Research Article

A Data Mining Approach on Lorry Drivers Overloading in Tehran Urban Roads

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The aim of this study is to identify the important factors influencing overloading of commercial vehicles on Tehran's urban roads. The weight information of commercial freight vehicles was collected using a pair of portable scales besides other information needed including driver information, vehicle features, load, and travel details by completing a questionnaire. The results showed that the highest probability of overloading is for construction loads. Further, the analysis of the results in the lorry type section shows that the least likely occurrence of overloading is among pickup truck drivers such that this likelihood within this group was one-third among Nissan and small truck drivers. Also, the results of modeling the type of route showed that the highest likelihood of overloading is for internal loads (origin and destination inside Tehran), and the least probability of overloading is for suburban trips (origin and destination outside of Tehran). Considering the type of load packing as a variable, the results of binary regression model analysis showed that the most probability of overloading occurs for packed (boxed) loads. Finally, it was concluded that drivers are 18 times more likely to commit overloading on weekends than on weekdays.

1. Introduction

Transport and logistics play an important role in the economies of countries, specifically road transport which is one of the most important modes of transport for freight and cargo transportation in developing countries [1].

In Iran, like other developing countries, freight transportation, mainly conducted by semiheavy and heavy vehicles, plays an important role in the distribution of exports and imports. According to the Ministry of Roads and Urban Development in 2017, the amount of goods transported in the country was 428.3 million tons conveyed through 29.9 million trips by heavy vehicles, which yielded an index of 224.836 million ton-km in this period.

The increasing freight traffic on the roads and consequently the increased likelihood of vehicles colliding have become a major concern for drivers and policy makers [2]. Traffic accidents are directly related to traffic offenses; in other words, traffic offenses are among the most important factors that lead to traffic accidents [3]. Drivers with more

offenses experience more accidents [4]. Therefore, reducing driving offenses can reduce accidents. The study of the causes of accidents shows that errors and violations are the main cause of 74% of accidents [5]. This requires researchers to identify the factors that lead to driving offenses and to reduce the impact of accidents. Most studies mention that accidents depend on three factors: humans, vehicles, and roads [6]. And the human factor is the most important factor in the analysis of traffic accidents [7]. Drivers' offenses are therefore among the most important human factors leading to accidents, which have been used in many studies to investigate driving behaviors that are related to behavioral characteristics and drivers characteristics [6–12]. According to the Ministry of Roads and Urban Development of Iran, there have been 63472 offenses in 2017 resulting in 121108 rural crashes leading to 16201 fatalities and 335995 injuries. Meanwhile, commercial vehicles drivers have a high importance in reducing traffic offenses and subsequent accidents due to the different dimensions and weight of their vehicles, besides their higher traffic rates as a group of

professional drivers [13]. Studies show that heavy vehicle driving is among the highest risk occupations for injury and death [14]. Heavy vehicles have fewer accidents considering their mileage; nevertheless, a very high percentage of traffic accidents are attributed to heavy vehicle accidents [15].

Additionally, among the costliest cargo fleet offenses by overloaded trucks, especially in developing countries, are the safety and structural problems caused by the demolition of bridges and pavements [16]. Overload is the amount of cargo that exceeds the legal value of the truck's carrying capacity [17]. Overloading creates several problems, including accidents, increasing the severity of accidents, damaging infrastructure [18–20], and creating a market with unfair competition between modes of transport and transportation carriers [16]. Overloading is commonplace in developed countries and is dealt with systematically via additional licenses. It is identified and enforced by using off-road weighing systems (WIM).

However, in developing countries this has been overlooked or neglected. According to official statistics released by the Ministry of Roads and Urban Development of Iran, a total of 5 WIM devices have been used to date, none of which are used for urban routes. As the capital of Iran, Tehran has 650 kilometers of urban road crossings, with a high volume of semiheavy- and heavy-duty freight vehicles traveling in and out of Tehran. According to statistics released by the Tehran Transportation and Traffic Organization, a total of about 128 million kilometers have been traveled in highways within Tehran in the past year by freight vehicles, 23% of which are overloaded. Therefore, the increase in the volume of freight vehicles with overloading in the urban roads of Tehran causes significant damage to urban infrastructures such as bridges and pavements, which will make the need for further studies in this regard.

2. Literature Review

Despite the importance and necessity of controlling overloading infringement in the freight fleet mentioned in the introductory section, few studies have been carried out in this regard and only descriptive statistics of overloading have been investigated. The parameters and characteristics affecting the commission of overloading have not been addressed. In a general classification, we can divide the total number of studies on cargo fleet offenses into three categories, which are displayed below.

Some studies have investigated the factors affecting the occurrence of accidents and devised models of accident prediction for cargo fleets. Among the most important parameters affecting the occurrence of commercial vehicle accidents reported in previous studies have been the age and the working hours of the driver [1–4, 12]. Researchers have also concluded in other studies that factors such as drowsiness, fatigue, and the way in which salaries are paid increase the risk of accidents [8]. Other variables used in modeling commercial vehicle accidents include driving experience [3, 4, 6], physical health characteristics [3, 4], sleep duration [2, 6, 12], mileage [6, 12], and gender [1–3, 5–7].

In some other studies, the effect of committing driving offenses on the occurrence of commercial vehicle crashes has been considered. One of the most important offenses identified in past studies as a major contributing factor to the occurrence of accidents is speeding [9–11, 13–15, 21–23]. Other studies in this field have found that offenses such as maintaining safe distance to front vehicle [21, 23], fastening seat belt [14, 22], technical defect [13, 22], alcohol abuse [15, 22], and other related factors such as a history of a crash [14, 21, 22], a history of misconduct [24–26], and some parameters of the Driving Behavior Questionnaire [9, 11, 21] have a significant impact on the occurrence of accidents for commercial fleets.

Other studies have also addressed the issue of offenses among commercial vehicle drivers and the variables affecting them. The parameters studied in this category included driving behavior and behavioral characteristics, driver demographic information [19, 27], mileage [2, 14, 28], and fatigue/drowsiness [10, 23]. The results of some studies show that there is a significant relationship between driving experience and driving offenses such as speeding and not fastening seat belts [2, 25]. In other studies, it was understood that the amount of cognitive errors [12], individual behaviors, anger and perceived behavior control [29], differences in drivers' behavior, and the price of heavy-duty vehicles have a significant association with committing traffic offenses. Overall, studies of offenses of commercial vehicle drivers can be summarized in Table 1.

As summarized in previous section, no study has specifically addressed the factors affecting the committing of overloading by drivers. While the above studies were carried out using information obtained from on-board weighing devices (approximate weighing), the use of accurate weighing information from portable scales was not conducted. Additionally, none of the previous studies were for urban routes. Variables such as type of cargo, route (origin, destination, and route), cargo characteristics including type of packing and dimensions of the cargo, age and gender of driver, and vehicle life are evaluated for the first time in this study.

3. Methodology

The aim of this study is to identify the important factors influencing overloading on Tehran's urban roads. To achieve this goal, all independent variables are categorized first, and the chi-square Pearson test with a p value of 0.05 is used to investigate the relationship between each independent variable and the dependent variable that is driving offenses in this research. Then, with the significant variables in committing known driving offenses, a binary logistic regression model was developed, and using this method, the effect of variables on the perpetration of infringements by lorry drivers was evaluated. It should be noted in this study that driving offenses were classified into two categories as dependent variables: overloading and nonoverloading; the effective factors identified within the category for each truck comprised driver, vehicle, mileage, etc.

In the next step, after identifying meaningful variables, binary logistic regression modeling has been used to

TABLE 1: Summary of studies carried out in the field of cargo fleet offenses.

No.	Authors	Country	Case study	Type of offenses	Analysis method	Findings and results
1	Edward us Kay Fappa et al. (1993)	Ghana	1182 trucks and trailers of all types of two, three, four, and five axes	Overloading	Nonlinear regression	For any heavy-duty vehicle and any road, an index should be considered to limit the amount of overload to prevent the damage to the road pavement as well as committing overloading. In the three speeds and precautions and safety variables, there were errors in their statements, but there was no error in their skill. With regard to speed and precaution, it became clear that the reason for this error was to underestimate other drivers in these areas.
2	Walton (1999)	America	Completion of 1013 behavioral questionnaires in collaboration with 680 transport agencies	Speeding	Use of the xyz logic pattern, the XYZ schemata models, chi-square curve, and the triple method	Four factors (error, slip, normal driving offenses, and aggressive violations) identified, and only the factor of driving offenses showed a significant relationship with the prediction of accidents.
3	Sullman et al. (2002)	America	Out of 1065 questionnaires sent to drivers of transport companies, 382 completed questionnaires analyzed	DBQ driving behavior	Factor analysis	Many highway driving offenses are associated with aggressive driving behaviors, and the only parameter that can predict driving offenses is the mileage in a year.
4	Davey et al. (2007)	Australia	443 volunteers working for a large Australian insurance company	DBQ driving behavior	PCA method for analyzing cases of driving behavior questionnaire (DBQ)	There is a significant relationship between respondents' views about belt closure and driver's age, and the use of seat belts and driving experience and education.
5	Oladebo et al. (2011)	Nigeria	228 professional drivers at Ibadan University	Failure to use seat belts	Descriptive statistics and chi-square model curves	Individual rules and perceived behavior control can indicate the amount of inclination to drive at a speed that is permitted.
6	Tavafian et al. (2011)	Iran	246 commercial vehicle drivers	Speeding	Driving behavior questionnaire and planned behavior theory and multiple regression model	Many factors indicate a significant amount of speed and driving in drunkenness, clearly referred to as the driver's gender, vehicle type, and lack of light in the streets at night and limited visibility.
7	Zhang et al. (2014)	China	11055 cases of speeding and 10035 driving offenses of alcohol consumption	Unauthorized use and alcohol consumption	Logistic regression	Using heavy lorry driver simulated systems, it was found that drivers who are paid per km/trip are more likely to face problems such as lack of certification, fatigue while driving, and increased risk of accidents and fines, compared to drivers who have a fixed salary.
8	Thompson et al. (2015)	Australia	Information on driving offenses and accidents of heavy lorry drivers over a year	Fatigue and drowsiness and no certificate	Simulation by TST	

TABLE 1: Continued.

No.	Authors	Country	Case study	Type of offenses	Analysis method	Findings and results
9	Tseng et al. (2016)	Taiwan	2101 male drivers of heavy vehicles	Speeding	Binary logistic regression	The demographic characteristics of drivers, the quality of sleep, and the amount of mileage over a year at night are significantly related to speeding. Extrovert drivers have less efficiency. Also, with increasing driving experience, the number of driving offenses increases and productivity decreases.
10	Vries et al. (2016)	India	49 drivers' information of a shipping company in India for 370 trips	Speeding	Dual statistical analysis and statistical correlation	Anger, passenger presence, and differences in individual driving behavior are among the main causes of misconduct, excitement, and distraction.
11	Precht et al. (2017)	America	Dangerous driving of 3500 people participating voluntarily was surveyed for three years	Speeding	GLMM model (organized linear mixed model)	Speed violation with 33 percent and dangerous driving with 23 percent are the most violent occurrences in the Harcourt city. The results show a correlation between nonprofessional drivers and ordinary and aggressive offenses and errors, while professional drivers are associated with positive behaviors.
12	Aminic et al. (2017)	Nigeria	Dangerous driving of 394 interviewees in 6 areas of the Port Harcourt city	Speeding	Statistical and inferential methods	The more drivers have grievances about their sleep state, the more lapses, errors, and violations occur. Also, the more expensive a vehicle is, the lower the fatigue felt by the driver.
13	Maslać et al. (2018)	Serbia	918 nonprofessional drivers and 504 professional drivers	Driving behavior (DBQ)	Nonparametric analysis (PCA)	
14	Naderi et al. (2018)	Iran	In-person interviews of 474 heavy vehicle drivers	Driving behavior (DBQ)	Structural equation modeling	

construct the driving offenses model. Logistic regression is usually used to categorize discrete variables. These models can be used to categorize binary response variables, such as variables with two solutions, and also can be used for response variables with r category (r can be greater than 2). These models use the $r - 1$ logit model formatting for response variables, so that each of the variable's classifications can be compared with the reference classification. In this study, because the dependent variable is a binary nominal variable, binary logistic regression is used for modeling.

In this study, the dependent variables were defined in two categories: "overloading" and "nonoverloading"; "overloading" driving offenses have been used as a reference classification to be compared with nonoverloading.

Driving offenses displayed with Y is a response variable, and the environmental and human variables, vehicle, and mileage are the response variables and are represented by $x_{i1}, x_{i2}, x_{i3}, \dots, x_{ip}$, where i is the number of observations and p represents the number of independent variables. It is assumed that $Y_i = (Y_{i1}, Y_{i2}, \dots, Y_{ir})^T$ has a polynomial

distribution with the index $n_i = \sum_{j=1}^r Y_{ij}$ and the parameter $(\prod_{i1}, \prod_{i2}, \dots, \prod_{ir})^T$.

When the categories $1, 2, \dots$ and the response variable's r are irregular, $\prod_i$ is associated with independent variables through the set of $r - 1$ basic classification of logit function.

$$\log\left(\frac{\prod_{ij}}{\prod_{ij^*}}\right) = x_i^t \beta_j, \quad j \neq j^*. \quad (1)$$

Since 2 classifications for the response variable in this study do not have any particular order, 1 generalized logit model is defined for calculations and represented by j . Also, since x_i has a number of P , this model has $(r - 1) \times p$ parameters arranged in matrix form.

In this model:

Each of the classifications is selected as a reference classification. In this case, only the amount and manner of interpretation of the coefficients will be different.

The k element of β_j is considered as an agent for increasing the chance of placing the answer in the j

classification versus the j^* classification. Hence, an increment in the k independent variable occurs, and at the same time, other independent variables remain constant. For nonbase classifications $j \neq j^*$, $\prod_i$ is defined using β as follows:

$$\prod_{ij} = \frac{\exp(x_i^T \beta_j)}{1 + \sum_{k \neq j^*} \exp(x_i^T \beta_k)} \quad (2)$$

To classify the base (reference), $\prod_i$ is defined using β as follows [30]:

$$\prod_{ij} = \frac{1}{1 + \sum_{k \neq j^*} \exp(x_i^T \beta_k)} \quad (3)$$

In this study, overloading driving offense is used as a reference classification. SPSS 24 software is used for statistical analysis of binary logistic regression model.

4. Materials (Data Collection)

Field data collection method was used to collect the required information in this study. Thus, initially, traffic volumes at the inbound and outbound routes of Tehran, as shown in Table 2, were obtained from the Road and Transportation Organization for one hour each day to use the vehicle traffic information. The urban highways have the highest freight traffic as well as the peak hour of pickup. After selecting the highways with the heaviest traffic and also the peak hour for field data gathering, suitable locations for stopping freight vehicles along the road to collect their information were selected.

The survey consisted of 10 stations on the Tehran urban highways according to Figure 1, selected with considerations such as sufficient space for truck lanes, low road slope, sufficient stop-gap distance, appropriate length of merging areas, and brightness. After selecting the 10 stations, field data collection operations were carried out in cooperation with Tehran Traffic Police during 30 working days in July and August of 2018. In this data collection, the cargo vehicles were first accidentally stopped by the traffic police and their weighting information was recorded using a pair of portable scales. Regarding the number of data collection days, the following explanations are provided:

This number of collection days was only on weekdays in Tehran, i.e., Saturday to Wednesday. This means that the collection field operation took about two months.

Statistical calculations through Cochran's relationships showed that 560 information records were needed to perform statistical analysis according to the size of the statistical population and the statistical sample. However, due to the provision of about twice the above record, there was no need to continue collecting information.

Collecting field data using portable scales adjacent to intercity highways is a costly and high-risk operation due to

the possibility of collisions with cargo vehicles. Therefore, due to the collection of a sufficient number of statistical samples in 30 working days, there was no need to continue field operations. Subsequently other information needed, including driver information, vehicle, cargo, and travel, was obtained by completing the questionnaire; after filtering and correcting incomplete data, 856 data records were used for statistical analysis.

Then, the type of overloaded truck drivers was selected as the dependent variable in two categories. For the analysis, 12 independent variables related to driver, vehicle, cargo, and travel as shown in Table 3 were selected. Kendall's non-parametric test (discrete variables) was used to investigate the dependence of the independent variables. The results showed that all the independent variables have a correlation coefficient less than 0.5, and therefore the independent variables are not highly correlated. In Table 3, the classifications considered for all variables are shown along with the percentage of frequency for each of them. All independent variables were classified and SPSS 24 software was used for statistical analysis.

5. Results and Analysis

In this study, the effect of each of the independent variables on the overloading offense of truck drivers was evaluated, and the results of chi-square test are shown in Table 4. As indicated by the results of the chi-square test, 7 variables out of the 12 independent variables studied were significant at 95% confidence level ($Sig < 0.05$). In addition, binary logistic regression model was used to analyze the data and identify the factors affecting the overloading of cargo fleet drivers' offense, and the forward likelihood ratio prediction method was used to develop the model in SPSS software. All significant variables in describing the proposed model of this study were identified and entered into the model in the first step. The modeling results for overloading in two classifications are presented in Table 5. It should be noted that in the classifications defined for the model variables, the last classification has been evaluated as the reference.

The results displayed in Table 5 (output of the statistical model) show that the most probability of committing overloading occurs among freight drivers with a capacity of 3.5 to 19 tons. This probability is about 26 times higher than that of cargo fleet drivers with a capacity of more than 40 tons. Also, the analysis of the results in the lorry type section shows that the least likely occurrence of overloading is among pickup truck drivers such that this likelihood within this group was one-third among Nissan and small truck drivers.

Considering the type of load packing as a variable, the results of binary regression model analysis showed that the most probability of overloading occurs for packed (boxed) loads. This higher probability is about 20 percent more likely than cargo of bulk goods. Further, and in accordance with the results of regression analysis in Table 5 and in the load type section, the results showed that the maximum likelihood of overloading transport within urban areas was for

TABLE 2: Traffic volumes at the inbound and outbound routes of Tehran.

No.	Inbound and outbound route	Peak hour	PCU per peak hour	Percentage of heavy vehicles in peak hour (%)
1	Tehran-Karaj freeway	7-8	6174	6
2	Tehran-Shahriyar	17-18	6103	6
3	Tehran-Pakdasht	7-8	5363	5
4	Tehran-Qom highway	18-19	4520	4
5	Rey-Qarchak	7-8	4266	7
6	Tehran-Jajrood	8-9	4038	4
7	Tehran-Chitgar	6-7	3998	8
8	Tehran-Karaj highway	16-17	2669	22
9	Hemmat-Vardavard	7-8	2369	1
10	Tehran-Saveh freeway	19-20	1349	0
11	Tehran-Pardis	8-9	1811	1
12	Tehran-Lavasan	7-8	1641	3
13	Tehran-Robat Karim	7-8	2278	10
14	Tehran-Hasanabad	11-12	1246	33
15	Tehran-Sohanak	19-20	564	3
16	Tehran-Shomal	17-18	291	4

FIGURE 1: The location of survey stations in Tehran urban highways.

loads of construction materials. The probability of over-tonnage for this type of load was 10, 6, and 2.5 times higher than that for other loads, scrap, and metal loads, respectively. Modeling results in traffic type section also showed that the highest likelihood of overload was for inner-city loads (origin and destination inside Tehran), and the least probability of overloading was for passing cargos (origin and destination outside of Tehran). The probability of carrying excess tonnage for inner-city loads is 5 and 1.5 times the passing cargo, respectively. Finally, it was concluded that heavy vehicle drivers are 18 times more likely to commit overloading offense on weekends than on weekdays, and drivers commit more overload offenses on holidays.

The trend of changes in the variables affecting the overloading of truck drivers is shown in Figure 2. As the diagrams analyzed show, changes in some of the independent variables in the defined classification have a significant trend that will be described further in the study. The

descriptive analysis of the variables in the load type section shows that the highest overload ratio occurs for scrap and construction type loads. As shown in Figure 2, about 74 percent of litter trucks in Tehran are overloaded. One of the most important reasons for the high percentage of overweight loads for these types of cargo is the lack of weighing tools at the source or destination. Considering the route of the overloaded cargos, the freight vehicles passing Tehran have the lowest percentage of overloading. It seems that one of the most important reasons for the reduction of overloading offenses for this group of drivers is the weight control provision of heavy vehicles for intercity loads. The graph of the descriptive analysis of the type of registration plate also shows that the highest amount of tonnage occurs between freight vehicles with general plates and the least for personal plates. Drivers who own heavy vehicles appear to be more attentive to their vehicles and are less likely to overload them due to the potential deleterious effects of overloading on the vehicle.

TABLE 3: Estimated variables with frequency of each classification.

Variable	Category	Frequency (%)
Driving offense	Overloading	53
	Nonoverloading	47
Survey time	Day	79
	Night	21
Holiday status	Workday	82
	Holiday	18
Lorry type	Pickup truck	23
	Small truck	21
	Truck	39
	Trailer	17
Truck tonnage capacity section	Under 3.5	16
	3.5 to 19	30
	19 to 40	34
	More than 40	20
Vehicle's age	1 to 10	42
	11 to 20	34
	More than 20	24
Vehicle ownership	Drive is owner	66
	Driver is partner	13
	Driver is not owner	21
Registration plate	Private	21
	Public	79
Load type	Metal	11
	Constructional	25
	Scrap	23
	Agricultural	18
Packing type	Other	23
	Packed	48
	Bulk	46
	Oversize load	6
Traffic type	Inner	39
	Passing	9
	Input	26
	Output	27
Driver's age	Under 40	51
	41 to 50	29
	More than 50	20
Driver's experience (year)	1 to 10	41
	11 to 20	37
	More than 20	22

TABLE 4: Chi-square test results for independent variables.

Variable	Chi-square	Degree of freedom	Significant
Survey time	10.122	1	0.48
Holiday status	46.079	1	0.000
Lorry type	13.324	3	0.010
Truck tonnage capacity	23.626	3	0.023
Vehicle's age	45.541	2	0.115
Vehicle ownership	32.877	2	0.69
Registration plate	24.840	1	0.002
Load type	54.665	4	0.000
Packing type	7.811	2	0.012
Traffic type section	28.567	3	0.027
Driver's age	33.707	2	0.215
Driver's experience	8.904	2	0.35

TABLE 5: The results of logistic regression analysis.

Variable	Category	Reference category	Model coefficient	Standard deviation error	Sig	Odds ratio	95% confidence interval for EXP (B)	
							Lower bound	Upper bound
Constant			-9.73	2.508	0.000			
Truck tonnage capacity	TC1	TC4	5.036	2.073	0.015	15.25	5.031	46.07
	TC2		7.901	1.768	0.000	26.99	14.74	49.42
	TC3		5.53	1.315	0.000	25.4	2.92	220.8
Lorry type	LT1	LT4	-1.856	0.958	0.053	0.156	0.032	0.755
	LT2		-0.913	0.948	0.335	0.401	0.084	1.907
Packing type	PT1	PT3	4.078	1.183	0.001	59.02	8.43	413.18
	PT2		4.023	1.176	0.001	55.86	8.07	386.62
Load type	LOT1	LOT5	1.49	0.483	0.002	4.439	2	9.83
	LOT2		2.31	0.472	0.000	10.16	4.675	22.10
	LOT3		0.543	0.499	0.0277	1.721	0.757	3.915
	LOT4		1.24	0.395	0.003	3.47	1.815	6.654
Traffic type section	TS1	TS4	0.031	0.349	0.93	1.031	0.581	1.83
	TS2		-1.404	0.554	0.011	0.246	0.099	0.611
	TS3		-0.289	0.393	0.462	0.749	0.392	1.429
Holiday status	HS1	HS2	-2.183	0.762	0.000	0.056	0.016	0.198

(a)

(b)

FIGURE 2: Continued.

FIGURE 2: The trend of changes in variables affecting overloading.

6. Conclusion

The main purpose of this study was to investigate important and influential factors in cargo drivers committing the overloading and excess tonnage offense in Tehran. Field collection method was used to collect the required information. Initially, the highways with the most freight traffic, as well as suitable locations for stopping the vehicles along the road for field surveys, were selected, including 10 stations on the Tehran urban roads. The field collection operation was then carried out in cooperation with Tehran Traffic Police authorities. The heavy and semiheavy vehicles were initially stopped by the traffic police and their weighting information was collected using a pair of portable scales. Then, other information needed including driver information, vehicle, cargo, and travel was completed by filling out a questionnaire, and after correcting or deleting incomplete data, 856 data records were used for statistical analysis.

The results showed that the highest likelihood of overloaded transport was obtained in inner-city trips carrying construction material loads. Overloading of this type of load often happens for two main reasons. Firstly, currently in Tehran, due to city traffic, these trips are shifted to night, with traffic police agents being less present in the roadways and as a result having less control over the transportation of cargo. Secondly, these loads do not have a recorded document of loading and are not weighed at the origin. As elaborated, transporting such loads in addition to reducing traffic safety may cause damage to urban infrastructure. It seems that if the weighing devices are used in the dumping of construction waste in the city of Tehran for preventing the violation of the law by offensive drivers, the amount of traffic in the type of waste dumping and construction carrying overloading in the inner-city roadways can be decreased.

Also, the results of modeling for the origin destinations indicated that the highest likelihood of overloading was for

inner-city loads (origin and destination inside Tehran), and the least probability of overloading was for trips with origin and destination outside of Tehran. One of the most important reasons for the less tonnage load of passing trips is the weighing of freight vehicles at police checkpoints using off-road weighing scales in suburban areas. Since it is not possible to use fixed weighing scales in the inner-city axes, the use of weighing-in-motion (WIM) scales is especially important in the urban highways which have high freight traffic. This can lead to a reduction in the overloading in these routes.

Finally, it was concluded that truck drivers are 18 times more likely to commit excessive tonnage offense on weekends than on weekdays. In this regard, it seems that the presence of law enforcement agents on weekends is less than on working days. In addition to the presence of most traffic police agents on weekends on the heaviest freight routes, the use of weighing-in-motion (WIM) scales at urban highways, as well as the requirement for freight companies to implement rigorous freight measurements, is suggested to reduce overloading, especially on urban roads.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

- [1] L. Brodie, B. Lyndal, and I. J. Elias, "Heavy vehicle driver fatalities: learning's from fatal road crash investigations in Victoria," *Accident Analysis & Prevention*, vol. 41, no. 3, pp. 557–564, 2009.

- [2] J. de Vries, R. de Koster, S. Rijsdijk, and D. Roy, "Determinants of safe and productive truck driving: empirical evidence from long-haul cargo transport," *Transportation Research Part E: Logistics and Transportation Review*, vol. 97, pp. 113–131, 2017.
- [3] D. Ketabi, A. Barkhordari, S. J. Mirmohammadi, and A. H. Mehrparvar, "Aberrant behaviors and road accidents among Iranian truck drivers," *Health Promotion Perspectives*, vol. 1, no. 2, pp. 130–139, 2011.
- [4] P. E. Fergenson, "The relationship between information processing and driving accident and violation record," *Human Factors: The Journal of the Human Factors and Ergonomics Society*, vol. 13, no. 3, pp. 173–176, 1971.
- [5] M. J. M. Sullman, M. L. Meadows, and K. B. Pajo, "Aberrant driving behaviours amongst New Zealand truck drivers," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 5, no. 3, pp. 217–232, 2002.
- [6] D. E. Cantor, T. M. Corsi, C. M. Grimm, and K. Özpolat, "A driver focused truck crash prediction model," *Transportation Research Part E: Logistics and Transportation Review*, vol. 46, no. 5, pp. 683–692, 2010.
- [7] M. Mehdizadeh, A. Shariat-Mohaymany, and T. Nordfjaern, "Accident involvement among Iranian lorry drivers: direct and indirect effects of background variables and aberrant driving behaviour," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 58, pp. 39–55, 2018.
- [8] J. C. F. de Winter and D. Dodou, "National correlates of self-reported traffic violations across 41 countries," *Personality and Individual Differences*, vol. 98, pp. 145–152, 2016.
- [9] M. Maslač, B. Antić, K. Lipovac, D. Pešić, and N. Milutinović, "Behaviours of drivers in Serbia: non-professional versus professional drivers," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 52, pp. 101–111, 2018.
- [10] H. Naderi, H. Nassiri, and S. Sahebi, "Assessing the relationship between heavy vehicle driver sleep problems and confirmed driver behavior measurement tools in Iran," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 59, pp. 57–66, 2018.
- [11] L. Precht, A. Keinath, and J. F. Krems, "Identifying the main factors contributing to driving errors and traffic violations—results from naturalistic driving data," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 49, pp. 49–92, 2017.
- [12] D. Walton, "Examining the self-enhancement bias: professional truck drivers' perceptions of speed, safety, skill and consideration," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 2, no. 2, pp. 91–113, 1999.
- [13] D. R. Poulter, P. Chapman, P. A. Bibby, D. D. Clarke, and D. Crundall, "An application of the theory of planned behaviour to truck driving behaviour and compliance with regulations," *Accident Analysis & Prevention*, vol. 40, no. 6, pp. 2058–2064, 2008.
- [14] J. Davey, D. Wishart, J. Freeman, and B. Watson, "An application of the driver behaviour questionnaire in an Australian organisational fleet setting," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 10, no. 1, pp. 11–21, 2007.
- [15] J. Reason, A. Manstead, S. Stradling, J. Baxter, and K. Campbell, "Errors and violations on the roads: a real distinction?" *Ergonomics*, vol. 33, no. 10–11, pp. 1315–1332, 1990.
- [16] B. Jacob and V. Feypell-de La Beaumelle, "Improving truck safety: potential of weigh-in-motion technology," *IATSS Research*, vol. 34, no. 1, pp. 9–15, 2010.
- [17] J. Mohammadi and N. Shah, "Statistical evaluation of truck overloads," *Journal of Transportation Engineering*, vol. 118, no. 5, pp. 651–665, 1992.
- [18] G. Fiorillo and M. Ghosn, "Procedure for statistical categorization of overweight vehicles in a WIM database," *Journal of Transportation Engineering*, vol. 140, no. 5, Article ID 04014011, 2014.
- [19] G. Zhang, Y. Li, M. J. King, and Q. Zhong, "Overloading among crash-involved vehicles in China: identification of factors associated with overloading and crash severity," *Injury Prevention*, vol. 25, no. 1, pp. 36–46, 2019.
- [20] G. Fu and O. Hag-Elsafi, "Vehicular overloads: load model, bridge safety, and permit checking," *Journal of Bridge Engineering*, vol. 5, no. 1, pp. 49–57, 2000.
- [21] M. S. Attarchi, F. Dehghan, S. M. Seyedmehdi, and S. Mohammadi, "Traffic accidents and related injuries in Iranian professional drivers," *Journal of Public Health*, vol. 20, no. 5, pp. 499–503, 2012.
- [22] T. Rosenbloom, E. Eldror, and A. Shahar, "Approaches of truck drivers and non-truck drivers toward reckless on-road behavior," *Accident Analysis & Prevention*, vol. 41, no. 4, pp. 723–728, 2009.
- [23] J. Thompson, S. Newnam, and M. Stevenson, "A model for exploring the relationship between payment structures, fatigue, crash risk, and regulatory response in a heavy-vehicle transport system," *Transportation Research Part A: Policy and Practice*, vol. 82, pp. 204–215, 2015.
- [24] D. Blower, P. E. Green, and A. Matteson, "Condition of trucks and truck crash involvement," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2194, no. 1, pp. 21–28, 2010.
- [25] O. Oladepo and C. R. Onyema, "Knowledge and attitude of safety belt use among professional drivers in a tertiary Nigerian institution," *International Journal of Injury Control and Safety Promotion*, vol. 18, no. 1, pp. 57–64, 2011.
- [26] M. Rezapour, S. S. Wulff, and K. Ksaibati, "Predicting truck at-fault crashes using crash and traffic offence data," *The Open Transportation Journal*, vol. 12, no. 1, pp. 128–138, 2018.
- [27] G. X. Chen, W. K. Sieber, J. E. Lincoln et al., "NIOSH national survey of long-haul truck drivers: injury and safety," *Accident Analysis & Prevention*, vol. 85, pp. 66–72, 2015.
- [28] C.-M. Tseng, M.-S. Yeh, L.-Y. Tseng, H.-H. Liu, and M.-C. Lee, "A comprehensive analysis of factors leading to speeding offenses among large-truck drivers," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 38, pp. 171–181, 2016.
- [29] S. S. Tavafian, T. Aghamolaei, and A. Madani, "Predictors of speeding behavior among a sample of Iranian commercial automobile drivers: an application of the theory of planned behavior," *Traffic Injury Prevention*, vol. 12, no. 3, pp. 274–278, 2011.
- [30] G. H. Bham, B. S. Javvadi, and U. R. Manepalli, "Multinomial logistic regression model for single-vehicle and multivehicle collisions on urban US highways in Arkansas," *Journal of Transportation Engineering*, vol. 138, no. 6, pp. 786–797, 2011.