrez-osorio, C. & Pedraza C., 2019. Modern data sources and techniques for analysis and forecast of road accidents : A review. *Journal of Traffic and Transportation Engineering, 7*(4), 432-446.

Haghighattalab, S., Chen, A., Fan, Y., & Mohammadi, R., 2019. Engineering ethics within accident analysis models. *Accident Analysis and Prevention*, *129*(May), 119–125.

Im, S., & Park, D., 2020. Crane safety standards : Problem analysis and safety assurance planning. *Safety Science*, *127*(February), 104686.

Iqbal, K., Yin, X., Hao, H., Ilyas, Q. M., & Ali, H., 2015. An Overview of Bayesian Network Applications in Uncertain Domains. *International Journal of Computer Theory and Engineering*, *7*(6).

Juana-espinosa, S. De, & Luj, S., 2020. Open government data portals in the European Union: A dataset from

2015 to 2017. *Data in Brief, 29*.

Juned, M., & Bouwer, I., 2014. Human fatigue' s effect on the risk of maritime groundings – A Bayesian Network modelling approach. *Safety Science*, *62*, 427–440.

Kabir, S., & Papadopoulos, Y., 2019. Applications of Bayesian networks and Petri nets in safety, reliability and risk assessments: A review. *Safety Science*, *115*(April 2018), 154–175.

Marcos, D., Wijesiri, B., Vergotti, M., & Glória, E., 2018. Ecotoxicology and Environmental Safety Assessing mercury pollution in Amazon River. *Ecotoxicology and Environmental Safety*, *166*(June), 354–358.

Martos, A., Pacheco-torres, R., Ordóñez, J., & Jadraque-gago, E., 2016. Towards successful environmental performance of sustainable cities: Intervening sectors. A review. *Renewable and Sustainable Energy Reviews*, *57*, 479–495.

Mccann, M., 2003. Deaths in construction related to personnel lifts, 1992 – 1999. *Journal of Safety Research, 34*, 507-514.

Michalaki, P., & Quddus, M. A., 2015. Exploring the factors affecting motorway accident severity in England. *Journal of Safety Research, 55*, 89–97.

Montgomery, D. C., & Runger, G. C., 2014. *Applied Statistics and Probability for Engineers* (6th ed.). Wiley.

Mujalli, R. O., Calvo, F. J., & O, J. De., 2011. Analysis of traffic accident injury severity on Spanish rural highways using Bayesian networks. *Accident Analysis and Prevention*, *43*(1), 402–411.

Mukashema, A., Veldkamp, A., & Vrieling, A., 2014. Automated high resolution mapping of coffee in Rwanda using an expert Bayesian network. *International Journal of Applied Earth Observations and Geoinformation*, *33*, 331–340.

Nannapaneni, S., Mahadevan, S., & Rachuri, S., 2016. Performance evaluation of a manufacturing process under uncertainty using Bayesian networks. *Journal of Cleaner Production*, *113*, 947–959.

Neil, J. O., Steele, G. K., Huisingh, C., & Smith, G. A., 2008. Escalator-related injuries among older adults in the United States, 1991 – 2005. *Accident Analysis and Prevention, 40*, 527–533.

Perez, S., & Exposito, M., 2009. *Descriptive statistics*, *37*(6), 314–320.

Pearl, J., 2019. The seven tools of causal inference, with reflections on machine learning. Communication of the ACM, 62 (3), pp. 54-60.

Raviv, G., Fishbain, B., & Shapira, A., 2017. Analyzing risk factors in crane-related near-miss and accident reports. *Safety Science*, *91*, 192–205.

Ropero, R. F., Renooij, S., & Gaag, L. C. Van Der., 2018. Discretizing environmental data for learning Bayesian-network classifiers. *Ecological Modelling*, *368*, 391–403.

Rubin, Donald (2005). "Causal Inference Using Potential Outcomes". *J. Amer. Statist. Assoc.* 100 (469): 322–331.

Shao, B., Hu, Z., Liu, Q., Chen, S., & He, W., 2019. Fatal accident patterns of building construction activities in China. *Safety Science, 111*(September 2017), 253–263.

Shin, I. J., 2015. Factors that affect safety of tower crane installation / dismantling in construction industry. *Safety Science*, *72*, 379–390.

Swuste, P., 2013. A "normal accident" with a tower crane? An accident analysis conducted by the Dutch Safety Board. *Safety Science*, *57*, 276–282.

Swuste, P., Groeneweg, J., Gulijk, C. Van, Zwaard, W., Lemkowitz, S., & Oostendorp, Y., 2020. The future of safety science. *Safety Science*, *125*(February), 104593.

Tang, C., Yi, Y., Yang, Z., & Sun, J., 2016. Risk analysis of emergent water pollution accidents based on a Bayesian Network. *Journal of Environmental Management*, *165*, 199–205.

Ugurlu F., Yildiz S., Boran, M., Ugurlu O. & Wang, J., 2020. Analysis of fishing vessel accidents with Bayesian network and Chi-square methods, *Ocean Engineering, 198* (August 2019), 1-13.

Warren, M. (2011, November 25). Elevator drop kills one man, injures three. Retrieved October 27, 2020, from https://www.thelocal.fr/20111125/1864

Wood, G. R. (2005). Confidence and prediction intervals for generalised linear accident models, *37*, 267–273.

Wu, X., Hou, L., Wen, Y., Liu, W., & Wu, Z., 2019. Research on the relationship between causal factors and consequences of incidents. *Journal of Loss Prevention in the Process Industries*, *61*(July), 287–297.

Xing, Y., Dissanayake, S., Lu, J., Long, S., & Lou, Y., 2019. An analysis of escalator-related injuries in metro stations in China , 2013 – 2015. *Accident Analysis and Prevention*, *122*(October 2017), 332–341.

Zarikas, V., Loupis, M., Papanikolaou, N., & Kyritsi, C., 2013. Statistical survey of elevator accidents in Greece. *Safety Science*, *59*, 93–103.

Zarikas, V., E. Papageorgiou, and P. Regner., 2015. "Bayesian Network Construction using a Fuzzy Rule Based Approach for Medical Decision Support." Expert Systems 32 (3): 344-369.

Zarikas, V., 2007. "Modeling Decisions Under Uncertainty in Adaptive User Interfaces." Universal Access in the Information Society 6 (1): 87-101.

Zarikas, Vasilios (2020), "Elevator accidents France", Mendeley Data, V1, doi: 10.17632/sstxdjj32h.1

Zhou, Q., Diew, Y., Shan, H., & Fai, K., 2018. A fuzzy and Bayesian network CREAM model for human reliability analysis – The case of tanker shipping. *Safety Science*, *105*(February), 149–157.

Zong, F., Xu, H., & Zhang, H., 2013. Prediction for Traffic Accident Severity: Comparing Bayesian Network and Regression Models. *Mathematical Problems in Engineering.*