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Screening out accident-prone Iranian drivers: Are their at-fault accidents related to driving behavior?

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A R T I C L E I N F O

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A B S T R A C T

To provide a scientific background in road safety domain a better understanding of human risk factor is crucial. The aims of the present study were the following: (1) developing an accident prediction model for estimating the at-fault accidents of drivers (2) controlling for the regression-to-the-mean and screening out the accident-prone drivers (3) identification of significant behavioral predictors in at-fault accident occurrences and delving into the relationship between the aberrant driving behaviors and at-fault accidents of those identified as accident-prone. A questionnaire survey compiling various measures of personality type, aberrant driving behavior, demographic and accident history information of 1762 Iranian drivers was conducted in which 1375 male and 387 female participants were of the average age of 35.6 (S.D. = 11.987). To analyze the obtained data, the generalized linear modeling (GLM) approach was taken resulting in four models with various independent variables. The results indicated that age, gender, education level, years of active driving, and especially exposure had an effect on drivers' at-fault accidents while there was no discernible effect from income level, personality type and area of residence. In the screening procedure, 715 drivers were identified as accident-prone. Behavioral comparison analyses indicated that the lapses, errors, ordinary and aggressive violations are different for the accident-prone drivers. A comparison between the accident-prone and non-accident-prone drivers revealed that the ordinary violations have considerably higher effect than the others on at-fault accidents. Implications of the results are discussed with regard to insurance policies and education interventions.

1. Introduction

In Iran, the road traffic deaths per 100,000 population (fatality rate) in road traffic casualties (RTCs) has declined from 38 per 100,000 population in 2004 to 31 in 2011 (Ayati, 2009; Bahadorimonfared et al., 2013). However, during that time, the death rate in RTCs has been on increase from 51 cases per 1000 accidents to 65 (Bahadorimonfared et al., 2013). Despite

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minor decline in fatality rate in RTCs in Iran, it is still higher than the worldwide rate of 17.4 per 100,000 (World Health Organization, 2015). In Iran the burden of traffic injuries in terms of disabled-adjusted life years (DALYs) was over 1,300,000 years lost in year 2005 (Naghavi et al., 2009). The economic cost of traffic accidents was estimated 6% of Gross National Product in year 2013 (World Health Organization, 2015), whereas, car and motorcycle industry accounts for 4% of Iran's Gross Domestic Products (GPD) (Naghavi et al., 2009). Thus, RTCs are a serious public health problem and it is necessary to place greater emphasis on improving the prediction of accident involvement in Iran.

Some drivers are more likely to experience RTCs. Demographic factors influencing RTCs are being male, young, novice driver, and having higher exposure rate, and lower socioeconomic status (World Health Organization, 2015). WHO (2004) reported that males are nearly 3 times more likely to suffer RTCs as compared to females in Iran, it is nearly 4 times more likely (Bahadorimonfared et al., 2013; Rasouli, Nouri, Zarei, Saadat, & Rahimi-Movaghar, 2008). Regarding experience, young novice drivers in the second and third decades of their life represented the majority of RTCs, worldwide (Lourens, Vissers, & Jessurun, 1999; Mohammadi, 2009; Rajalin, 1994; Roudsari, Sharzei, & Zargar, 2004; Shope, 2006; Tseng, 2012). Several studies explored the interaction of age and gender in RTCs. For example, in Britain, men at 16–24 years of age were at the most risk, while women over 75 years old were at the greatest risk. There was an increase of 21% between 25 and 59 years of age for women while there was no corresponding increase for men (Holland & Hill, 2007). Iran police records show that males within the age group of 26–33 have more involvement in accidents whereas females within the same age group have a lower percentage of accidents (Mohammadi, 2009). Considering that, however, study of Zhang, Yau, and Chen (2013) in China indicated that driving experience takes over the effect of driver's age for accident severity, pointing to the importance of driving skills. With respect to education, there have been some evidence suggesting that drivers with lower level of education and low status occupations have a higher chance of being involved in traffic accidents even when the rate of exposure are accounted for (World Health Organization, 2015). However, the level of education has had little impact on accident involvement among Dutch and Taiwanese drivers (Lourens et al., 1999; Tseng, 2012), though for the drivers in China it had (Zhang et al., 2013). A study in Iran shows that RTCs are more common among women and men with low level of education and socio-economic status. The risk of RTCs among illiterates is 1.8 times more than that of people with higher education (college) in the adjusted model (Sehat, Holakouie Naieni, Asadi-Lari, Rahimi Foroushani, & Malek-Afzali, 2011). A cluster analysis study in Iran indicates that drivers with intermediate education are less risky compared with those of lower and higher education level throughout the age groups (Mohammadzadeh Moghaddam & Ayati, 2014).

Personality constitutes relatively enduring characteristics, revealing a particular pattern of behavior which may predispose individuals to commit risky driving and in accident involvement. A range of studies have directly associated certain personality traits to accident involvement or risky driving behaviors which in turn lead to accidents. For example, a study in Iran and Turkey pointed out that personality traits of sensation seeking and normlessness are among significant predictors of risky driving behavior (Nordfjærn et al., 2014). Examining personality types super-ordinations of specific associated traits revealed the contribution of Type-A behavior pattern to a person's likelihood of engaging in risky driving behaviors (West, Elander, & French, 1993). People with Type-A personality pattern tend to be competitive, hostile, aggressive and impatient (Friedman & Rosenman, 1974). Miles and Johnson (2003) found that respondents in the violators sample compared to control group did report significantly higher Type-A behavior pattern. People classified in Type-A behavior pattern are more likely to get stressed-out and exhibit aggressive driving behavior (Galovski & Blanchard, 2004). However, Type-A personality was not a direct factor in the accident involvements in West et al. (1993)'s study. In Iran, Type-A personality has shown meaningful effect on driving violations, accidents and fines. In fact, younger Type-A and B men and also younger Type-A women with lower level of education have been the riskiest groups (Mohammadzadeh Moghaddam & Ayati, 2014).

Studies have demonstrated the tendency of accident-involved drivers to high risk behaviors or unsafe road practices (Chen et al., 2009; Chliaoutakis et al., 2002; Lajunen, Parker, & Summala, 2004; Reason, Manstead, Stradling, Baxter, & Campbell, 1990; Sümer, 2003). Drivers prominently fined for committing driving violations were more often involved in traffic accidents; and the relationship between violation and accidents were independent of exposure rate (Lourens et al., 1999; Stamatiadis, Agent, Pigman, & Ridgeway, 1999). Moreover, self-reported aberrant driving behaviors have also been proved to be related to accident involvement and severity (Iversen & Rundmo, 2002; Kim, Nitz, Richardson, & Li, 1995; Parker, West, Stradling, & Manstead, 1995; Reason et al., 1990). Kim et al. (1995) used police officers' database and showed that driver behavior particularly alcohol or drug use and not using seat belt had the greatest impact on severity of accidents. A framework to study aberrant driving behavior has classified errors and violations (Parker et al., 1995; Reason et al., 1990). Errors are regarded as unwanted results of involuntary actions while violations are due to the conscious deviation from a rule or safe practice. Errors were additionally classified into slips and lapses (resulting from action) and mistakes (errors of intention) (Chliaoutakis et al., 2002; Lajunen et al., 2004; Parker et al., 1995). Also, violations were further divided into aggressive (i.e., showing hostility) and ordinary (deliberate breaking of traffic rules). The contribution of this taxonomy of aberrant driving behavior in explaining accident involvement has been well established in different countries (Reason et al., 1990; Warner, Özkan, Lajunen, & Tzamalouka, 2011). Also, the taxonomy shows some demographic discrepancies. Violations are consistently reported with higher frequency by male drivers, by younger drivers, and by high-mileage drivers. Young novice drivers (18–20) and especially young male drivers showed more violating driving rules than middle-aged novice drivers (31–50) (Laapotti, Keskinen, Hatakka, & Katila, 2001). Ordinary and aggressive violations are more prevalent in younger males, whereas, females and older novice drivers report more errors and slips (Rowe, Roman, McKenna, Barker, & Poulter, 2015). Driving violations are recognized to be a stronger factor related to accident involvement (Chliaoutakis et al., 2002).

Additionally, culture is often reflected in drivers' driving behavior and in predicting the number of traffic accidents (Özkan, Lajunen, Chliaoutakis, Parker, & Summala, 2006). In Iran, more than half of drivers exceed the posted speed limit. The risky behavior of speeding is way more likely to be witnessed among drivers owning modern vehicles, drivers not using seat belts, and male drivers (Moradi, Motevalian, Mirkoohi, McKay, & Rahimi-Movaghar, 2013). Iranian male drivers not using a seat belt had a higher involvement rate in RTCs (Mohammadi, 2009). A relationship between aggressive violations and the number of accidents has also been demonstrated in Iran (Özkan et al., 2006).

1.1. Aims of the study

A bulk of studies on RTCs have tried to determine the variables which are supposedly best correlated with accidents or risky behaviors and are more likely to lead to accidents. The indications are that several demographic features (e.g., gender, age), psychological factors (e.g., personality type) and driving behaviors (e.g., errors, lapses, and violations) could well define accident involvement.

The current study had three aims, (1) developing an at-fault accident prediction model, (2) controlling for regression-to-the-mean phenomena and screening out accident-prone drivers by estimating the expected at-fault accidents of drivers using the empirical Bayes (EB) method and thereby introducing a threshold congruent with drivers' characteristics via potential for improvement technique in order to indicate and assess risky drivers, (3) identifying significant behavioral predictors of at-fault accident involvement and comparing the relationship between the aberrant driving behaviors and at-fault accidents for those identified as accident-prone and non-accident prone. Accident-prone drivers were screened out based on the following characteristics; age, gender, educational level, car price, area of residence, income level, driving experience, traffic exposure and personality types.

2. Method

2.1. Instruments

For the current study three questionnaires were administrated:

1. Demographic questionnaire: It consisted of demographic information including age, gender, educational level, area of residence, car price, household income, at-fault accident (defined as number of at-fault accidents during last three years), driving experience (defined as years of active driving), exposure rate (defined as average KM driven during last three years). An accident was defined as any kind of crash with the results ranging from a minor damage to the car to the death of a person. Also, driver's at fault accident was defined as the accident in which driver is recognized as guilty.
2. Type-A Personality questionnaire: The translated Friedman and Rosenman (1974) and Rosenman and Chesney's (1982) type A personality questionnaire including 25 items was administered. Type A is associated with a high score while Type B is associated with a low score. Cronbach's alpha was reported 0.761, indicating the reliability of the questionnaire.
3. Driving Behavior Questionnaire (DBQ): The 28-item DBQ (Lajunen et al., 2004; Lawton, Parker, Manstead, & Stradling, 1997) was administered. The items included ordinary violations, aggressive violations, errors and lapses. Participants were required to report how often they commit each of the items. Their responses were recorded on a six-point scale from 0 = "Never", to 5 = "nearly all the times". Scores ranged from 0 to 140, with higher scores indicating more frequent aberrant driving behavior. DBQ has been normalized by Goodarzi and Shirazi (2006) in Iran. However, for the current study reliability of the questionnaire was reassessed using Cronbach's alpha. Results were 0.65, 0.66, 0.77 and 0.81 for lapses, errors, ordinary and aggressive violations, respectively. Additionally, the 19-item version of DBQ including 8 violations, 8 errors and 3 aggressive violations has been previously administered in Iran by Özkan et al. (2006). The distinction between errors and violations has consistently been found across cultures (Lajunen et al., 2004; Özkan et al., 2006).

2.2. Participants

A total of 3000 questionnaires were distributed to residents of Mashhad. 1752 questionnaires were returned (58% response rate) of which 78% were by male and 22% were by female respondents. The sample is comparable to the general population of drivers in Iran, where the overall percentage of male/female drivers are 70–30% (Ahmadi, 2011). Participants were recruited from public places, universities, government bureaus, private sectors and public agencies. The selection was on volunteer basis. Where possible, questionnaires were handed into the participants directly. Otherwise questionnaires were distributed among the members of the organizations/agencies and were returned after a while. Participants were assured of the anonymity of their responses and their consent was obtained before handing out the questionnaires. All participants held a valid driving license for average of 10.53 years (S.D. = 9.84), ranging between 1 and 52 years. Their mean age was 35.6 years (S.D. = 11.987) and ranged from 19 to 76. Of these, 14.2% did not have completed compulsory schooling, 40.7% had completed compulsory education and 45.1% had high education qualifications. During their last 3 years, participants had driven on average for 74822.43 (S.D. = 76096.82) kilometer and reported an average of 1.01 (S.D. = 1.223) at-fault accidents.

Among participants, 41.5% reported no accidents, 33.4% were involved in one at-fault accident, and 25.1% had two or more at-fault accidents during their last 3 years of driving. A summary of the variables is provided in Table 1.

3. Modeling

3.1. Modeling development

Usually generalized linear regression models (GLMs), such as Poisson models, negative binomial (NB) models are employed to describe the relationship between accident occurrence and a variety of possible covariates. The basic assump-

Table 1
A summary of variables measured in the study.

Variable	Category/Description	Number of participants	Percentage (%)	Mean at-fault accident (S.D.)
Gender	Male	1367	78	1.13(1.286)
	Female	385	22	0.58 (0.742)
Age	18–25	458	26.1	1.02 (1.244)
	26–30	296	16.9	1.16 (1.315)
	31–35	215	12.3	1.02 (1.144)
	36–40	225	12.8	1.14 (1.215)
	41–50	303	17.3	0.97 (1.169)
	51–65	233	13.3	0.72 (1.085)
	Over 65	22	1.2	1.04 (0.85)
Driving experience	Years of active driving (continuous; M = 10.53, S.D. = 9.84)	1752	–	1.01 (1.223)
Exposure	km driven during past three years (continuous; M = 74822.43, S.D. = 76096.82	1752	–	1.01 (1.223)
Education level	Illiterate	17	0.9	1 (0.791)
	Less than Diploma	234	13.3	1.29 (1.346)
	Diploma[a]	508	29	1.09 (1.272)
	Final Diploma[b]	203	11.7	0.89 (1.1)
	Graduated	624	35.6	0.96 (1.190)
	Post-graduated	121	6.9	0.727 (1.931)
	Doctor of Philosophy	45	2.6	0.733 (0.939)
Income level	<3,500,000 Rials	258	14.7	1.05 (1.139)
	[3,500,000 Rials, 5,000,000 Rials]	482	27.5	1.16 (1.375)
	[5,000,000 Rials, 8,000,000 Rials]	377	21.5	1.02 (1.217)
	[8,000,000 Rials, 10,000,000 Rials]	249	14.2	0.91 (1.141)
	[10,000,000 Rials, 15,000,000 Rials]	152	8.7	0.87 (1.12)
	[15,000,000 Rials, 20,000,000 Rials]	104	5.9	0.88 (0.889)
	[20,000,000 Rials, 30,000,000 Rials]	73	4.2	0.89 (1.137)
	[30,000,000 Rials, 50,000,000 Rials]	32	1.8	0.75 (0.984)
	>50,000,000 Rials	25	1.4	0.6 (0.866)
	Missing data	83	4.74	–
Car price	Low; [<50,000,000 Rials]	352	20.8	1.29 (1.422)
	Fairly low; [50,000,000 Rials, 80,000,000 Rials]	695	39.7	0.99 (1.167)
	Moderate; [8,000,000 Rials, 13,000,000 Rials]	376	21.5	0.85 (1.097)
	Fairly high; [13,000,000 Rials, 20,000,000 Rials	241	13.8	1 (1.171)
	High; [200,000,000 Rials, 350,000,000 Rials]	50	2.9	0.94 (1.077)
	Luxury; >350,000,000 Rials	34	1.9	0.97 (0.662)
	Missing data	61	3.48	–
Personality Type (PT)	Type A	1166	66.6	1.06 (1.216)
	Type B	656	33.4	0.92 (1.192)
Driving behavior	Lapses	1752	100	1.23 (0.81)
	Errors	1752	100	1.20 (0.79)
	Ordinary violation	1752	100	1.05 (0.876)
	Aggressive violation	1752	100	1.37 (0.978)
Residential area (RA)	Central Business district (CBD)	353	20.1	1.017 (1.107)
	Non-CBD	1336	79.9	1.013 (1.231)
	Missing data	63	3.6	–
At-fault accident	Frequency of at-fault accidents	1752	100	1.01 (1.223)

M: mean, S.D.: standard deviation.
[a] 12 years of study.
[b] 14 years of study.

tion of Poisson's distribution is that the mean of the count process equals its variance. When the data is subjected to over-dispersion, negative binomial regression should be adopted (e.g. Cafiso, Di Graziano, Di Silvestro, La Cava, & Persaud, 2010; Elvik, 2008; Hauer, Persaud, Smiley, & Duncan, 1991; Huang & Abdel-Aty, 2010; Naderan & Shahi, 2010; Poch & Mannering, 1996). The probability function of Poisson and NB models can be respectively defined as:

$$\begin{cases} \Pr(y_i) = \frac{\exp(-\lambda_i)-\lambda_i^{y_i}}{y_i!} & \text{(a)} \\ \Pr(y_i) = \frac{\Gamma(\Phi+y_i)}{\Gamma(\Phi)+y_i!}\left\{\frac{\Phi}{\Phi+\lambda_i}\right\}^{\Phi}\left\{\frac{\lambda_i}{\Phi\times\lambda_i}\right\}^{y_i} & \text{(b)} \end{cases} \tag{1}$$

Thereby, λ_i denotes the mean of at-fault accidents for the ith entity, $\Gamma(.)$ is a gamma function and Φ is the inverse over-dispersion parameter. Cameron and Trivedi (1990) suggested a hypothesis test to examine the existence of over-dispersion in the data, of which the null and alternative hypotheses are stated as:

$$\begin{cases} H_0 : \mathrm{Var}(y_i) = E(y_i), & \text{Poisson model} \\ H_1 : \mathrm{Var}(y_i) = E(y_i) + \frac{1}{\Phi}E(y_i)^2, & \text{NB model} \end{cases} \tag{2}$$

Then, a simple linear regression model on U can be defined as: $U = \xi W$, where $U_i = \frac{(y_i - E(y_i))^2}{\sqrt{2}E(y_i)}$ and $W_i = E(y_i)^2/\sqrt{2}E(y_i)$ and $E(y_i)$ is the predicted at-fault accident frequency. If ξ is statistically significant in NB model, then H_0 is rejected in support of H_1. Therefore, the data is said to be over-dispersed, and the negative binomial regression model should be taken into account. Based on the present literature (e.g. Lord, Washington, & Ivan, 2005; Maher & Summersgill, 1996; Naderan & Shahi, 2010), the general form of accident prediction model selected is:

$$E(y_i) = e^{\alpha_0+\alpha_1\times \mathrm{Ln}(E)} \times e^{\sum_{i=1}^{n}\beta_i X_i} \tag{3}$$

where E is exposure, which is the number of kilometers driven during the last three years; X_i are any covariates or explanatory variables in addition to E; and α_0, α_1 and β_i are model coefficients.

Returned questionnaires with missing data as much as 4.74% were excluded from the main analyses for developing the prediction models. However, they were used to validate the obtained model outside the range of the main data. To establish the prediction model, identifying primary accident predictors is of high importance at the outset. Thus far, in the context of drivers' factors associated with the accidents a massive body of studies have used different predictors based on the idea of developing the model, including demographic, socio-economic, personality type and behavioral factors (Chandraratna, Stamatiadis, & Stromberg, 2006; Dobbs, Heller, & Schopflocher, 1998; Hauer et al., 1991; Naderan & Shahi, 2010; Pakgohar, Tabrizi, Khalili, & Esmaeili, 2011; Siddiqui, 1997; Tseng, 2012). Since the main purpose of this study was set to screen out the accident-prone drivers to investigate their driving behavior, variables as summarized in Table 1 were designated for the model. The variables of driving behavior were not considered in the modeling process on account of two main reasons:

1. In practice, this kind of data is not readily available for drivers' at-fault accident estimation.
2. In the present study they are considered as mediated links to distinguish behavioral differences between accident-prone and non-accident-prone drivers.

In order to select the continuous and categorical predictors in developing the model, the following measures were taken:

- An initial analysis was carried out to identify the Spearman's correlation between two independent variables as well as dependent variable (at-fault accidents) among those reported in Table 1. Explanatory variables that either were strongly and significantly correlated in pairs (higher than ±0.5 and P-value below 0.05 indicating statistically significant non-zero correlations at the 95% confidence level) were excluded. In addition, The Variance Inflation Factor (VIF) was calculated for assessing multicollinearity in the modeling process. As a rule of thumb, the VIF of all variables should be less than 10 in order to avoid troubles with the stability of the coefficients.
- The logical considerations deriving from literature review and authors experience were taken into account; e.g. categorizing the age variable in Table 2 (Abdel-Aty, Chen, & Schott, 1998; Mohammadzadeh Moghaddam & Ayati, 2014; Reimer et al., 2005; Shi, Bai, Ying, & Atchley, 2010; Verschuur & Hurts, 2008).
- The results for different combinations of the categorical variables were kept so that not only was the variable's estimated coefficient significant at 5% level, but also improving the Akaike's Information Criteria (AIC) of the model was met.

Based on the results of the over-dispersion hypothesis test (P-value: 0.022), the at-fault accident data is dependent on significant over-dispersion at the 5% level of significance, Therefore, the negative binomial regression model should be adopted to model the at-fault accident occurrence.

The coefficients and NB over dispersion parameter were estimated from the calibration procedure by maximum likelihood estimation (MLE) method. The models were developed for distinctive combinations of non-correlated variables. The results are illustrated in Tables 2 and 3 for the variables, the estimated coefficients, corresponding P-values and VIFs. As shown, four models have been obtained. Generally, by capturing all the obtained models, and particularly, considering

Table 2
Significant explanatory and dummy variables in the estimated NB models.

Variables	Description
Gender (G)	Male:1, Female:2
Age Groups (AG)	[18–25]:1, [26–30]:2, [31–35]:3, [36–40]:4, [41–50]:5, Over 50:6
Driving Experience (DE)	Years of active driving (continuous)
Exposure (E)	KM driven during past three years (continuous)
Education Level (EL)	{illiterate, less than Diploma}:1, {Diploma, Final Diploma, Bachelor of Science/Art}:2, {Master of Science/Art, Doctor of Philosophy}:3
Car Price (CP)	{<50,000,000 Rials)/low, [50,000,000 Rials, 80,000,000 Rials)/fairly low, [130,000,000 Rials, 200,000,000 Rials)/fairly high, [200,000,000 Rials, 350,000,000 Rials)/high}:1 {[800,000,000 Rials, 1,300,000,000 Rials)/moderate, >3,500,000,000 Rials/luxury}:2

Table 3
Models results for the model form based on Eq. (1).

Factor	Model 1		Model 2		Model 3		Model 4	
	Coefficient	*P*-value (VIF)	Coefficient	*P*-value (VIF)	Coefficient	*P*-value (VIF)	Coefficient	*P*-value (VIF)
G 1	–	–	0.5170	<0.0001 (1.126)	0.5172	<0.0001 (1.118)	0.4651	<0.0001 (1.097)
G 2	–	–	0.0000	–	0.0000	–	0.0000	–
AG 1	–	–	–	–	–	–	0.5021	<0.0001 (1.035)
AG 2	–	–	–	–	–	–	0.8850	<0.0001 (1.035)
AG 3	–	–	–	–	–	–	1.1664	0.0006 (1.035)
AG 4	–	–	–	–	–	–	1.7772	<0.0001 (1.035)
AG 5	–	–	–	–	–	–	1.2735	0.0159 (1.035)
AG 6	–	–	–	–	–	–	0.000	–
EL 1	–	–	–	–	0.3886	0.0018 (1.023)	0.3963	0.0016 (1.042)
EL 2	–	–	–	–	0.4600	0.0356 (1.023)	0.4754	0.0301 (1.042)
EL 3	–	–	–	–	0.0000	–	0.0000	–
CP 1	–	–	0.1494	0.0286 (1.017)	–		0.1543	0.0242 (1.016)
CP 2	–	–	0.0000	–	–	–	0.0000	–
DE	–	–	−.0171	<0.0001 (1.071)	−.0179	<0.0001 (1.054)	–	–
E	0.2928	<0.0001	0.2657	<0.0001 (1.113)	0.2565	<0.0001 (1.129)	0.2508	<0.0001 (1.140)
Intercept	−3.1587	<0.0001 (1)	−3.2399	<0.0001	−3.2536	<0.0001	−3.8222	<0.0001
Dispersion parameter ($1/\Phi$)	0.2829		0.2286		0.2260		0.2195	
Full log likelihood	−2218.9506		−2182.3408		−2179.6016		−2177.7650	

the km driven exponent less than one, it is obvious that the relationship between at-fault accidents and exposure element is nonlinear as with increasing the km driven less at-fault accidents could be expected. Doing so for that of gender, male drivers are observed highly more vulnerable to being involved in at-fault accidents than female drivers.

In addition to the exposure predictor and gender that were common in the whole and last three models, Model 4 takes in age, education level and car price which influence the frequency of at-fault accidents. In terms of age, drivers' likelihood to be more frequently at-fault in accidents increases until the middle ages period (36–40). Afterwards, it tends to decrease. Comparably, drivers with low-to-moderate education level are associated with having higher potential for being involved in at-fault accidents. Car price also accounts for the number of at-fault accidents in such a way that owners of low, fairly low, fairly high and high price cars are likely to have more at-fault accidents than the others. Model 2 includes the effect of years of active driving as well as the car price variable. As can be seen in Table 2, for the car price variable the same result is achieved as in Model 4; therefore, confirming it. Regarding the years of active driving, the estimated coefficient is negative which means that with the increase of driving experience on roads over years, the probability of being at-fault in accident decreases. It may be by virtue of increasing driving skills especially required in circumstances of spontaneous decision making for a proper maneuver. As Model 2 and 4, Model 3 also considers years of holding a driving license and education levels. The estimated coefficient of years of driving is negative and approximately the same as in Model 2. This reasons that the more experienced the driver is, the less at-fault accident involvements can be expected. It should be mentioned that for the education level, the coefficient estimate is close to Model 4, which confirms a reduction in the probability of being at-fault in an accident for highly educated people.

3.2. Model selection and validation

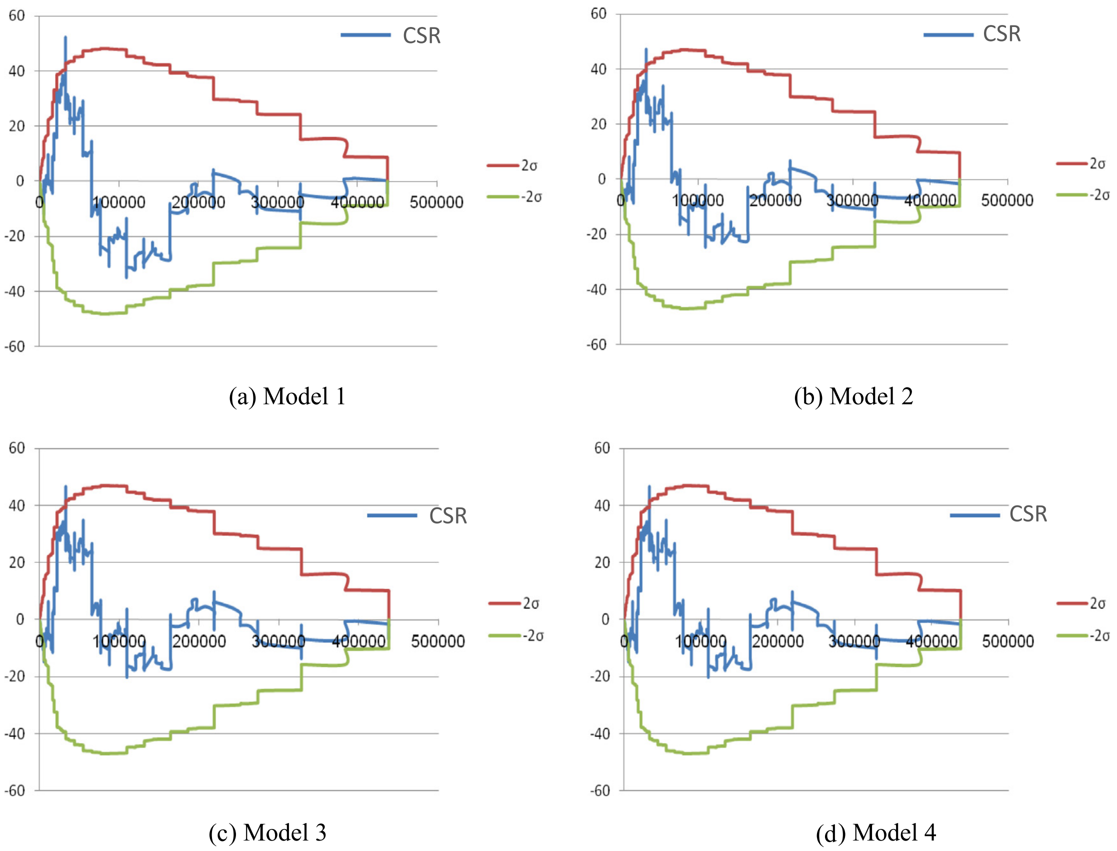
To seek out accident-prone drivers in the subsequent steps, one model had to be selected. The AIC, were utilized for evaluation of model fitting, and the prediction accuracy was compared by the cumulative standardized residual (CSR) plot. Principally, the smaller the value of AIC, the better is the model data fit (e.g. Abdel-Aty & Radwan, 2000; Zhang & Ivan, 2005).

Also, the more the CSR curve lays down the horizontal coordinates and the less oscillation turns up around it, the better the model form is selected. When a CSR curve does not stray from the 95% significance level boundaries, around two standard deviations, the model could behave satisfactorily (Hauer & Bamfo, 1997).

The AIC measures are 4443.8183, 4376.6817, 4373.2707 and 4379.5300 for model 1, 2, 3 and 4, respectively. Considering AIC, Model 3 results in the lowest value followed by Model 2, Model 4, and Model 1, even though except for Model 1 they are very close. Model 4 presents more explanatory variables, perhaps this is why it has a slightly larger AIC than Model 2 and 3. The reason for Model 1 is the existence of unexplained variation owing to the lack of non-exposure variables. Furthermore, in Fig. 1, cumulative standardized residuals versus Km's driven during the last three years are shown. It is evident from the plots that the models CSRs oscillate admissibly between $\pm 2\sigma$ boundaries and stray just a little from the upper limit, which is negligible and thus show the proper fit of the models. As illustrated in Fig. 1, and based on AICs, all of the four models show considerable, close and acceptable statistical fit. Furthermore, all the models depict the similar plot results with a little exception for Model 4 and 3 concerning 80,000–160,000 km driven interval which reveals better predictions than Model 2. They are more precise than those of Model 1. However, all of these models can be practical in an EB procedure to assess the drivers' potential for safety improvement. Ultimately, in this study Model 3 was adopted for the analysis ahead, as it outperforms the others considering all of the addressed model evaluation measures. In order to validate the selected model, the nearly 5% holdout questionnaires were recorded in a database and were analyzed. For this purpose, the drivers' at-fault accidents were initially estimated based on the designated model (Model 3). Then, a paired t-test was carried out on the values to compare them with those reported by drivers at 95% level. The result of the analysis (P-value: $0.67 > 0.05$) endorses the model's estimation accuracy; there was no difference between the reported and estimated at-fault accidents.

4. Comparing accident-prone and non-accident prone groups

In this research PFI analysis method was selected to screen out accident-prone drivers for further study. The PFI can be drawn from the difference between the expected accident frequency resulting from EB method and the accident frequency predicted from the accident prediction model. As long as the potential for improvement value is greater than zero, a driver experiences more accidents than expected, denoting accident-prone. Otherwise, if the potential for improvement value is less than zero, a driver experiences fewer accidents than expected, which means non-accident-prone. By analyzing the drivers based on Model 3, 715 out of 1665 drivers were identified as unsafe. Table 4 presents a summary of characteristics



(a) Model 1 (b) Model 2 (c) Model 3 (d) Model 4

Fig. 1. Cumulative standardized residuals plot for exposure for (a) Model 1, (b) Model 2, (c) Model 3, (d) Model 4.

with respect to the identified drivers as accident-prone as well as non-accident-prone. As indicated in Table 4, the mean of at-fault accidents for the accident-prone ones was considerably higher than the others, so was it for the both accident-prone males and females. Both groups also had closely the same mean age. Considering the gender factor, the females in the non-accident-prone group showed a smaller mean age. On average, the driving experience appears to be similar for both, while it was not the case regarding the gender. As seen, male and female drivers as non-accident-prone turned up with higher and lower mean driving experience than their counterparts in the other group, respectively. This was identical to the case about exposure where especially this difference was of significance for the female drivers. Generally, men are more active and start driving earlier in life than women. It almost sounds true as in Iran men are customarily supposed to take more of the outdoor responsibilities. Having comparatively looked at the females' at-fault accidents in both groups, it can be explained that although non-accident-prone females have less driving experience, they drive less and for this very reason have lower exposure and at-fault accidents, too. For male drivers, it can be accounted for as they have more exposure in non-accident-prone group, but these drivers are more experienced in comparison to the accident-prone ones.

An independent *t*-test was conducted for comparing driving behavior of the two groups, i.e. identified accident-prone and non-accident-prone drivers. The results are given in Table 5 which shows that in all measures of DBQ, scores of accident-prone group were significantly higher than that of non-accident-prone group.

To figure out the predictability of at-fault accidents by self-reported tendency to perpetrate the aberrant driving behaviors, a correlation analysis has been run. Since accidents could not be assumed to follow normal distribution, Spearman's rank correlation, which is a nonparametric measure of statistical dependency, was employed to measure the extent to which as the at-fault accidents increase, the lapses, errors, ordinary and aggressive violations tend to increase or decrease.

By analyzing the correlation analysis linking the at-fault accidents with driving behavior factors, as illustrated in Table 6, fairly correlated findings, albeit significant, appeared for both groups of drivers with an exception for the relationship between lapses and at-fault accidents. Neither in accident-prone nor in non-accident-prone group, the lapses were significantly associated with at-fault accidents and revealed too small correlation; so having no direct effect on being involved in at-fault-accidents. Considering both groups in Table 6, the errors, ordinary and aggressive violations were moderately and significantly correlated with at-fault accidents while these associations were stronger for the accident-prone group than the other one. Investigation of within driving behavior factors revealed that the highest correlation was between the ordinary violations and at-fault accidents in the accident-prone group, and between those of aggressive and at-fault accidents in the other group. On the other hand, the lowest ones appeared to be for the errors in both groups. Therefore, resting on the results, the at-fault accidents for both types of drivers are related to the errors, ordinary and aggressive violations and would have an effect on drivers' at-fault accidents disregard of being accident-prone or not. The alternative question was that whether the correlations (between the at-fault accidents and driving behavior factors) differ across the two identified groups of subjects. Thus, the Z statistic was computed (Kullback, 1959; Steiger, 1980). The results are shown in Table 6. Having seen the Z statistic P-values, one can say that neither the errors nor aggressive violations correlations with at-fault accidents revealed significant differences between both groups at 95% level. However, the ordinary violations appeared to have a significantly stronger correlation with the at-fault accidents for the accident-prone drivers. It could be interpreted as the more the driver commits the ordinary violations, the more they are liable to be accident-prone and accordingly the higher the likelihood of holding responsible for at-fault accident could be. It suggests that countermeasures against the ordinary violation behavior for those of accident-prone have to be devised in order to rationally improve safety.

Table 4
Results of identified drivers based on PFI method.

Factor	Accident-prone drivers						Non accident-prone drivers					
	Male		Female		Total		Male		Female		Total	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
At-fault accident	2.20	1.30	1.27	0.59	1.99	1.24	0.35	0.50	0.01	0.10	0.28	0.47
Age	35.73	12.12	34.39	10.68	35.43	11.82	36.27	12.48	33.66	10.39	35.74	12.12
Driving license (year)	10.90	9.80	7.36	7.00	10.10	9.35	12.05	10.61	6.66	7.39	10.94	10.27
Exposure (km driven)	77867.7	79199.7	52927.5	67449.9	72216.9	77,359	85902.1	78780.7	31,988	38221.5	74835.5	75527.7
Frequency	553 (77.3%)		162 (22.7%)		715 (42.9%)		755 (79.5%)		195 (20.5%)		950 (57.1%)	

Table 5
t-test for driving behavior factors.

Factor	Lapses		Errors		Ordinary violations		Aggressive violations	
Group (1665)	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Non-accident-prone drivers (950)	1.1719	0.78459	1.1403	0.75379	1.1415	0.81937	1.2817	0.95920
Accident-prone drivers (715)	1.3102	0.85188	1.2910	0.84140	1.3218	0.87388	1.4781	1.01362
P-value	0.001		0.000		0.000		0.000	

Table 6
Spearman rank correlation between at-fault accidents and driving behavior factors plus *Z*-test for correlation comparison.

Factor	Lapses	Errors	Ordinary violations	Aggressive violations
Accident-prone drivers (At-fault accidents rank)	0.044	0.110	0.202	0.168
P-value	0.24	0.003	0.000	0.000
Non-accident-prone drivers (At-fault accidents rank)	0.004	0.101	0.104	0.115
P-value	0.907	0.002	0.001	0.000
Correlations comparison (*Z*-test *P*-value)	–	0.981	0.043	0.275

5. Conclusion

This research has developed accident prediction models of at-fault accident involvement considering NB error structure and various drivers' characteristics. The results of the model development indicated that given different control variables, drivers having higher to lower likelihood of experiencing at-fault accidents are drivers aged between 31 to 50, 18 to 30 year-old drivers, drivers holding a Diploma or Bachelor degree, male drivers, illiterate drivers or drivers having educational level lower than Diploma, drivers with higher exposure and drivers who drive low to fairly high car prices. Although, these findings are consistent with a wealth of studies indicating that the youth and males are more likely to involve in accidents (Bahadorimonfared et al., 2013; Lourens et al., 1999; Mohammadi, 2009; Rasouli et al., 2008; Roudsari et al., 2004; Shope, 2006; Tseng, 2012). The study indicates the higher vulnerability of Iranian middle aged drivers especially those aged between 36 and 40 years old. Additionally, diploma-graduated drivers who have good to fairly high educational level showed a high probability of experiencing at-fault accidents. The significance of car price may point to the impact of vehicle type in accidents. However, the weaker significance of it may support the view that human factors have stronger role than vehicle type in at-fault accidents.

Further results indicated that those identified as accident-prones, compared to non-accident prones, exhibited higher aberrant driving behaviors. The result confirms the reliability of the model since these behavioral differences can also imply the reliability of the applied screening method. The correlations between the aberrant driving behavior factors and at-fault accident in both groups of drivers revealed that errors, ordinary and aggressive violations fairly but significantly linked with at-fault accidents while it was not so for the lapses. Drivers tending to speed up, following vehicles too closely, making illegal lane changes, and weaving through traffic, put themselves and others at risk. This result is consistent with Reason et al. (1990)'s proposition that errors and violations are potentially dangerous and may result in accidents, lapses are less likely. However, employing *Z*-test analysis revealed that the ordinary violations factor had significant effect on at-fault accidents and would well distinguish the accident-prone individuals from the others at least as a mediated link.

Clearer and more paramount picture of these findings would be beneficial in devising appropriate countermeasures for reducing at-fault accidents and accordingly the total accidents by a thorough understanding and consideration of ordinary driving violations along with identification of effective demographic factors. Regarding demographic factor, the common factor in four models which could identify and categorize accident-prone drivers was exposure. This approves exposure$*$risk-based insurance policies fixing fair charges regarding these drivers in developed countries (Ayuso, Guillén, & Pérez-Marín, 2014). Tailoring training programs or a procedure for issuing or renewing driving license for middle aged, young aged, well educated, male drivers who intend to become or continue as professional drivers are recommended.

In conclusion, the concern for authorities to identify accident-prone drivers was addressed in the current study. The results can accordingly be used to devise relevant and effective countermeasures in the framework of refining driver behavior attitudes and operational constraints (e.g., insurance cost, driving time, etc.) to mitigate accidents.

6. Recommendations and limitations of the study

Further studies in Iran are suggested to examine the high involvement of middle aged, young aged, well educated, male drivers in at-fault accidents. The reason for this may stem from the driving habits, skills, styles, attitudes and behaviors that these groups have developed and that pushes its members to higher level of risk-taking while driving and in turn in higher degrees of actual involvement in at-fault accidents. Moreover, considering the significance of ordinary driving violations for at-fault accidents of accident prone drivers, further studies are required first to identify the most common types of violations that each of these groups of Iranian drivers commit and second, to identify the underlying factors and to design appropriate intervention programs, accordingly.

Although the findings yield a comprehensive procedure resulting in low-cost data surveying, model development and identification of accident-prone drivers based on at-fault accidents, limitation of the study should be noted. First, sampling was on a volunteer basis which may not be representative of the population. However, the ratio of male to female drivers in the sample was comparable to the general population of drivers in Iran. Second, for assessing driving behavior a questionnaire was used which may not represent real world driving behavior. However, considering the size of the sample, questionnaire is the most cost effective way to assess driving behavior. Also, anonymity of responses may have decreased socially desired responses. Also, huge numbers of studies have used this methodological approach in driving for decades (for review see de Winter and Dodou (2010)). Third, instead of using police records, the self-reported measure of at-fault accidents was utilized. Police records might be regarded a more reliable measure. However, it may underestimate the number of accidents; as in Iran, due to the high frequency of traffic accidents, police call for minor accidents are less recommended. Additionally, there exist several well-established validation techniques (like cross validation) that either could be used. While, cross validation technique is a well-established approach, but the use of other methods, like that adopted in this study, is duly acceptable (e.g. Chandraratna et al., 2006). Also, it is recommended to compare a set of screening methods (like PFI, EB, etc.) to gain an effective technique for the risky drivers' identification.

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