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Research Note

Modeling Truck Accident Severity on Two-Lane Rural Highways

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Truck accidents are an issue of concern due to their severity. Logit modeling and Neural Network modeling are performed to investigate factors such as vehicle, roadway, environment and driver characteristics that can potentially contribute to the severity of truck accidents. The objective of this study is to present models that can predict the severity of truck accidents and to identify the important factors causing these accidents. Comparison between neural networks and logit modeling are made using vehicle crash data on two-lane rural highways in Iran. A variety of variables related to roadways, vehicles, environment and drivers, such as, driver fatigue, head-on collision and lack of vehicle control, are found to have a significant bearing on the severity of truck accidents. Also, investigating the marginal effects of variables showed the same variables to be significant. The results of the comparison between the logit and neural network model indicated that they both show similar patterns regarding the effects of different variables causing truck accidents, with the logit model providing better results.

INTRODUCTION

The impact that traffic accidents have on society is significant. The individuals injured or the families of those killed in traffic accidents must deal with pain and suffering, medical costs, wage loss, higher insurance premium rates and vehicle repair costs. For society as a whole, traffic accidents result in enormous costs in terms of loss of productivity and property damage. Clearly, efforts to improve our understanding of factors that influence accident severity are warranted. Although there have been numerous research efforts to understand traffic accident severity, the relationships between risk factors and accident severity are still not completely understood. One of the major reasons for this is that the causes leading to accident severity levels are always complicated by the presence of multiple factors, including characteristics of the individual (e.g., gender, age and use of restraint systems), the vehicle (e.g., vehicle type), the environment (e.g., weather conditions), the roadway (e.g., geometric designs) and etc. (e.g., collision types). Safety issues relating to large trucks have been of considerable importance to highway engineers, policy makers and the general public. Large trucks have many unique operational characteristics such as high gross weight, longer vehicle length and poor stopping distance, which have an impact on accident severity. Overall, accidents involving trucks have an increased risk of producing a severe injury or fatality, due to car/truck size disparity and other factors. Although there has been an abundance of previous research studies on truck safety, there have been comparatively few studies concentrating on factors contributing to the causes of truck accidents. The objective of this research is to identify the important factors contributing to the occurrence of truck accidents, using logit and neural network modeling.

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LITERATURE REVIEW

Previous research on accident severity has been diverse, both empirically and methodologically. From an empirical standpoint, numerous research studies have focused on the casualty of accidents and attempted to isolate the risk factors that have contributed to truck accident severity [1-3]. Also, a number of studies have attempted to identify driver characteristics (e.g., age and gender) that may influence accident severity [4-6].

From a methodological standpoint, a variety of statistical approaches have been applied to study accident severity [6-10].

Many of these analysis methods are applied using aggregate data. The disadvantage of using aggregate data is that it can result in a loss of information on the relationships between accident severity and contributing factors. Disaggregate data include, not only the capability of testing a broad range of factors that influence accident severity, but also, the capability of capturing powerful disaggregate information about how individual factors influence accident severity. One commonly used disaggregate model is logistic regression, as applied by Jones et al. [11] and Lui et al. [12]. In addition, O'Donnell et al. [13] estimated an ordered logit model and an ordered probit model to identify risk factors that increase the probability of serious injury and death. Shanker et al. [14] applied a multinomial logit model to analyze single-vehicle motorcycle accident severity.

Most of the research studies that specifically examine accident characteristics have focused on safety issues for truck configurations [15-18]. Braver et al. [19] examined the accident involvement rates for different truck configurations (e.g., singles and doubles) to identify whether one configuration is significantly safer than the other. Jovanis et al. [20] statistically compared the accident involvement rates for motor vehicle accidents to identify whether large trucks have higher fatality and/or injury rates than other types of vehicle. Campbell [21] addressed the issue of a minimum age for drivers of large trucks by comparing the fatal accident involvement rates against driver age. Another study by Khasnabis et al. [22] used a time series analysis to forecast truck accidents. Saccomanno et al. [23] used generalized log-linear models and Miao [24] applied Poisson and negative binomial regression models to explore the relationships between truck accident occurrence and highway geometric designs and other factors (e.g., traffic characteristics).

Although most of the research dealing with the analysis of large trucks has focused on the occurrence of truck accidents, there have been relatively few studies that have concentrated on the severity of accidents involving trucks. In one of these, Golob et al. [25] statistically compared the mean number of injuries and fatalities by collision type and the number of involved vehicles for truck-involved freeway accidents. Alassar [26] used a log-linear modeling approach to examine the accident severity of truck-involved accidents and identified the contributing factors (e.g., collision types and road class) for fatal and injury accidents. Finally, Chira-Chavala et al. [27] applied logit models to study the four types of factor, with great effect, on truck accident severity. They found that collisions with passenger cars, collisions on dry surface roads at night and collisions on undivided rural roads usually resulted in higher fatality and injury ratios. Nukoolkit et al. used a neural network to investigate the effect of different variables on accident severity to identify dangerous accident patterns [28].

METHODOLOGY

Injury severity in truck-involved crashes relates to a variety of factors. The nature of single vehicle crashes indicates that the set of factors affecting severity may be very different from those of the crashes involving multiple vehicles. The severity of a single-vehicle accident, for example, a run-off the road accident, is related to what the vehicle and the driver experience outside the roadway. In multiple vehicle collisions, severity is highly related to the type of collision, size/weight ratio of impacting vehicles and points of contact, etc. In this study, multiple vehicle collisions that involve trucks are studied. Logit models and Neural Network Modeling are estimated to identify the set of factors that affect the severity of multiple truck-involved accidents. Additionally, the models are used to provide a numeric relationship between the factors and the marginal probability of a fatal or injury accident, given that the crash has occurred.

ACCIDENT DATA

In this analysis, the 1996-1998 accident data on 10 undivided two-lane rural highways in Iran with a total length of 836 kilometers was analyzed. The data is obtained from Accident Report forms that are collected by the Highway Patrol Police at accident scenes. The accident records contain a broad range of information. Although it would be desirable to have information about the number of highway segments and total accidents per segment, the original data do not provide such information. It should be noted that lack of this information does not affect the modeling process since there is no need to identify the factors contributing to the severity of truck accidents in such detail. The total reported number of accidents that occurred on two-lane rural roads during 1996-1998 was 19353, out of which were 3524 accidents that involved trucks and 2961 were multiple vehicle accidents (i.e., trucks involved in accidents with other vehicles). Of the 2961 accidents, 2486 (84%) cases were property damage only accidents. 446 (15%) cases were injury and 29 (1%) cases were fatality accidents.

Although it is more appropriate to group accident severity into different categories, such as fatal, injury type A, injury type B, etc., severity data are grouped into only two categories of injury/fatality and property damage only accidents. This is done to insure a sufficient number of observations for estimation purposes since the percentage of fatal accidents is low.

After screening out the records for incomplete information, 62 cases of accident data were omitted, resulting in a database of 2899 accident cases for this analysis. Of this data, 2434 (84%) are property damage only and 465 cases (16%) are injury/fatality accident data.

MODELING

Logit Modeling

Logit structures are one of the common models for the study of decision-making, based on increasing utility consideration constraint. In logical models, people are assumed to behave logically and make the most desirable selections. The assumption of being logical is based on certain fixed functions, but, because individuals may not be aware of all the parameters of utility functions, a random factor is used to show and analyze desire. It is assumed that individuals, by assessing and selecting from competing choices, maximize their utility functions [29]. However, all aspects of the utility function cannot be observed or measured. In practice, the utility function, U_i, has two parts, the measurable part, V_i, and the random error part, E_i, such that [30]:

$$U_i = V_i + E_i. \tag{1}$$

The definite part of the desirability function depends on the properties of the choice, economic and social characteristics of the person deciding and E_i, the error part, is used for parameters that cannot be observed.

Using the random desirability function, the selection of one choice among a collection of choices follows this probability:

$$p_i = p\lfloor U_i > U_j, \forall_j \neq i \rfloor, \tag{2}$$

In the above equation, p_i is the probability of choosing "i". By knowing the error distribution of i, the probability of choosing i can be defined. If part of i error has an independent distribution and is of the Gumble type, then, it can be shown that:

$$p_i = \frac{\exp(V_i)}{\sum_j^A \exp(V_j)}, \tag{3}$$

where P_i is the probability of choosing i from the collection of choices, (A), and V_i is the defined part of the function. V_i is usually shown as:

$$V_i = \alpha_i + \beta_{1i} X_{1i} + \beta_{2i} X_{2i}, \tag{4}$$

where:

V_i	utility that can be measured (for choice i),
$\mathcal{X}_{ji}$	jth property of choice i,
α_i	constant part of function (for choice i)
β_{ji}	jth property weight of choice i.

The results of the logit model evaluation contain the following indicators:

$L(0)$ = Log likelihood function when all the coefficients are zero, meaning that each alternative has an equal likelihood of being chosen,

$L(c)$ = Log likelihood function for only the constant terms in the utility function, which is equal to the market share of each alternative studied,

$L(\beta)$ = Log likelihood function at convergence (estimated parameters),

$\rho_c^2 = 1 \quad \frac{L(\beta)}{L(c)}$ = Explanatory power of the model when compared with the market share of each alternative. It is a measure of goodness of fit,

$\rho^2 = 1 \quad \frac{L(\beta)}{L(o)}$ = Explanatory power of the model compared with the case in which no information is available, meaning each alternative is equally likely to be chosen.

It is always assumed that in logit models the choices are independent of each other, so that the property of selecting one choice is independent of the existence of other choices. Logit models are suitable for situations when the objective is to predict the occurrence or non-occurrence of a variable among different variables. It is used to estimate probabilities for binary data or discrete ordinal data. In this study, two severity classes of property damage only and fatal/injury accidents are used. A logistic regression was applied using SPSS (Statistical Package for Social Scientists) [31]. The logistic regression can predict the presence or absence of a characteristic or outcome (i.e., fatal/injury or property damage only), based on the values of a set of predicting variables.

The formulation of the logit model is as follows:

$$P_{\text{FIA}} = \frac{e^{V_{\text{FIA}}}}{e^{V_{\text{FIA}}} + e^{V_{\text{PDA}}}}, \tag{5}$$

$$P_{\text{PDA}} = \frac{e^{V_{\text{PDA}}}}{e^{V_{\text{FIA}}} + e^{V_{\text{PDA}}}}, \tag{6}$$

$$P_{\text{FIA}} = \frac{1}{1 + e^{V_{\text{PDA}} \quad V_{\text{FIA}}}}, \tag{7}$$

$$P_{\text{PDA}} = 1 \quad P_{\text{FIA}}, \tag{8}$$

where:

P_{FIA}	the probability that an injury or fatal accident will occur,
P_{PDA}	the probability that a property damage only accident will occur.

With this definition, the variables with a negative sign show an increase in accident severity and variables with a positive sign show a decrease in accident severity in an injury/fatality function.

To identify the independent variables, first, the correlation coefficients between them are examined and some of the variables with high correlations are omitted in order to minimize the problem of multicolinearity. Then, based on the significance of each variable and values of $L(\beta)$ for the model, the final variables are selected. Of the 75 different variables which were originally examined, 25 are finally selected, which are significant, with 95% confidence, and which are shown in Table 1. The correct percentages of the model for predicted versus observed values are shown in Table 2. In this table, zero value indicates fatal/injury accidents and the value of 1 indicates property damage only accidents. As shown for the case of injury/fatality accidents, the model correctly predicated 103 cases (22.2%) of all injury/fatality accidents. For the case of property damage only, the model prediction was not correct in only 61 cases.

The results from estimated model coefficients, as presented in Table 1, in the "roadway characteristic" category, curve radius and longitudinal grade indicators with values of -0.679 and -0.698, respectively, show that, with an increase in their values, the severity of truck accidents increases. This may be as a result of restricted sight distance at highway curves and the difficulty of maneuvering, excessive speeds on the downgrade and lack of ability to brake. However, the positive value of the lane width indicator (i.e., 0.453) shows that in two-lane highways with lane width less than 7.4 meters (both directions), truck accidents are less severe, due to lateral restriction, which causes them to travel at lower speed.

In the "temporal characteristic" category, the negative value of the night time indicator (i.e., -0.479) shows that truck accidents are more severe at night.

In the "environmental characteristic" category, negative values of the dry road surface indicator (i.e.,-0.480) and the wet road surface indicator (i.e., -0.801) show that although both types of pavement condition have an effect on the severity of truck accidents, the severity increases for wet surfaces. This may be a result of the hydroplaning phenomenon, causing the truck to skid.

In the "driver characteristic" category, all indicators have negative values, ranging from -0.624 for lack of truck driver attention to -2.282 for driver fatigue, which was the major cause of severe truck accidents.

The defect in the truck braking system with a negative value (i.e., -0.769) and, also, eroded tires with a negative value of -0.500 in the "vehicle characteristic" category show that they both have an effect on the severity of truck accidents.

In the "accident characteristic" category, the indicator values ranged from -1.9818 for lack of vehicle control to +1.548 for side-end collision. In this category, lack of vehicle control, head-on collision and exceeding the speed limit caused severe truck accidents, while side-end accidents are not so severe.

Neural Network Modeling

Artificial neural network applications have recently received considerable attention. The methodology of modeling or estimation is somewhat comparable to statistical modeling [32]. A typical neural network is composed of input units, $X_1, X_2, \ldots$, corresponding to independent variables (in our case, accident characteristics), a hidden layer known as the first layer and an output layer (second layer), whose output units, $Y_1, Y_2, \ldots$, correspond to dependent variables (severity of accidents).

Hidden units of $H_1, H_2, \ldots$ correspond to intermediate variables. These interact by means of weight matrices, $W(1)$ and $W(2)$, with adjustable weights. The values of hidden units are:

$$H_j = f\left(\sum\nolimits_k W_{jk}^{(1)} X_k\right). \tag{9}$$

One multiplies the first weight matrix by the input vector $X = (X_1, X_2, \ldots)$ and, then, applies an activation function, f, to each component of the result. Likewise, the values of the output units are obtained by applying the second weight matrix to the vector $H = (H_1, H_2, \ldots)$ of hidden unit values and, then, applying activation function f to each component of the result. In this way, one obtains an output vector, $Y = (Y_1, Y_2, \ldots)$:

$$Y_i = f\left(\sum\nolimits_j W_{ij}^{(2)} H_j\right). \tag{10}$$

The activation function, f, is typically of sigmoid form and may be a logistic function, hyperbolic tangent, etc. Usually, the activation function is assumed to be the same for all components but it is not necessary. Values of $W(1)$ and $W(2)$ are assumed at the initial iteration. An interactive learning process improves the accuracy of the estimated output. In this process, the outputs for various input vectors are compared with targets and an average error term, E, is computed:

$$E = \frac{\sum_{n=1}^{N} \quad Y^{(n)} \quad T^{(n)}\big)^2}{N}, \tag{11}$$

where:

N	number of observations,
$Y(n)$	estimated value for $n = 1, 2, \ldots, N$,
$T(n)$	observed value for $n = 1, 2, \ldots, N$.

After one pass through all observations (the training set), a gradient descent method may be used to calculate the improved weight values, $W(1)$ and $W(2)$, that make E smaller. After re-evaluation of the weights with the gradient descent method, successive passes can be made and the weights further adjusted until the error is reduced to a satisfactory level. The computation, thus,

Table 1. Estimated model coefficients.

Characteristics	Estimated Coefficient	Sig.
Roadway		
Curve Indicator (CI) (1 if accident occurred on horizontal curve, 0 otherwise)	-0.679	0.000
Grade Indicator (GI) (1 if accident occurred on grade, 0 otherwise)	-0.698	0.028
Lane Width Indicator (LWI) (1 if lane width less than 7.4 (m), 0 otherwise)	0.453	0.001
Temporal		
Night Time Indicator (NTI) (1 if accident occurred at night time, 0 otherwise)	-0.479	0.000
Environmental		
Dry Road Surface Indicator (DRSI) (1 if accident occurred on a dry roadway surface, 0 otherwise)	-0.480	0.001
Wet Road Surface Indicator (WRSI) (1 if accident occurred on a wet roadway surface, 0 otherwise)	-0.801	0.000
Snowy Weather Indicator (SWI) (1 if accident occurred in snowy weather, 0 otherwise)	1.116	0.017
Driver		
Driver Education Indicator (DEI) (1 if driver was not educated, 0 otherwise)	-0.632	0.000
Driver Fatigue Indicator (DFI) (1 if driver was sleepy and tired, 0 otherwise)	-2.282	0.000
Driver attendance to driving laws indicator (DAI) (1 if driver did not attend, 0 otherwise)	-0.624	0.013
Driver Controlling Indicator (DCI) (1 if driver was in hurry, 0 otherwise)	-0.874	0.001
Driver Fault Indicator (DFAI) (1 if driver did fault on purpose, 0 otherwise)	-1.022	0.009
Vehicle		
Defect in brake system indicator (DBI) (1 if vehicle had defect, 0 otherwise)	-0.769	0.059
Eroded Tire Indicator ETI (1 if tires were eroded, 0 otherwise)	-0.500	0.002
Accident		
Head On Indicator (HOI) (1 if the collision type was head-on, 0 otherwise)	-1.147	0.000
Side End Indicator (SEI) (1 if the collision type was side end, 0 otherwise)	1.548	0.011
Side to Side Indicator (SSI) (1 if the collision type was side to side, 0 otherwise)	0.809	0.000
Following too Closely Indicator (FCI) (1 if following too closely was the cause, 0 otherwise)	0.534	0.022
Right of Way Indicator (RWI) (1 if not paying attention, 0 otherwise)	-0.554	0.001
Vehicle Control Indicator (VCI) (1 if not able to control the vehicle was the cause, 0 otherwise)	-1.9818	0.000
Exceeding Speed Limit Indicator (ESLI) (1 if exceeding speed limit was the cause, 0 otherwise)	-0.9485	0.028
Encroaching left lane while passing (LLEI1) (1 if encroachment was the cause, 0 otherwise)	-0.9472	0.000
Encroaching left lane (LLEI2) (1 if encroachment was the cause, 0 otherwise)	-0.7599	0.000
Wrong turning maneuver (TMI) (1 if wrong turning maneuver was the cause, 0 otherwise)	-0.8540	0.045
Driving with rear gear (RGI) (1 if rear gear driving was the cause, 0 otherwise)	1.1725	0.007
Constant	3.668	0.000

Variable	**Value**	**Variable**	**Value**
N = No. of observation	2899	$L(c)$	-1276.52
$L(O)$	-2009.433	ρ^2	0.48157
$L(\beta)$	-1041.744	ρ_c^2	0.18392

Table 2. Percentage correctly predicted by the final model.

Observations	Predicted		
	0.00	1.00	Percentage of correct prediction
0.00 (injury/fatal)	103	362	22.20
1.00 (property damage only)	61	2373	97.5
Total percentage of correct prediction by the model			85.4

Table 3. Percentage of correct prediction in the training set of neural network model.

Observations	Predicted		
	0.25	0.75	Percentage correct
0.75 (injury/fatal)	352	90	20.03
0.25 (property damage only)	2286	71	96.2
Total percentage of correct prediction by the model			84.8

Table 4. Percentage of correct prediction in the testing (unseen) set.

Observations	Predicted		
	0.25	0.75	Percentage correct
0.75	18	5	21.7
0.25	73	4	94.8
Total percentage of correct prediction by the model			78.68

has two modes, the mapping mode, in which outputs are computed and the learning mode, in which weights are adjusted to minimize E. Although the method may not necessarily converge to a global minimum, it generally gets quite close to unity if an adequate number of hidden units are employed.

As mentioned in logit modeling, two severity classes are used. For comparison purposes, the same variables are used in neural network modeling. The objective is to present an effective and efficient neural network prediction model, which automatically predicts either the injury/fatality or property damage only outcome, when a crash takes place. The accuracy of the prediction model plays an important role in detecting dangerous accident patterns. There are a total of 2799 training records and 100 testing records (unseen set) for neural network evaluation. The unseen set are the data which are not trained by the model. For representation to the network (training set), 0.75 is introduced for fatal/injury accidents and 0.25 is introduced for property damage only accidents. The obtained numeric, Y, (Accident Severity Index) will be in the range of [0,1], where a value greater than 0.5 implies that the outcome of a crash will be likely more toward injury/fatality than the property damage only accident. In the proposed approach, the network was trained with the popular gradient-base back-propagation algorithm. The network consists of 25 input nodes, 14 hidden nodes, and one output node. The input and output nodes have a linear activation function and hidden nodes have a sigmoid function. The learning process ends when pre-defined prediction accuracy is met. Then, the performance of the trained network is measured by applying unseen testing data to the network. The results are shown in Tables 3 and 4.

As shown in Table 3, for the training set, the model only predicts 90 cases of injury/fatality correctly. For the case of property damage, it predicts 2286 cases out of the total of 2357 cases correctly. In Table 4, for the unseen set (100 cases), the model predicts 5 out of 23 cases of injury/fatality accidents and 73 out of 77 cases of property damage only correctly.

Marginal Effect

The coefficients of the logit model do not provide the marginal effects of the independent variables. That is, one cannot determine the effect of an injury/fatality of a unit change in independent variables from the model coefficients alone. In order to compute the marginal change in the probability of an injury/fatality accident, a value of zero or 1 is assigned to each variable, while the value of other variables is kept at their mean values [33]. The same procedure is used to compute the marginal effect of each independent variable in the neural network modeling. Table 5 shows the marginal

Table 5. Marginal effect of variable in logit and neural network modeling.

Variable	Neural Network	Logit Function
CI	0.02779	0.08264
GI	0.01103	0.08861
LWI	-0.01491	-0.04352
NTI	0.02535	0.05154
DRSI	0.01818	0.04713
WRSI	0.24398	0.10082
SWI	-0.02165	-0.07361
DEI	0.02198	0.07516
DFI	0.04950	0.43355
DAI	0.00425	0.06109
DCI	0.01047	0.09774
DFAI	0.02313	0.14457
DBI	0.01590	0.10044
ETI	0.02328	0.04435
HOI	0.06186	0.16086
SEI	-0.02696	-0.08997
SSI	-0.02178	-0.06806
FCI	-0.01402	-0.04542
RWI	0.01304	0.06365
VCI	0.06108	0.35903
ESLI	0.01694	0.13208
LLEI1	0.04356	0.12240
LLEI2	0.01366	0.09354
TMI	0.04031	0.11483
RGI	-0.02367	-0.07973

effects of each variable in both logit and neural network models. Comparison between marginal effects shows that each variable has a similar sign (i.e., "+" or "-") in the two models, meaning that the models have the same predicting patterns.

Driver fatigue has the largest marginal effect on the severity of truck accidents, with a value of 0.443 for the logit model and 0.049 for the network model. Lack of vehicle control, with a marginal effect of 0.359 for logit and 0.061 for the neural network, and head on accidents, with a value of 0.160 for logit and 0.061 for the neural network, were observed. The lowest marginal effect was observed for driving while backing up, with the values of -0.079 for the logit model and -0.023 for the neural network.

CONCLUSION

The models show that driver fatigue has the highest effect on the severity of truck accidents. Also, lack of vehicle control is one of the major causes of truck accidents. Of the different types of accident, head on accidents had the highest severity. Not obeying traffic laws was the fourth major cause of accident severity. Exceeding the speed limit and reencroaching onto the left lane while passing were the following causes of severity in truck accidents.

It also indicates that longitudinal highway grades, driving at night and wet road surfaces increase the possibility of severe accidents. Also, drivers with a low education level, defects in the brake system, eroded tires, not respecting other drivers' right of way and the use of wrong turning maneuvers are important factors in accident severity. Variables such as snowy weather, side end accidents, narrow lane width and following too closely do not prove to be effective on accident severity.

The main policy implications are that there is a potential for constructing rest areas that reduces the severity of truck accidents, which may also have a positive effect on the lack of vehicle control resulting from driver fatigue. To reduce the number and severity of head on accidents, it is recommended to separate opposing traffic directions through the use of a median. A greater presence of traffic law enforcement officials on the highways and strict law enforcement can also be effective in reducing the severity of truck accidents.

The marginal effects of different variables on the logit and neural network model indicate that both models show the same pattern of change in value and sign for each variable.

The models validation, based on percentages of correct results, as shown in Tables 2 and 4, indicates that logit modeling provides a higher percentage of correct prediction.

In neural network modeling, the individual relations between the input and output variables are not developed by engineering judgments, so that the model tends to be a black box on the input/output table without analytical basis. As mentioned in computing the marginal effects, the effect of each variable (sign and value) on accident severity is computed, which is a new application of neural network modeling.

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