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Modeling crash frequencies by transportation mode using micro/macro level variables

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ABSTRACT: In this study, traffic and geometric factors affecting accidents occurring in road segments are investigated across different transportation modes (vehicle, motorcycle, and pedestrian) using micro and macro levels variables simultaneously while accounting for the effect of intra-zone correlation due to the same independent variables for accidents occurring within a zone. The data relating to 14903 accidents that had occurred in 96 Traffic Analysis Zones (TAZ) in Tehran were collected and imported into Geographic Information System (GIS) application. Negative Binomial models and multilevel models were adopted to predict the number of traffic accidents. Due to considering the multilevel structure of the data in multilevel models, it showed a better performance in explaining the factors affecting accidents. Moreover, based on the results obtained from analyzing the sensitivity analysis of variables for final models, the effect size of one variable in accidents varies across different modes of transport. This discloses the necessity of investigating accidents across modes of transport. According to the results, variables like the high intensity of intersection in one TAZ and the length of the road segment increase the number of traffic accidents in all three modes of transport. Variable of the ratio of the principal arterial length to total roads available in one zone has almost 3.2 times stronger effect on motorcycle accident than vehicle and pedestrian accidents. So that adding 1 unit to this variable increases the number of vehicle and pedestrian accidents by a factor of 1.7, whereas, this variable increases motorcycle accidents by a weight of 5.4.

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1- Introduction

One of the main concerns of transportation engineers is safety. In 2016, 19.9 people out of each 100000 have died of accidents in Iran; while the same statistic for the same year is 5.1 people in Europe [1,2]. However, a lot of investigations in different aspect of transportation was done. As regards, by considering the mentioned statistics, the necessity of carrying out more research especially in the developing country seems unavoidable.

Since effective factors and the extent of their impact on accidents, across diverse transportation facilities and modes are different, it is essential to consider separate investigations on the accidents of each facility and mode. The studies done over recent years have mostly addressed accidents of all modes together or have considered only a single-mode (vehicle, motorcycle, pedestrian) [3]. This has led to an inaccurate understanding of the factors affecting accidents since one factor might increase accidents in one mode while decreasing them in the other. Therefore, the significance of reaching an accurate understanding of the factors leading to accidents necessitates a separate investigation of accidents across different transportation facilities and modes.

On the other hand, most of the previous studies on transportation safety have investigated the effect of micro level factors on traffic accidents which are related to variables such as the road width or the road lighting quality. Most of them are carried out at the operation time of transport facilities and based on the data related to the accidents which have previously occurred. Then based on the obtained results some engineering solutions are proposed [4]. On the macro level factors, some studies have recently investigated the factors affecting accidents at this level. These factors, like economic and demographic variables, have been considered at different geographical levels like regions [5], Traffic Analysis Zones (TAZ) [6], and census tracts [7]. The development of accident prediction models based on macro level variables has increased the amount of attention paid to safety in studies related to road network planning. These models result in the enhancement of safety in the areas under study before the operation of transportation facilities. To do a comprehensive investigation, both micro level and macro level factors need

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to be attended to simultaneously. Mitra and Washington investigated the effect of variables at the micro and macro level on the number of accidents, through comparing the models developed based on traffic parameters and the models developed based on all variables, the researchers found out that the omission of macro variables can significantly increase the effect of other factors like Annual Average Daily Traffic (AADT) [8]. That's why a limited number of studies have recently addressed the factors affecting accidents while considering the factors at both micro and macro levels simultaneously [9]. Hence in this study, the effect of variables at the micro and macro level on accident in the road segment by different modes (vehicle, motorcycle, and pedestrian) is investigated.

Since in the present study macro variables are extracted at the level of TAZs, these variables are the same for the accidents that have occurred at the road segments available in one zone. Therefore, the present study has adopted a multilevel model for investigating the amount of intra-TAZ correlation resulted from similar macro variables. Multilevel models are more suitable for sets of data which are multilevel and in which low-level data are nested in higher-level data [10]. So in this study, the data are categorized into two levels. The first level accommodated the micro variables related to each accident that occurred in a road segment and the second level included the macro variables related to TAZs. The two-level structure of the data using in this study is shown in Fig.1

Base on what was discussed, three aims of this study can be summarized as follows: firstly, investigating the traffic and geometric variables affecting accidents on road segments across different modes (vehicle, motorcycle, and pedestrian) and surveying the amount of their effect at various modes. Secondly, considering the factors affecting accidents at both micro and macro levels simultaneously and finally, measuring the intra-zone correlation effect using a multilevel model.

Therefore, the next section reviews the related researches in this regard. Then, Section 3 addresses the data collection and Section 4 explains the methodology of the study. Next, the results obtained from the final models are presented and, in the end, the conclusion of the present study is given.

2- Literature review

Finding a suitable method of analysis and selecting influential independent variables are two factors that affect the development of safety models. In the past years, researchers have proposed numerous methods such as negative binomial [11,12], Poisson regression model [13,14], zero-inflation [15], multivariate [16-18], finite mixture/latent class [19], multilevel [20-22] to develop accident prediction models using different variables. The details and assessments of crash frequency models are presented in review papers by [23,24].

The accident prediction models are mostly developed using micro level variables [25-27]. These studies have helped determine solutions for decreasing the number of accidents in different transport facilities like intersections or road segments. On the other hand, prediction models using macro level variables have been developed in recent years. These variables include traffic data like road length with different functional classification in a zone [28] and trip generation and trip distribution of TAZ [29], environmental conditions like land-use specifications [30,31], and socioeconomic factors like household income [32]. The results of these researches have led to the consideration of safety indices in road network planning.

Lee et al. had developed series crash intersection models base on macro variables from seven geographic units. The results imply that medium size geographic units display a good performance for intersection crash models [9].

Cai et al. investigated the influence of macro level variables at the level of TAZs on pedestrians and cyclists' accidents using Dual-State models [33]. In their study, they were also trying to measure the influence of the neighboring zones on the accidents of one zone. According to their results, some factors like population density, employment rate, and the number of public transport users in one TAZ increase the number of accidents. Moreover, the influence of adjacent zones on the accidents of one zone turned out to be significant and Dual-State models, especially the Zero-Inflated Negative Binomial model, showed a better performance in comparison to single-state models.

To reach an accurate understanding of the factors affecting accidents, it seems necessary to consider suitable variables at both micro and macro levels simultaneously and develop appropriate models. Guo et al. developed accident prediction models for signalized intersections based on variables at micro and macro levels. Based on the results of this study, the researchers found that at the corridor level, Poisson models have a better performance in comparison to other models [34].

Huang et al. developed accident prediction models at micro and macro levels and compared the performance of these models in predicting hot zones [35]. The authors developed, accident prediction models for TAZs using macro level variables, and for intersections and road segments using micro level variables. The results indicated that models have a better performance at the micro level and present a better picture of the micro variables affecting traffic accidents. Whereas, for investigating safety at TAZs, using accident models at the macro level is more fruitful because detailed data are less needed here.

In this study, the variables are considered at both micro and macro levels. Since the macro variables available for the accidents which have occurred in one TAZ are the same, the structure of data in this study is multilevel. The data which consider the correlation among observations and inter-group independence and in which lower-level data are nested in the higher level is regarded as multilevel data. When accident data is multilevel, using multilevel models, which consider the intra-group correlation of accident data, is useful [10]. Detailed information about multilevel data and the adoption of multilevel models could be found in [36].

Huang and Abdel-Aty adopted a five-level structure (geographic region level, traffic site level, traffic crash level, driver-vehicle unite level, and occupant level) as the general

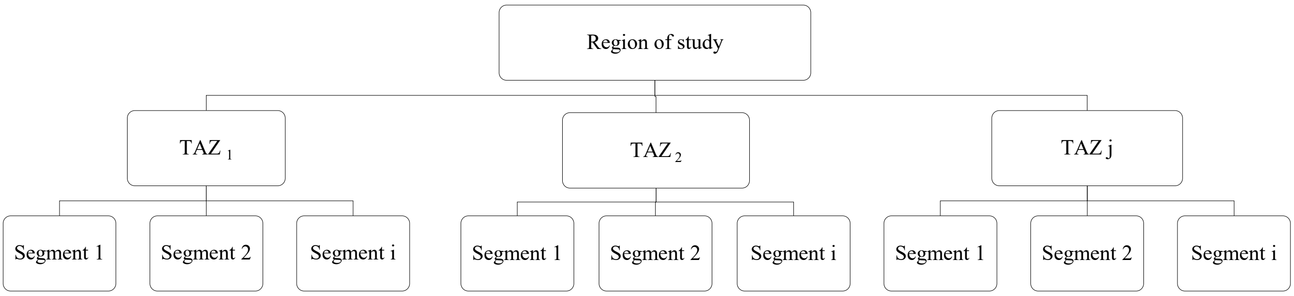

Fig. 1. The hierarchical structure of the data

structure of accident data. Macro analysis is considered based on the three high levels of geographic region level, traffic site level, and traffic crash level; and micro analysis has considered the three low levels of traffic crash level, driver-vehicle unite level and occupant level. The authors have proposed different methods for investigating multilevel data including analysis of accident data at intersections and time level [37].

Shi et al. investigated the number of highway accidents using multilevel and negative binomial models [38]. In their research, the highway was divided into 196 segments based on its geometrical specifications. The traffic data used in their study were obtained through Automotive Vehicle Identification (AVI) systems installed on the highway. Since the output data of AVI systems divided the highway into 43 segments, each AVI system represented the data related to some segments. Due to the dual-level structure of the data, a multilevel model was used for investigating traffic accidents. Based on the obtained results, the multilevel model had a better performance than the negative binomial model. Moreover, results showed, increasing some factors like the speed or the horizontal degree of curvature decrease the number of accidents.

Considering the information presented above, in this study, both micro level and macro level independent variables for the accidents which have occurred at road segments are collected across transport modes (vehicle, motorcycle, and pedestrian) so that a comprehensive investigation can be carried out. Besides, the performance of multilevel models in estimating the number of traffic accidents was evaluated as well.

3- Data Collection

In the present study, for developing accident prediction models using micro and macro variables, the data related to the accidents over the years 2014 and 2015, were collected for the west and the southwest main areas of Tehran, Iran. Therefore, in general, the data related to 14903accidents (9807 vehicle accidents, 2838 motorcycle accidents, and 2258 pedestrian accidents) which have occurred in 96 TAZs were collected. Tehran, as the capital of Iran, has 5 main areas which in total comprise 22 regions. The west and the southwest main areas are composed of regions 9, 10, 17, 18, and 19.

The accident data was obtained through the database available in Tehran Traffic Police Center. And, the traffic data was collected through Tehran Transportation and Traffic Organization and based on the results obtained from running Tehran traffic model.

After collecting the required data, all information was imported to GIS. Then the objected variables related to each accident were obtained after doing the required calculations. The macro variables used in this study have been collected at the level of TAZs. The use of TAZs is more common than other geographical levels (like census tract and country) because zone divisions are more in line with the studies related to transport planning models and their pertinent traffic variables (like trip generation and trip distribution) are more readily accessible.

The prepared independent variables are shown in fig.2 and Table 1 lists the variables used in this study at the micro and macro levels in road segments across modes of transport along with their descriptive statistics. It should be noted, road segments are considered between two intersections in arterial roads.

Since in regression models there is usually a logarithmic relation between independent variables and the response variable, using the logarithm of independent variables in the modeling process makes interpretation of the results much easier. This is also very common in previous studies [39]. Moreover, this method also decreases the variance among variables [40]. Due to the mentioned reasons, the present study uses the logarithmic conversion of the variables related to the road segment and vehicle-kilometer traveled of each road segment.

4- Methodology

Poisson model is a type of statistical model which, due to the random and non-negative and sporadic nature of accident data, has had remarkable and successful applications. One of the fundamental assumptions of this model is the equality of accidents' mean frequency and variance. To consider the over-dispersion of accident data, a negative binomial model (NB) was adopted. By adding a gamma-distributed error term to the average available in the Poisson model, this model considers the over-dispersion available in accident data and thus is preferred over the Poisson model.

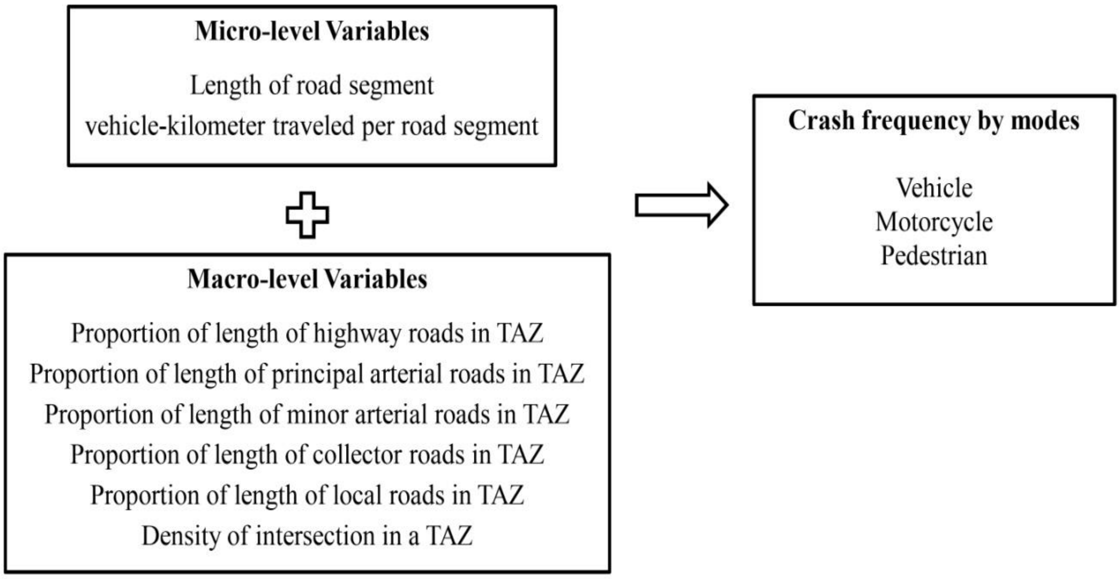

Fig. .2. Micro and macro level variables connected with crash frequency models

The formula for the negative binomial model is presented in the following equations:

$$Y_i \sim Poisson(\lambda_i) \tag{1}$$

$$Ln\lambda_i = \beta_0 + \beta X_i + \varepsilon_i \tag{2}$$

where:

- Y_i represents the crash frequency by modes at road segment i;
- λ_i shows the expectation of Yi;
- X_i indicates a vector of explanatory variables;
- β_0 is the intercept;
- β is a vector of estimable parameters;
- ε_i represents the error term which is considered to be independent X and has a two-parameter gamma distribution.

One of the main assumptions in NB models is the independence of observations. However, it is hardly possible in practice to consider accidents independent from one another. For instance, the accidents occurring in one area might have unobserved common factors [23]. To enhance accident models for road segments and to consider the correlation among accidents occurring in one zone due to their common macro variables, the present model adopted a multilevel model.

The general equation for the single-level model or the frequently-used simple regression model is as follows:

$$y_i = \beta_0 + \beta_1 X_{1i} + e_i \tag{3}$$

In the above equation, the subscript I represents an individual respondent, y and x stand for the dependent and independent variables, respectively. There are also two fixed parameters (β_0 and β_1) that show the intercept and the slope, and a random part (e) that makes it possible to have fluctuations around the fixed part. The word “random” here means “allowed to vary”.

The micro level of the individual is the sole place where this equation is specified. For developing a multilevel model, this micro model needs to be re-specified through differentiating TAZ with the subscript j. This provides the following for the random intercept and random slope model:

$$y_{ij} = \beta_{0j} + \beta_{1j} X_{1ij} + e_{ij} \tag{4}$$

At TAZ, two macro models exist:

$$\beta_{0j} = \beta_0 + u_{0j} \tag{5}$$

$$\beta_{1j} = \beta_1 + u_{1j} \tag{6}$$

The first macro model allows for differential TAZ intercept (β_{0j}) to change from one TAZ to another around the overall intercept (β_0) through the addition of random component u_{0j}. The second macro model allows for differential slope (β_{1j}) to change around the overall slope (β_1) through the addition of random component u_{1j} [41].

Table 1. Descriptive statistics of variables

Variable	Definition	Vehicle				Motorcycle				Pedestrian			
		Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD
Count	Count of accident at road segment	1.00	277.00	69.14	69.29	1.00	33.00	11.14	8.44	1.00	35.00	9.81	8.70
Pro_Highway	Proportion of length of highway roads in TAZ	0.00	0.51	0.19	0.13	0.00	0.51	0.14	0.13	0.00	0.51	0.13	0.12
Pro_Arterial1	Proportion of length of principal arterial roads in TAZ	0.00	0.33	0.05	0.08	0.00	0.33	0.06	0.09	0.00	0.33	0.05	0.08
Pro_Arterial2	Proportion of length of minor arterial roads in TAZ	0.00	1.00	0.29	0.22	0.00	1.00	0.32	0.24	0.00	1.00	0.34	0.25
Pro_Collector	Proportion of length of collector roads in TAZ	0.00	1.00	0.45	0.18	0.00	1.00	0.45	0.20	0.00	1.00	0.43	0.21
Pro_Local	Proportion of length of local roads in TAZ	0.00	0.36	0.03	0.05	0.00	0.36	0.04	0.07	0.00	0.36	0.04	0.07
Log(S-L)	Logarithm of road segment	1.26	3.33	2.59	0.32	1.26	3.33	2.51	0.30	1.26	3.33	2.49	0.28
Log(V-K)	Logarithm of vehicle-kilometer traveled per road segment	2.25	7.66	6.32	0.75	2.43	7.61	5.96	0.70	2.41	7.61	5.91	0.71
int_density	(Number of intersections in a TAZ/area of TAZ)*10000	0.01	0.58	0.17	0.14	0.01	0.58	0.22	0.14	0.01	0.58	0.22	0.14

Once more, the micro model is regarded as an intra-TAZ equation, whereas the macro models are two between-TAZ equations where the parameters of the within the model are the responses.

It is worthy of notice that this is easily observable when the notation is used with e_{ij} as a part of the micro model as opposed to the macro model for in that case just the micro model includes both subscripts i and j, and this demonstrates a within the situation, whereas the macro model in that case just includes subscript j, which demonstrates a between situation. The completely random two-level model includes a combination of all three equations:

$$y_{ij} = \beta_0 + \beta_1 X_{1ij} + (u_{1j} X_{1ij} + u_{0j} + e_{ij}) \tag{7}$$

The best accident model for road segments in each mode of transport was chosen based on three criteria, namely log-likelihood, Akaike's Information Criterion Corrected (AICC), and Bayesian Information Criterion (BIC). What follows are the formulae for this measure:

$$AICC = 2k - 2LL(full) + \frac{2k(k+1)}{n-k-1} \tag{8}$$

$$BIC = k \ln(n) - 2LL(full) \tag{9}$$

In the above formulae k represents the number of parameters, n indicates the number of observations, and LL(full) shows the log-likelihood for the full model.

5- Results and discussion

As already mentioned, in the present study NB models and multilevel models were used for the accidents occurring in road segments within each mode of transport (vehicle, motorcycle, pedestrian), and the roles of both micro and macro variables were investigated. As it has been shown in table 2, Based on the criteria of Model Goodness of Fit (Log-Likelihood, AICC, and BIC), multilevel models show a better performance for the data with multilevel structures because they consider within-zone correlation. Table 3 lists the significant variables (p-value < 0.05) along with the coefficient of each across different modes of transport.

Considering the coefficients obtained from the final models, a higher length of the highway in one zone increases the number of vehicle and motorcycle accidents. This variable did not prove significant in pedestrian accidents. Since the traffic volume of vehicles on highways is more than that in other urban roads, the likelihood of crashes increases as well.

A higher length of principal arterial roads in one zone increases the number of accidents in all three modes of transport. This variable has a stronger effect on motorcycle accidents in comparison to other modes of transport. Since such road networks play the main role in transportation in urban road networks, any increase in such networks in one zone results in more traffic which, in turn, increases the likelihood of vehicle crashes.

As the ratio of collector roads increases in one zone, vehicle accidents decrease, while motorcycle accidents increase Considering the features of such roads, for example, less width and narrower lane, the vehicle volume of this type of roads are fewer than the highway and arterial, moreover in the region considered in this study collector road place in zones that the number of the motorcyclists is more because of cultural features. So the likelihood of accident related to vehicle and motorcycle, decrease and increase respectively.

According to the obtained results, the number of pedestrian and vehicle accidents decreases as the proportion of local roads increases. In such road networks, the speed of vehicles decreases due to their less width. Moreover, the drivers drive more carefully because of different land-use related to pedestrians on such roads. This decrease in vehicles' speeds and the increase in drivers' carefulness can be taken as some reasons decreasing the number of vehicle and pedestrian accidents on such roads.

As the road segments lengths increase, the number of accidents in all three modes of transport increase as well. As the road length increases, the number of intersections in one route decreases. Since the existence of intersections in each route decreases the speed of vehicles, as the number of intersections in one route decreases the speed of vehicles increases which can, in turn, decrease the control of the driver on the vehicle and increase the likelihood of accidents. This result is in line with the results of [35].According to the results obtained from the final models, as the vehicle-kilometer traveled in road segments increases, the number of accidents increases in all three modes of transport. Obviously, as the vehicle-kilometer traveled increases, the traffic volume of vehicles and the amount of activity in one road segment increases. Therefore, heavier traffic of different modes of transport in one road segment would naturally increase the likelihood of collision and accident.

As the density of intersection increases in one TAZ, the number of accidents occurring in road segments in that zone increase in all three modes of transport. Based on the results of previous studies, as the road network density increases in a zone, the likelihood of accidents increases as well [29, 42]. This can be due to the heavy traffic of vehicles and the increased activity in this type of zones. Moreover, the zones with a high density in the road network are always in contact with the zones that have a high density of land use. This connection can be one of the main reasons behind the accident increase in these zones [31].

5.1. Sensitivity analysis of variable

To run a quantitative comparison of the effects of different variables on the accidents occurring in road segments, the sensitivity analysis of variables obtained from the final models, is analyzed. This analysis helps easily understand how important a variable is in the accidents of each mode of transport (vehicle, motorcycle, and pedestrian). Based on equation (10) for the multi-level model, is calculated how much of the variance in the response variable for segment i in TAZ j is accounted for by one unit of change in the independent variable by sensitivity analysis.

$$y_{ij} = e^{(\beta_0 + \beta_1 X_{1ij} + \beta_2 X_{2ij} + \ldots + \beta_k X_{kij})} \tag{10}$$

The results obtained from the sensitivity analysis of variables for the final models are listed across modes of transport in Table 4.

Thus, adding 1 unit to the ratio of highway length to the total road length of one TAZ increases vehicle accidents in road segments by a factor of 4.53 (353%) and its motorcycle accidents by a factor of 1.37 (37%). Therefore, the influence of this variable on vehicle accidents is 3.3 times stronger than that of motorcycle accidents.

Regarding the variable of the ratio of the principal arterial length to total roads available in one zone, adding 1 unit to this variable puts an almost similar effect on the vehicles and pedestrians accidents and increases the number of such accidents by a factor of 1.7 (70%). Whereas, this variable increases motorcycle accidents by a weight of 5.4 (440%) which is almost 3.2 times stronger than the effect of the same variable on vehicle and pedestrian accidents. The same interpretation is also true for the other variables available in Table 4.

Table 2. The goodness of fit measures for different models

Type of Model	Multilevel			NB		
Mode of Transportation	Vehicle	Motorcycle	Pedestrian	Vehicle	Motorcycle	Pedestrian
Count of accident	9807	2838	2258	9807	2838	2258
Akaike Information Criterion Corrected (AICC)	95123.22	18409.66	14495.73	97078.74	19279.62	14859.76
Bayesian Information Criterion (BIC)	95187.92	18463.16	14547.15	97136.25	19327.17	14905.5
- Log Likelihood	47561.61	9204.83	7247.865	48539.37	9639.81	7429.88

Table 3. Models results for road segments by mode of transportation

Variable	Vehicle		Motorcycle		Pedestrian	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Intercept	-2.404	0.0	-1.504	0.0	-0.914	0.0
Pro-Highway	1.511	0.0	0.317	0.018	-	-
Pro-Arterial1	0.578	0.0	1.686	0.0	0.541	0.02
Pro-Collector	-0.228	0.0	0.383	0.0	-	-
Pro-Local	-2.091	0.0	-	-	-1.954	0.0
Log(S-L)	0.269	0.0	0.496	0.0	0.483	0.0
Log(V-K)	0.859	0.0	0.356	0.0	0.325	0.0
int-density	0.366	0.0	0.747	0.0	0.73	0.0

Table 4. Sensitivity analysis of variables for final models

Variable	dy/dx		
	Vehicle	Motorcycle	Pedestrian
Intercept	0.09	0.222	0.401
Pro-Highway	4.533	1.372	-
Pro-Arterial1	1.782	5.396	1.717
Pro-Collector	0.796	1.466	-
Pro-Local	0.124	-	0.142
Log(S-L)	1.308	1.643	1.621
Log(V-K)	2.362	1.428	1.384
int-density	1.442	2.11	2.076

Based on the results obtained from analyzing the sensitivity of the significant variables of the final models, it is observable that a variable influences the accidents in various modes of transport differently. Therefore, the necessity of investigating the factors influencing accidents across different modes of transport becomes evident.

6- Conclusion and recommendation

The present study investigated the factors affecting the accidents occurring in road segments at both micro and macro levels simultaneously and across different modes of transport (vehicle, motorcycle, pedestrian). To this end, the data related to 14903 accidents that had occurred in 96 TAZs in Tehran in 2014 and 2015 were collected. The length of the road segment and the vehicle-kilometer traveled in each segment were taken as the independent variables at the micro level. At the macro level, the ratio of road length, while considering their functional classification (highway, principal arterial, minor arterial, collector, local), to the total length of all roads of one zone and the density of intersections in one TAZ were taken as the independent variables. The traffic data used in this study were obtained by running the traffic model of Tehran. The required database was imported into GIS for modeling purposes. Considering the two-level structure of the data, a multilevel model was used for modeling. An NB model was also used for making comparisons and investigating the performance of the multilevel model. The final models were selected based on the criteria of Model Fit including log-likelihood, AICC, and BIC.

Based on the obtained results, the multilevel model has a better performance than the NB model because the former considers the within-zone

correlation resulted from the same macro variables for the accidents occurring in one TAZ. Moreover, increasing, the length of the principal arterial roads, the density of intersections in one TAZ, the length of the road segments and the vehicle-kilometer traveled of the road segment lead to more accidents in all modes of transport. Increasing the length of highways, and collector roads in one TAZ, respectively, increases and decreases the number of vehicle accidents. With regard to motorcycle accidents, both variables increase the number of accidents in this mode of transport. Also, increasing the ratio of the local roads in one TAZ decreases the number of vehicle and pedestrian accidents in road segments. Based on the results obtained from analyzing the sensitivity of the significant variables of the final models, the effect size of one variable on accidents varies in different modes of transport. For example, for one unit increase in the ratio of highway length to the total length of roads in one TAZ, the number of vehicle and motorcycle accidents increases with the factor of 4.53 and 1.37, respectively. This discloses the necessity of investigating accidents across different modes of transport.

For further research, it is recommended to investigate the other variables affecting accidents at micro and macro levels and also to investigate the accidents which have occurred in intersections across modes of transport and determine the effect size of different factors causing accidents.

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