Article

Analysis of Risk Factors Affecting Urban Truck Traffic Accident Severity in Korea

Maowei Chen ¹ , Lele Zhou ¹, Sangho Choo ² and Hyangsook Lee ^{1,*}

¹ Graduate School of Logistics, Incheon National University, Incheon 22012, Korea; muwi@inu.ac.kr (M.C.); lelezhou123@gmail.com (L.Z.)

² Department of Urban Design & Planning, Hongik University, Seoul 04066, Korea; shchoo@hongik.ac.kr

* Correspondence: hslee14@inu.ac.kr

Abstract: Due to increases in truck traffic, truck traffic safety has become an unavoidable societal issue in Korea. Truck traffic accidents were responsible for 24% of all traffic deaths in 2019, and the fatality rate was significantly higher than that of other forms of traffic. This study analyzes not only the driver and environmental factors, but also the traffic condition factors which are considered to contribute to the severity of truck traffic accidents, and presents practical truck safety solutions based on the findings. This study examines the fatal and serious injury truck traffic accidents in Incheon, which has large logistics facilities and the highest fatality rate (3.3) in Korea's capital area. According to the regression analysis results, 'Nighttime', 'Vehicle-single', 'Vehicle to Pedestrian', 'Lane violation', and 'Signal violation' contribute to the severity of truck traffic accidents. Furthermore, truck traffic accidents in the logistics influencing area are more likely to be serious than in the non-influencing area. In terms of the traffic condition factors, the number of lanes, the maximum speed, and the number of road property-changing nodes were significant. The results of this study will provide useful data for establishing traffic safety policies in urban areas.

Keywords: urban area; severity of truck traffic accident; regression analysis; traffic safety policy

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1. Introduction

Based on the Korean 'Automobile Management Act', a truck is a vehicle that has a cargo storage space suitable for transporting cargo, and the total weight of cargo in the storage space is greater than the weight of all passengers (except the driver) in the boarding space. With economic growth, the Korean freight transportation market has developed rapidly. According to the Korea Transport Database (KTDB), Korean truck registration is approximately 3.6 million (December 2019). The O/D traffic volume of trucks increased from 4.45 million in 2017 to 4.46 million in 2020, and will probably exceed 5.00 million by 2030. However, the problem of truck traffic safety has become an inevitable social issue, due to truck traffic volume increasing in urban areas. In an emergency, a truck braking is more difficult due to its huge and hefty body. Compared to other vehicle types, truck traffic accidents have a high risk of personal injury [1]. In 2019, traffic accidents caused by trucks accounted for 13% of all traffic accidents, and the proportion of deaths caused by truck traffic accidents was 24% in Korea. The fatality rate (deaths of every 100 traffic accidents) of truck traffic accidents fell from 3.6 in 2016 to 2.8 in 2019, but it was still significantly higher than that of other vehicles (bus: 1.5, passenger car: 1.0). Since Korea's traffic safety index (deaths caused by traffic accidents per 100 thousand people) was in the lower level (18th, 2019) among the 35 Organization for Economic Co-operation and Development (OECD) countries, the government of Korea is contemplating efficient policies to prevent traffic accidents (Ministry of Culture, Sports and Tourism, the Republic of Korea, 2021).

Due to the difficult driving circumstances in densely populated areas, there is considerable risk of traffic accidents. Areas with high severity of truck traffic accidents are not

only highways, but also urban areas that have large logistics facilities generating a high volume of truck traffic [2]. The majority of previous studies concentrated on the accidents that happened on the highways or at specific intersections. The objective of this study was to identify the severity factor of truck traffic accidents that happened in an urban area, and propose practical truck traffic safety policies to improve social health. Incheon, a major logistics city in Korea has large logistics facilities (airport, seaport, industrial complex), and the fatality rate of truck traffic accidents in 2019 was 3.32, the highest in Korea's capital area (Figure 1). This study analyzes the truck traffic accidents that occurred in Incheon to ensure the representativeness of the study.

Figure 1. Fatality rate of truck traffic accidents in Korea, 2019.

In this research, the factor analysis is divided into two parts: (1) using Ordinal Probit Regression to verify how temporal factors, types of accidents, road and weather conditions, and driver behaviors affect the severity of truck traffic accidents; (2) using Poisson and Negative Binomial Regression to identify how traffic condition factors affect the number of deaths and serious injuries caused by truck traffic accidents. The factors not only include the conventional items proposed in previous studies, but also contain additional aspects such as whether logistics facilities affect the severity of truck traffic accidents or not. As the importance and emergence of traffic safety issues in urban areas has increased, a comprehensive factor analysis on truck traffic accidents, such as this study, is required. The findings of this study will enable the government to implement traffic safety programs more efficiently.

2. Literature Review

Factor analysis of traffic accidents started with technical statistical analysis around 1980. Many researchers have studied the subject in various ways since then. The causes of traffic accidents are complicated, involving the interaction of a combination of factors such as the drivers, the vehicles, the weather condition, the traffic condition, and the way these interact [3]. When trucks are involved, the severity of the accident increases due to the stronger impulse [4]. In terms of driver factors, several studies presented that the decreasing of physical function makes the elder drivers react slowly in urgent situations [4,5]. However, Dong et al. [6] indicated younger drivers contribute to the frequency of truck-involved crashes. Different types of violations also show a significant influence on the truck traffic accident severity. Alcohol and illegal drugs are both dangerous behaviors and distractions such as work pressure, as well as inattention, also increase a

driver's injury level significantly [7]. Rezapur and Ksaibati [8] applied Multinomial and Ordinal Probit Regression to clarify how the different types of violations impact on truck traffic accident severity, and presented that driver distraction contributes to single-truck crashes. Given driving under server weather conditions is hard for drivers with regards to vision and vehicle handling, several studies proved that the weather condition significantly impacts truck traffic accidents. Foggy, rainy, or snowy weather has a higher probability of causing serious traffic accidents [6,9,10]. Truck freight transportation on the highway is more frequent in the nighttime to avoid traffic jams. However, drowsy driving leads to severe traffic accidents that usually happen at nighttime [11]. Behnood and Mannering [12] also indicated that dark areas with streetlights increase severe injury crash outcomes. As another important factor, the relationship between traffic condition and truck traffic accident severity is also mentioned frequently. Choi et al. [13] applied the traffic condition including speed, lane, curve, and other parameters as independent variables to analyze truck traffic accident severity that happens on the highway. As a result, speed was carried out as a significant variable. Cho et al. [14] used structural equation modeling (SEM) to develop different models for truck-involved and non-truck-involved accidents on highways, and found that the driver factor had a significant effect on increasing the severity of truck-involved accidents but not non-truck-involved accidents. Several studies have proven that the installation of road barriers can decrease the severity of truck traffic accidents on the highway [6,15]. Kopelias et al. [16], Islam and Hernandez [17], Lee and Li [18], and other studies have focused on the geometry and traffic condition factors in truck traffic accidents. However, most studies selected truck traffic accidents that happened on highways and rural ways to clarify the influence of geometry and traffic condition factors.

Overall, previous studies have applied drivers, vehicles, weather condition, traffic condition, and other elements as the independent variables to identify which indicators contribute to the severity of truck traffic accidents. In comparison to previous studies, this paper adds several parameters, such as the influence of the logistics facility's location, and more detailed violation types. Furthermore, this study focuses on truck traffic accidents that happened in urban areas with more complicated traffic conditions.

3. Research Structure and Regression Model

3.1. Research Structure

This study aims to identify which factors significantly affect the severity of truck traffic accidents. As truck traffic accidents happen due to several factors interacting, we conducted a comprehensive analysis in two phases, as shown in Figure 2.

Figure 2. Research structure.

In the first phase, the purpose was to identify which variables of the driver and environmental factors directly selected from the accident sites contributed to the severity of the truck traffic accidents. Given the dependent variable of accident severity showing an

ordinal relation, the Ordinal Probit Regression was considered as the most suitable model to conduct in the first phase. According to the ‘Road Traffic Law’, slightly injured accidents are injuries that require treatment for more than 5 days and less than 3 weeks due to a traffic accident. Seriously injured accidents are those that require treatment for more than 3 weeks due to a traffic accident.

Since previous studies have demonstrated that the traffic condition factors are closely related to traffic accidents, the second phase of this study was to explore the relationship between urban traffic conditions and the severity of truck traffic accidents by considering the intermittent flow road sections as the observations. The dependent variable was the number of deaths and serious injuries caused by truck traffic accidents on an intermittent flow road. As shown in Figure 3, the independent variables acquired various attributes such as average length, average lanes, average maximum speed, and other traffic condition variables. Although traffic volume has been identified as an important factor affecting traffic accidents [13,19], this study focused on the truck accidents that happened on the intermittent flow roads in urban areas which have no traffic volume data. Therefore, the traffic volume was excluded from this study.

Figure 3. Concept of an intermittent flow road.

3.2. Regression Model

3.2.1. Ordinal Probit Regression

Traditionally, the Poisson model, Logit model, Probit model, Negative Binomial model, and general linear model (various models such as generalized linear models) have been applied [20]. When analyzing variables that have characteristics of order or rank such as severity, Ordinal Probit Regression was commonly used in the previous studies. In this study, to analyze the factors that affected the severity of truck traffic accidents, the dependent variable was set as an accident grade with an order. An accident in which a slight injury appeared was designated as 0, an accident in which a serious injury appeared was 1, and lastly, an accident in which death appeared was presented as 2. In the case of general regression analysis, we were unable to identify the difference between the dependent variables $y = 1$ and $y = 2$, and the difference between $y = 2$ and $y = 3$. Therefore, there may be errors in the interpretation of the results using the general regression. To solve this limitation, the Ordinal Probit Regression is widely used. Yang et al. [21] assumed that Y represents the injury severity level, then a latent variable Y^* is introduced as:

$$Y^* = (X\beta + \varepsilon) \quad (1)$$

where X is the vector containing the full set values of explanatory variables, β is the vector of coefficients associated with the explanatory variables, and ε is a random error term following a standard normal distribution. The value of the dependent variable is then determined as:

$$Y = \begin{cases} 1 & \text{if } Y^* < \tau_1 \\ j & \text{if } \tau_{j-1} < Y^* < \tau_j \\ J & \text{if } \tau_{J-1} < Y^* \end{cases} \quad (2)$$

where J is the number of injury severity levels (in this case, $J = 3$), and τ_j is the threshold parameter (cut-off point) to be estimated for each level. From the above, it can be determined that the probabilities of Y taking on each of the values $j = 1, \dots, J$ are equal to:

$$P(Y = 1) = \Phi(\tau_1 - X\beta)P(Y = j) = \Phi(\tau_j - X\beta) - \Phi(\tau_{j-1} - X\beta)P(Y = J) = 1 - \Phi(\tau_{J-1} - X\beta) \quad (3)$$

3.2.2. Poisson and Negative Binomial Regression

As the most common model, Linear Regression is suitable for homoscedasticity. Analysis of probabilistic variances, such as the number of traffic accidents and the number of returning visitors, is not suitable for analysis with a general Linear Regression model. To solve this problem, Poisson and Negative Binomial Regression are introduced to interpret Discrete Random Variables.

The Poisson regression is a model that assumes that the expected value of the dependent variable Y following the Poisson distribution is explained by a linear combination of the independent variable X [22].

$$P(Y_i = y_i; X_1, X_2, \dots, X_k) = \frac{e^{-\mu_i} \mu_i^{y_i}}{y_i!}, y_i = 0, 1, 2, \dots, \log(\mu_i) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k \quad (4)$$

where the log transformation form of μ_i , which is the expected value of the Poisson distribution as above, is formed by a linear combination of independent variables. In this case, the reason for using the log link function is that the Poisson distribution is always greater than 0. μ_i is expressed in the form of an exponential function of the independent variables as follows:

$$\mu = \exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k) \quad (5)$$

The estimation of the regression coefficient β in the Poisson regression model mainly uses maximum likelihood estimation.

$$l(\beta_0, \beta_1, \beta_2, \dots, \beta_k) = \sum_{i=1}^n \log \frac{\mu_i^{y_i} e^{-\mu_i}}{y_i!} = \sum_{i=1}^n (-\mu_i + y_i \log \mu_i - \log y_i!), y_i = 0, 1, 2, \dots \quad (6)$$

However, this Poisson Regression must satisfy the basic prerequisite that the variance and the mean are the same. In the case of the actual number of deaths or serious injuries, the overdispersion problem occurs where the variance is greater than the average. Since the Negative Binomial Regression equation starts from the assumption that the variance is greater than the mean, it is preferred to use it in the case of variance greater than the mean [22].

$$P(Y_i = y_i; X_1, X_2, \dots, X_k) = \frac{\Gamma(y_i + a^{-1})}{\Gamma(a^{-1})\Gamma(y_i + 1)} \left(\frac{1}{1 + a\mu_i} \right)^{a^{-1}} \left(\frac{a\mu_i}{1 + a\mu_i} \right)^{y_i}, y_i = 0, 1, 2, \dots \quad (7)$$

In this case, α is a parameter representing overdispersion, and μ_i can be defined in the same way as the exponential average function shown in Equation (5). The log likelihood function for β in the Negative Binomial Regression model is as below:

$$l(y_i; a, \mu_i) = \sum_{i=1}^n \left\{ \left[\sum_{j=1}^n \log(a y_i + 1 - a_j) \right] - \left(a^{-1} + y_i \right) \log(1 + a\mu_i) + y_i \log \mu_i - \log(y_i!) \right\} \quad (8)$$

4. Model Estimation

4.1. Ordinal Probit Regression Analysis of Driver and Environmental Factors

4.1.1. Data Collection

In this study, the data of truck traffic accidents that happened in Incheon during 2017~2019 were collected from the Traffic Accident Analysis System (TAAS), which belongs to Korean Road Traffic Authority (KoROAD). KoROAD provides the per accident data with the information of all the driver and environmental factors considered in this study. However, the location information of each accident only appears by the administrative

district, and the coordinated location information was not able to be obtained due to the ‘Privacy Act’.

Because the goal of this study was to analyze the factors affecting the severity of truck traffic accidents, only the accidents with injuries were considered. Furthermore, just 2% of accidents resulted in no injuries. According to the data, there were 2506 truck traffic accidents in Incheon between 2017 and 2019, resulting in 3614 injuries. The number of fatal, seriously injured, and slightly injured accidents were 67, 791, 1648, respectively. The comprehensive information of the descriptive statistics is shown in Table 1.

Table 1. Descriptive statistics of truck traffic accidents in Incheon (2017–2019).

Section	Factor	Variable	Total		Fatal		Seriously Injured		Slightly Injured	
			Number of Accidents	Injuries	Number of Accidents	Number of Persons	Number of Accidents	Number of Persons	Number of Accidents	Number of Persons
Temporal factors	Season	Spring (March, April, May)	633	914	11	11	209	237	413	666
		Summer (June, July, August)	603	858	21	22	167	189	415	647
		Autumn (September, October, November)	668	954	17	18	217	249	434	687
		Winter (December, January, February)	602	888	18	18	198	222	386	648
	Day of week	Total	2506	3614	67	69	791	897	1648	2648
		Monday–Friday	2035	2864	54	55	644	716	1337	2093
		Saturday, Sunday	471	750	13	14	147	181	311	555
		Total	2506	3614	67	69	791	897	1648	2648
	Time	Morning peak (6:00 a.m.–10:00 a.m.)	484	627	16	16	152	165	316	446
		Daytime (10:00 a.m.–5:00 p.m.)	1119	1610	28	28	343	391	748	1191
		Evening peak (5:00 p.m.–9:00 p.m.)	509	745	6	6	148	172	355	567
		Nighttime (9:00 p.m.–6:00 a.m.)	394	632	17	19	148	169	229	444
	Type of accident	Total	2506	3614	67	69	791	897	1648	2648
		Vehicle to Vehicle	1963	3037	35	37	503	601	1425	2399
		Vehicle to Pedestrian	530	562	30	30	280	288	220	244
		Single-vehicle	13	15	2	2	8	8	3	5
Road and weather conditions	Road surface condition	Total	2506	3614	67	69	791	897	1648	2648
		Aridity	2292	3295	59	61	725	820	1508	2414
		Wetting/Freezing	214	319	8	8	66	77	140	234
	Weather condition	Total	2506	3614	67	69	791	897	1648	2648
		Lucidity	2299	3296	59	61	728	818	1512	2417
		Raining/Snowing/Fogging	207	318	8	8	63	79	136	231
	Road type	Total	2506	3614	67	69	791	897	1648	2648
		Intersection	1285	1805	32	32	436	482	817	1291
		Non-intersected road	1221	1809	35	37	355	415	831	1357
	Logistics facility's influence	Total	2506	3614	67	69	791	897	1648	2648
		Influencing area	1103	1630	31	32	358	412	714	1186
		Non-influencing area	1403	1984	36	37	433	485	934	1462
	Total	Total	2506	3614	67	69	791	897	1648	2648

Table 1. Cont.

Section	Factor	Variable	Total		Fatal		Seriously Injured		Slightly Injured	
			Number of Accidents	Injuries	Number of Accidents	Number of Persons	Number of Accidents	Number of Persons	Number of Accidents	Number of Persons
Truck driver behaviors	Driver gender	Male	2456	3543	67	69	778	883	1611	2591
		Female	50	71	0	0	13	14	37	57
		Total	2506	3614	67	69	791	897	1648	2648
	Driver age group	Under 30	180	252	7	7	64	68	109	177
		30s	341	508	6	7	105	115	230	386
		40s	539	791	17	17	201	222	321	552
		50s	837	1185	20	20	255	295	562	870
		Over 60	609	878	17	18	166	197	426	663
		Total	2506	3614	67	69	791	897	1648	2648
	Type of violation	Non-compliance of a safety distance	245	373	1	1	57	70	187	302
		Violation of cross traffic rules	117	161	1	1	31	33	85	127
		Lane violation	144	208	2	2	48	59	94	147
		Signal violation	309	509	7	7	143	170	159	332
		Non-compliance of safe driving	1558	2220	51	53	447	499	1060	1668
		Violation of pedestrian protection	133	143	5	5	65	66	63	72
		Total	2506	3614	67	69	791	897	1648	2648

Source: Traffic Accident Analysis System (TAAS), 2020.

4.1.2. Definition of Logistics Facility's Influence Area

Large logistics facilities are believed to cause a significant increase in truck traffic. Incheon is a multi-model logistics city with large logistics facilities such as ports, airports, and logistics/industrial complexes. Higher truck traffic volume takes place in Incheon than in other cities. This study intended to examine whether the sphere of influence of large logistics facilities affects the severity of truck traffic accidents or not. Considering the characteristic that trucks depart from the logistics facility and enter the nearest expressway IC, in many cases, the sphere of influence was selected as shown in Figure 4.

Figure 4. Influencing area decision of logistics facilities.

4.1.3. Result of Driver and Environmental Factors

As mentioned above, in this Ordinal Probit Regression model, the dependent variable of the severity of truck traffic accidents was implemented as slightly injured accidents: 0; seriously injured accidents: 1; fatal accidents: 2. Since the significant value of the omnibus test was smaller than 0.001 which is below 0.05, this Ordinal Probit Regression model was acceptable. The model estimate results were as follows. The factors of 'Time', 'Type of accidents', 'Logistics facility's influence', 'Driver age group', and 'Type of violation' appeared as affecting the severity of truck traffic accidents significantly with the values of significance being under 0.05.

According to the model estimate results (Table 2), 'Nighttime' was analyzed as the variable which might contribute to the severity of truck traffic accidents positively (B value: 0.482). As many studies have approved that driving at nighttime is more dangerous than the daytime due to the difficulty of vision, the necessity to take measures such as installing reflectors for traffic safety is also identified in this paper. In the 'Type of accidents', the 'Single-vehicle' was the riskiest type, even exceeding the type of 'Vehicle to Pedestrian'. Most of the single-vehicle accidents happened due to drowsy driving and drunk driving, and these dangerous behaviors always lead to serious accidents. Restrictions on drunk driving and drowsy driving should be enhanced by the government. On the other hand, transportation companies have to ensure the drivers have enough break time. Given that the B value was 0.225, 'Logistics facility's influence' appeared to have a positive effect on the severity of truck traffic accidents. Logistics facilities cause higher truck traffic volume that increases the risk of a traffic accident happening. Measures such as speed limitation need to be implemented on the roads nearby logistics facilities. In the 'Driver age group', only the age group of 'Over 60' showed a significant result, and the B value appeared with a minus pattern while the driver age increased. Recently, the education program has focused on aged drivers. However, younger drivers who lack truck driving experience may also need more attention. Lastly, 'Lane violation' and 'Signal violation' were brought out as the most pestilent types of violation with 0.458 and 0.822 B values. Strengthening the punishment on 'Lane violation' and 'Signal violation' has to be considered to reduce the risk of truck traffic accidents.

Marginal effect analysis is widely used to calculate how much the significant factors increase the probability of more serious traffic accidents happening [23]. The marginal effect is an estimate of the change in accident severity due to the one unit increase in the independent variable through partial differentiation. Table 3 shows the results of the marginal effect analysis. 'Nighttime', 'Vehicle to Pedestrian', 'Single-vehicle', 'Logistics facility's influencing area', 'Lane violation', and 'Signal violation' showed the probability of an increase in more serious truck accidents happening. However, the age of 'Over 60' presented an opposite pattern.

4.2. Poisson and Negative Binomial Regression of Traffic Condition Factors

4.2.1. Data Collection

The purpose of this phase is to explain the causal relationship between the severity of truck traffic accidents and traffic condition factors. An intermittent flow road in Incheon will be considered as the observation. The number of deaths and the number of serious injuries caused by truck traffic accidents on an intermittent flow road were conducted as the dependent variables. The more deaths and serious injuries that happened, the higher the severity of the truck traffic accident on the intermittent flow road. The data of the Incheon truck traffic accidents were taken from TAAS. Excluding the detailed information that could not be confirmed, we took 2171 truck traffic accidents as subjects. The information on Incheon traffic conditions was collected from KTDB (2018).

Table 2. Estimate results of the driver and environmental factors.

Section	Factor	Variable	B	Std. Error	Hypothesis Test		
					Wald Chi-Square	df	Sig.
Temporal factors	Season	Spring (March, April, May)		Set to zero because this parameter is redundant.			
		Summer (June, July, August)	−0.131	0.126	1.079	1	0.299
		Autumn (September, October, November)	−0.035	0.121	0.083	1	0.774
		Winter (December, January, February)	0.018	0.125	0.022	1	0.883
	Day of week	Saturday, Sunday		Set to zero because this parameter is redundant.			
		Monday-Friday	−0.018	0.114	0.025	1	0.874
	Time	Evening peak (5:00 p.m.–9:00 p.m.)		Set to zero because this parameter is redundant.			
		Daytime (10:00 a.m.–5:00 p.m.)	0.151	0.121	1.571	1	0.210
Morning peak (6:00 a.m.–10:00 a.m.)		0.214	0.142	2.285	1	0.131	
Nighttime (9:00 p.m.–6:00 a.m.)		0.482	0.148	10.664	1	0.001 *	
Type of accident	Type of accident	Vehicle to Vehicle		Set to zero because this parameter is redundant.			
		Vehicle to Pedestrian	1.441	0.117	152.213	1	0.000 *
		Single-vehicle	2.287	0.587	15.199	1	0.000 *
Road and weather conditions	Road surface condition	citation in the main text Wetting/Freezing	0.089	citation in the main text		1	0.751
	Weather condition	Lucidity		Set to zero because this parameter is redundant.			
		Raining/Snowing/Fogging	−0.104	0.285	0.132	1	0.716
	Road type	Intersection		Set to zero because this parameter is redundant.			
		Non-intersected road	0.035	0.099	0.123	1	0.726
Truck driver behaviors	Logistics facility's influence	Non-influencing area		Set to zero because this parameter is redundant.			
		Influencing area	0.225	0.090	6.318	1	0.012 *
	Driver gender	Female		Set to zero because this parameter is redundant.			
		Male	0.543	0.339	2.577	1	0.108
	Driver age group	Driver age group	Under 30		Set to zero because this parameter is redundant.		
30 s			−0.354	0.199	3.174	1	0.075
40 s			−0.006	0.183	0.001	1	0.972
50 s			−0.287	0.176	2.647	1	0.104
Type of violation	Type of violation	Over 60	−0.460	0.184	6.256	1	0.012 *
		Non-compliance of a safety distance		Set to zero because this parameter is redundant.			
		Violation of cross traffic rules	0.109	0.269	0.163	1	0.686
		Lane violation	0.458	0.234	3.835	1	0.050 *
		Signal violation	0.822	0.203	16.384	1	0.000 *
		Non-compliance of safe driving	0.071	0.167	0.180	1	0.671
		Violation of pedestrian protection	−0.118	0.263	0.200	1	0.655
Threshold	Threshold	Slightly injured accidents (0)	1.719	0.438	15.402	1	0.000
		Seriously injured accidents (1)					
		Fatal accidents (2)	4.861	0.457	113.354	1	0.000
Likelihood Ratio Chi-Square			264.245				
Pearson Chi-Square			3199.213				
Sig. of Omnibus Test			<0.001				

* Sig. < 0.05.

Table 3. Marginal effect analysis.

Factor		Slightly Injured Accidents (0)	Seriously Injured Accidents (1)	Fatal Accidents (2)
Time	Nighttime (9:00 p.m.–6:00 a.m.)	−0.0395	0.0339	0.0056
	Vehicle to Pedestrian	−0.2448	0.2142	0.0305
Type of accident	Single-vehicle	−0.4919	0.3568	0.1351
	Influencing area	−0.0103	0.0089	0.0014
Driver age group	Over 60	0.0214	−0.0189	−0.0025
	Lane violation	−0.0696	0.0634	0.0062
Type of violation	Signal violation	−0.1100	0.1018	0.0082

In this section, take note that the dependent variables' data were based on intermittent flow roads, whereas the independent variables' data were based on segments of intermittent flow roads. Therefore, the independent variables are represented as average values. There

were 688 intermittent flow roads with the traffic condition data available from KTDB in Incheon. Table 4 shows the variable description.

Table 4. Information of the variables of traffic condition factors.

	Variable	Definition	N	Minimum	Maximum	Mean	Std. Deviation
Dependent variable	Number of deaths	The number of deaths caused by truck traffic accidents on an intermittent flow road in Incheon during 2017–2019	688	0.00	3	0.08	0.33
	Number of serious injuries	The number of serious injuries caused by truck traffic accidents on an intermittent flow road in Incheon during 2017–2019	688	0.00	33	1.12	3.06
Independent variable	Average length (km)	The average segment length of a road	688	0.02	0.96	0.16	0.11
	Average lanes	The average number of segment lanes of a road	688	1.00	7.64	3.02	1.29
	Average max speed (km/h)	The average segment max-speed of a road	688	30.00	80.00	41.28	11.18
	Average traffic signal light density	The number of traffic signal lights per kilometer	688	0.00	27.78	3.53	3.12
	Average entry angle	The average entry angle of a road	688	0.00	179.00	85.00	28.98
	Average exit angle	The average exit angle of a road	688	0.00	179.00	87.45	30.66
	Number of road property-changing nodes	The complexity of the traffic network	688	1.00	223.00	15.31	27.54

To avoid the collinearity problem among the independent variables, a correlation analysis was carried out, as shown in Table 5. The correlation (0.423) between average lanes and the number of road property-changing nodes was the highest. According to the correlation result, there were no collinearity problems in this model.

Table 5. Correlations of independent variables.

Independent Variables		Average Length	Average Lanes	Average Max Speed	Average Traffic Signal Light Density	Average Entry Angle	Average Exit Angle	Number of Road Property-Changing Nodes
Average length	Pearson Correlation	1						
	Sig. (2-tailed)							
Average lanes	Pearson Correlation	−0.101 **	1					
	Sig. (2-tailed)	0.008						
Average max speed	Pearson Correlation	0.081 *	0.421 **	1				
	Sig. (2-tailed)	0.033	0.000					
Average traffic signal light density	Pearson Correlation	−0.269 **	0.232 **	0.070	1			
	Sig. (2-tailed)	0.000	0.000	0.067				
Average entry angle	Pearson Correlation	0.033	0.076 *	−0.018	−0.002	1		
	Sig. (2-tailed)	0.389	0.047	0.630	0.953			
Average exit angle	Pearson Correlation	0.026	0.001	0.070	−0.061	−0.035	1	
	Sig. (2-tailed)	0.500	0.974	0.067	0.108	0.360		
Number of road property changing nodes	Pearson Correlation	−0.149 **	0.423 **	−0.018	−0.002	0.011	−0.018	1
	Sig. (2-tailed)	0.000	0.000	0.630	0.963	0.766	0.635	

** : Correlation is significant at the 0.01 level (2-tailed). * : Correlation is significant at the 0.05 level (2-tailed).

4.2.2. Result of Traffic Condition Factors

Poisson and Negative Binomial Regression have been often used for studying topics with probabilistic characteristics such as traffic accident analysis. The difference between Poisson and Negative Binomial distribution is whether the mean is similar or lower than the variance of the dependent variable [24]. This can be verified through the one-sample Kolmogorov–Smirnov Test. According to the verification result (Table 6), the dependent variables had different distributions. In the number of deaths, the mean and variance values were 0.08 and 0.110. Given the Asymp. sig. was 1.000, which is greater than 0.05, the distribution of the number of deaths was able to be applied for Poisson Regression. On the other hand, the mean values were vastly lower than the variance values in the number of serious injuries. As all of the Asymp. sig. numbers were under 0.05, Negative Binomial Regression was better.

Table 6. Result of one-sample Kolmogorov–Smirnov Test.

Section		Number of Deaths	Number of Serious Injuries
N		688	688
Poisson Parameter	Mean	0.08	1.12
	Variance	0.110	9.331
Most Extreme Differences	Absolute	0.012	0.342
	Positive	0.012	0.342
	Negative	−0.007	−0.059
Kolmogorov–Smirnov Z		0.303	8.972
Asymp. Sig. (2-tailed)		1.000	0.000

The goodness of fit for the two models is shown in Table 7. The model of the number of deaths expressed a Pearson Chi-Square with 474.816, and a Value/df with 0.698. The closer the model's Value/df to 1.000, the better it is for the Poisson Regression model. The goodness of fit for the number of serious injuries model showed a Pearson Chi-Square with 721.034, and a Value/df with 1.060 (over 1.000).

Table 7. Goodness of fit.

Section	Number of Deaths (Poisson Regression Model)		Number of Serious Injuries (Negative Binomial Regression Model)	
	Value	Value/df	Value	Value/df
Deviance	183.600	0.270	518.033	0.762
Scaled Deviance	183.600		518.033	
Pearson Chi-Square	474.816	0.698	721.034	1.060
Scaled Pearson Chi-Square	474.816		721.034	
Log Likelihood	−138.515		−712.844	
Akaike's Information Criterion	293.031		1441.689	
Finite Sample-Corrected AIC	293.243		1441.901	
Bayesian Information Criterion	329.301		1477.959	
Consistent AIC	337.301		1485.959	

Since the significance values in both models were under 0.05, the results of the parameter estimates were significant statistically. As shown in Table 8, three of seven variables

showed significant results in the number of deaths model. The independent variable of ‘Average lanes’, ‘Average max speed’, and ‘Number of road property-changing nodes’ present the significance values under 0.05. Given that all the B values of the three variables were positive, the dependent variable (Number of deaths) increased on the intermittent flow roads which keep more lanes, higher max speed, and more property-changing nodes. In the number of serious injuries model, the independent variables of ‘Average max speed’ and ‘Number of road property-changing nodes’ showed positive effects on the dependent variable (Number of serious injuries) rising significantly.

Table 8. Result of parameter estimates.

Dependent Variables	Independent Variables	B	Std. Error	Hypothesis Test			Exp(B)
				Wald Chi-Square	df	Sig.	
Number of deaths (Poisson Regression Model)	(Intercept)	−3.71	1.12	11.02	1.00	0.00	0.02
	Average length	−3.81	2.68	2.03	1.00	0.15	0.02
	Average lanes	0.30	0.12	6.57	1.00	0.01 *	1.35
	Average max speed	0.03	0.02	4.13	1.00	0.04 *	1.03
	Average traffic signal light density	−0.04	0.07	0.31	1.00	0.58	0.96
	Average entry angle	−0.01	0.01	1.60	1.00	0.21	0.99
	Average exit angle	−0.01	0.01	1.34	1.00	0.25	0.99
	Number of road property-changing nodes	0.02	0.00	68.06	1.00	0.00 *	1.02
	Likelihood ratio Chi-Square sig.			122.104 <0.001			
Number of serious injuries (Negative Binomial Regression Model)	(Intercept)	−2.84	0.44	41.49	1.00	0.00	0.06
	Average length	0.84	0.68	1.52	1.00	0.22	2.31
	Average lanes	0.07	0.06	1.29	1.00	0.26	1.07
	Average max speed	0.04	0.01	37.25	1.00	0.01 *	1.04
	Average traffic signal light density	0.02	0.03	0.68	1.00	0.41	1.02
	Average entry angle	0.00	0.00	0.31	1.00	0.58	1.00
	Average exit angle	0.00	0.00	1.15	1.00	0.28	1.00
	Number of road property-changing nodes	0.03	0.00	116.00	1.00	0.00 *	1.03
	Likelihood Ratio Chi-Square sig.			590.914 <0.001			

* Sig. < 0.05.

An intermittent flow road with more lanes has a lot of traffic volume, probabilistically. Moreover, lane changes occur more frequently in multi-lanes. As lane violation increases the severity of truck traffic accidents mentioned previously, it is necessary to make efforts on lane separation. High-speed driving also promotes the severity of truck traffic accidents. Limiting the maximum speed on the accident black roads can prevent serious accident occurrences. The number of road property-changing nodes means the complexity of the traffic network. Policies to simplify the complexity of the traffic network (truck-only lane institution) on roads with a high large truck traffic volume have to be considered.

5. Conclusions

Since the fatality rate of truck accidents is twice as high as passenger car and bus accidents, researching the factors which contribute to the severity of truck traffic accidents is meaningful. This paper presented statistical analysis to clarify how drivers, environmental factors, and traffic condition factors affect the severity of truck traffic accidents in urban areas. The truck traffic accidents that happened in Incheon—which has large logistics facilities such as a port and an airport—was selected as the subject. In terms of driver and environmental factors, the Ordinal Probit Regression analysis presented that ‘Nighttime (9:00 p.m.–6:00 a.m.)’, ‘Vehicle–single’ and ‘Vehicle to Pedestrian’ accidents contributed to the truck traffic accident severity. In the logistics influencing area, truck traffic accidents had a higher possibility to be more serious than in the non-influencing area. The ‘Lane violation’ and ‘Signal violation’ also contributed to truck traffic accident severity significantly. In

terms of the traffic condition factors, the number of lanes, the maximum speed, and the number of road property-changing nodes were found to be significant.

According to the statistical analysis results, this study presents several traffic safety policies, as below. For reducing the risk of driving at nighttime, it is necessary to expand the installation of devices that can assist drivers, such as a fatigue detection device, in trucks. Attaching reflective papers on the trucks and setting up reflective road signs at hazard spots are also effective methods. Since lane or signal violations and speeding increase the probability of a severe truck traffic accident, the National Police Agency has to strengthen the crackdown on illegal U-turns, signal violations, and speeding. Given that large-scale logistics facilities are the main places that generate truck traffic, many truck traffic accidents occur in the vicinity, and the severity of the accident worsens. Lowering the truck speed limitation and installing safety facilities on local roads near large-scale logistics facilities are necessary measures. In the case of Japan and the United States, dedicated truck lanes were introduced on arterial roads between logistics cities. According to the report of Kang (2019) from the Korea Research Institute, the United States predicted that it would reduce the occurrence of traffic accidents by 40% in the section where a dedicated truck-only lane was introduced. In Korean logistics cities, the establishment of a truck-only lane designation policy on the main access roads connecting large logistics facilities and highway ICs in urban areas has to be seriously considered.

However, the traffic safety problem is a complicated social issue that needs the relative departments to cooperate closely. Improving the truck transportation market structure to make a less stressful condition for truck drivers, such as by implementing diversified education programs, and strengthening truck traffic violation inspection, should also be widely considered.

This study identified the factors contributing to truck traffic accident severity in urban areas, and suggested safety policies accordingly. The result of this study is suggested to be well utilized in preparing a traffic safety policy in preparation for the continuous increase in truck traffic in urban areas. However, due to data collection limitations, the size and types of trucks were not considered in this study. It will be necessary to conduct a comparative analysis including truck size and type after improving the traffic accident data provision system in the future.

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