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Smooth associations between the emergency medical services response time and the risk of death in road traffic crashes

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ABSTRACT

Background: Understanding the impact of emergency medical services (EMS) response times on the likelihood of death has received repeated attention in the literature. However, the current literature lacks definite and detailed results. This study seeks to contribute by revealing a smoothed conditional association between EMS response times and the odds of fatality, also allowing this association to be heterogeneous with respect to the statuses of other influential variables.

Methods: The 2015 Fatality Analysis Reporting System (FARS) national dataset of the United States was adopted as it was large enough to support the sample-size requirement for exhibiting heterogeneous smooth link functions of EMS response times, with higher confidence levels. An additive logistic regression model with smooth interaction terms was introduced. Two ordinary logistic models with different settings for the EMS response time were developed for comparison with the additive logistic model.

Results: The overall impact of the EMS response time, as well as age, gender, seating position and manner of collision, on the odds of death, was statistically significant. For the first time, the marginal smooth influential pattern of the EMS response time was found to be non-monotonic, such that, for cases with long EMS response times, it could be negatively associated with the odds of death. Similar phenomena were also found when the EMS response time interacted with several other factors.

Conclusion: Two critical values (5.5 minutes and 17 minutes respectively) of the EMS response time were found. The former represents the fastest decline in the chance of survival and the latter is just the “gold time” for operating rescues. Overestimation of the urgency level of certain types of crashes at the very early stages of rescues could be the main reason for observing a negative influential pattern of the EMS response time on the odds of death.

1. Introduction

The emergency medical services (EMS) response time is defined as the duration between the notification of an emergent event and the arrival at the scene of EMS personnel (Brown, 1979; Al-Ghamdi, 2002; Gonzalez et al., 2009; Meng and Weng, 2013; Harmsen

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et al., 2015; Jung et al., 2016). It is a key performance indicator reflecting the time traffic crash victims wait to be rescued and serving as a measurable quantity for evaluating and managing dispatch operations of EMS vehicles (Amorim et al., 2017). Mainstream opinions (e.g. Gonzalez et al., 2009; Wilde, 2013) acknowledge the considerable influence the EMS response time has on death likelihood, in that an increased EMS response time will lead to an elevated risk of fatality for general emergent events (Bunn et al., 2012; Heestermans et al., 2010; Saver et al., 2010) and traffic crashes (Delmelle et al., 2005; Li et al., 2008; Petzäll et al., 2011; Sánchez-Mangas et al., 2010; Arroyo et al., 2013; Peura et al., 2015). Thus, the emergency medical handling of the injured has become an acknowledged tactical approach for reducing the mortality rate from traumas, as many deaths would have been preventable if the victims had received quicker medical responses (Hussain and Redmond, 1994), especially in cases of brain- or heart-injured victims (MacLeod et al., 2007) or those requiring open airways or hemorrhage controls (Bansal et al., 2009; Bakke and Wisborg, 2017; Oliver et al., 2017). Many studies have been motivated by the goal of figuring out the detailed and specific influencing patterns of EMS response times on rescue results, because of this and because of the significant financial cost associated with lowering EMS response times (Pons and Markovchick, 2002).

There is an extensive literature (Mannering and Bhat, 2014) analyzing the impacts of various factors on the injury results for traffic crash victims, with special emphasis on the development of statistical models (e.g. Xiong et al., 2014; Ma et al., 2016), inferences about critical variables (e.g. Abdel-Aty, 2003; Abdel-Aty and Abdelwahab, 2004) or about driving behaviors (e.g. Ba et al., 2017; Wan et al., 2016). However, most of these studies have only considered pre-crash factors (e.g. geometric design of roadways, weather conditions and person-level characteristics of the driver), while to a large extent overlooking the post-crash intervention process of medical rescues. In fact, the latter is also important for lowering the injury severity levels of all traffic crash victims. One of the reasons impeding the consideration of post-crash attributes such as the EMS response time is that most of the current traffic crash datasets are lacking in variables describing the post-crash circumstances. Almost all quantitative studies have used data recorded by medical facilities, which are usually biased and have very small sample sizes, leading to unreliable results and controversies (Newgard et al., 2010; Kidher et al., 2012).

Some studies assert that there is no significant association between the EMS response time and the fatality likelihood (e.g. Jones and Bentham, 1995; Pons and Markovchick, 2002; McCoy et al., 2013). For example, McCoy et al. (2013) illustrate that there is no association between increased the odds of mortality and out-of-hospital times in blunt trauma victims; Funder et al. (2011) show no significant association for victims with penetrating trauma to the thorax, abdomen and/or neck. In fact, the detectability of correlative relationships between two observed variables is contingent upon many aspects, in particular including data selection, sample size, cohort characteristics of the victims' trauma situations, and statistical models. Therefore, it is probably true that shortening EMS response times will not reduce the risk of being killed in a traffic crash under very specific conditions (e.g. a minor collision or extremity-injury-only victims). However, it is difficult to perceive the overall situation of a victim and no one can guarantee the actual influence of the EMS response time on the death likelihood of the victim, especially in a traffic crash that looks serious. As a result, in practice, new technologies such as automated collision notification (Clark and Cushing, 2002) and quick response codes (Morales et al., 2016) have continued to emerge to shorten the rescue waiting time. In addition, under particular circumstances, it can be difficult for the person notifying the police or EMS facility to accurately and professionally describe the details of victims' trauma conditions, if they have not received proper medical training. EMS vehicles might try to reach the scene of an crash as quickly as they can, and may sometimes overspeed using lights and sirens, which is risky to themselves as well as other vehicles (Petzäll et al., 2011).

Hospital emergency rooms could become overcrowded after large-scale urban incidents, requiring diversion to alternative hospitals, under which scenario the EMS vehicles would need additional transport time, possibly leading to increased response times for future patients. In such situations, it is necessary to assess the risk of death for different waiting victims, and assign the most suitable EMS response time, to dispatch EMS resources efficiently.

These issues strongly demand detailed and refined depictions of the association between EMS response time and death likelihoods of victims. Over the past several decades, researchers have sought to find a deterministic impact of the EMS response time on victims' deaths. Most have tried to illustrate such an association by comparing the mortality rates of victims under different EMS response times (Pons and Markovchick, 2002; Blackwell and Kaufman, 2002; Nicholl et al., 2007; McCoy et al., 2013; Lam et al., 2015), or categorizing EMS response times into different intervals (Sánchez-Mangas et al., 2010; Clark et al., 2013; Arroyo et al., 2013; Dinh et al., 2013) in regression models. For example, Pons and Markovchick (2002) provide a depiction of EMS response times versus the survival percentages of patients using two-minute intervals of EMS response times; Blackwell and Kaufman (2002) plot the mortality odds for each minute of EMS response time. Essentially, the EMS response time is a continuous variable, and empirical data have illustrated that its impact on the risk of death could be non-linear and smooth (e.g. Blackwell and Kaufman, 2002; Clark et al., 2013; McCoy et al., 2013; Jaldell et al., 2014). It is natural and unproblematic to assume a continuous variable to have a non-linear and smooth influence on dependent variables, because such an assumption is simply a more flexible and general form of the traditional linear model. Current literature capable of handling such a feature statistically, however, is limited. One exception is Jaldell et al. (2014), who used logistic regression models to connect the EMS response time with the outcomes of traffic crashes. Jaldell et al. (2014) contribute to predicting the marginal money value of the EMS response time. However, their work lacks statistical considerations of the smooth feature of the influence of the EMS response time on the outcomes of traffic crashes, and they fail to include other explanatory variables.

In addition, the influence of the EMS response time could be heterogeneous with respect to the statuses of other factors. While previous literature has included clinical categories (Nicholl et al., 2007) (e.g. chest pain, respiratory problems, hemorrhage etc.), penetrating/blunt types (McCoy et al., 2013) and fire involvement (Bunn et al., 2012), we have not yet seen studies reporting the heterogeneous influence of EMS response times with respect to collision-level or engineering-level characteristics (e.g. manner of collision and facility type) or attributes which are easy for bystanders to describe when notifying the police or EMS facility (e.g. age

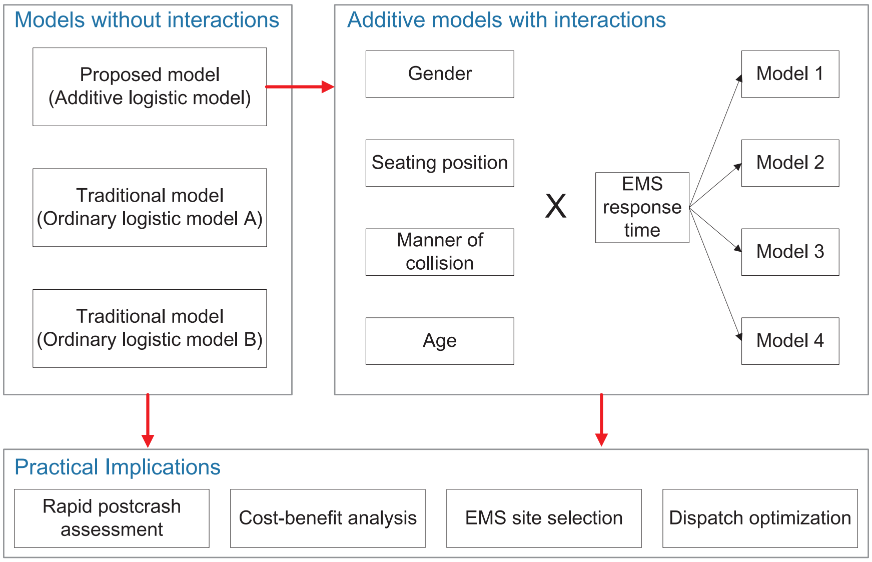

Fig. 1. Conceptual framework of this study.

and gender of victims).

Taking the abovementioned issues into consideration, this study seeks to deepen current research by allowing smooth and heterogeneous influencing patterns of EMS response times on the death likelihood, with controls of several key factors, and in the specific context of traffic crash victims. A semi-parametric additive logistic regression model (Hastie et al., 2009; Ma and Yan, 2014) is proposed to link smooth functions of the EMS response time with the odds of being killed in a traffic crash and, furthermore, to decompose such influencing functions with respect to different statuses of other factors.

2. Method

2.1. Motivations and conceptual framework

Fig. 1 illustrates the conceptual framework of this study. The dependent variable (fatality outcome) is a dummy variable indicating whether the person died in a traffic crash. To compare the proposed additive model with traditional settings, three models without interaction terms were developed, i.e. an additive logistic model, ordinary logistic model A and ordinary logistic B. Ordinary logistic model A treats the EMS response time as a scalar variable, while ordinary logistic model B adopts a categorized EMS response time. Further, the proposed additive model was extended to include interaction terms between the EMS response time and other explanatory variables, to investigate heterogeneous smoothing effects of the EMS response time.

Since all the data were collected after each crash, this study was not motivated by an attempt to reveal the pure causal effect of the EMS response time on the risk of death for traffic crash victims, but to depict fine associations between the two variables. Although the results from such studies are less persuasive, to some extent, this will be the furthest step taken to date towards understanding the statistical relationships between EMS response times and the severity of crashes. There are no methodologies able to fundamentally solve this problem, but some methods could contribute towards alleviating it. The most direct is to include important influential factors in regression models to reduce the impact of latent variables as well as the variance of error terms. That is what this study did. It considered several variables, including seating position, manner of collision, gender and age of victim, along with the EMS response time.

Those variables were chosen deliberately as they have long been recognized as highly influential for the fatality likelihood in traffic crashes (e.g. Zhu and Srinivasan, 2011; Mannering and Bhat, 2014; Yasmin et al., 2014; Ma et al., 2016). More importantly, they can be identified quickly at the scene of a crash. With their aid, the developed models could serve as a framework for the quick evaluation of the risk of death of traffic crash victims.

The proposed model also has potential at another level of practical implications. As will be presented shortly, the additive logistic model provides a continuous and differentiable relationship between the EMS response time and whether or not a fatality occurs. With the smoothed relationship, we know how the risk of death in traffic crashes changes with respect to the change in the EMS response time at any level of EMS response time. The results could be used in a cost-benefit analysis of the decision to invest in reducing the EMS response time, in forming mathematical optimization problems when selecting the sites of EMS facilities, or in assigning the dispatch priorities of EMS vehicles.

Table 1
Distribution of categorical explanatory variables.

Categorical variables	Fatal observations	Non-fatal observations	Total
Seating position			
Driver	9,369 (28.3%)	10,752 (32.5%)	20,121 (60.8%)
Other front seat	1,726 (5.2%)	3,921 (11.8%)	5,647 (17%)
Second and after second seat	1,158 (3.5%)	3,864 (11.7%)	5,022 (15.2%)
Not a motor vehicle occupant	2,107 (6.4%)	194 (0.6%)	2,301 (7%)
Manner of collision			
Front-to-rear	997 (3.0%)	2,405 (7.3%)	3,402 (10.3%)
Front-to-front	1,921 (5.8%)	3,018 (9.1%)	4,939 (14.9%)
Angle	2,875 (8.7%)	5,651 (17.1%)	8,526 (25.8%)
Sideswipe	422 (1.3%)	1,021 (3.1%)	1,443 (4.4%)
Not collision with motor vehicle in transport	8,145 (24.6%)	6,636 (20.0%)	14,781 (44.6%)
Gender			
Male	9,949 (30.1%)	11,575 (35.0%)	21,524 (65.0%)
Female	4,411 (13.3%)	7,156 (21.6%)	11,567 (35.0%)
Age			
age < 20	1562 (4.7%)	4274 (12.9%)	5836 (17.6%)
20 ≤ age < 40	5149 (15.6%)	7258 (21.9%)	12,407 (37.5%)
40 ≤ age < 60	4123 (12.5%)	4764 (14.4%)	8887 (26.9%)
66 ≤ age < 80	2667 (8.1%)	2126 (6.4%)	4793 (14.5%)
age ≥ 80	859 (2.6%)	309 (0.9%)	1168 (3.5%)
EMS response time			
time < 5	2907 (8.8%)	3918 (11.8%)	6825 (20.6%)
5 ≤ time < 10	5920 (17.9%)	7806 (23.6%)	13,726 (41.5%)
10 ≤ time < 15	3111 (9.4%)	3882 (11.7%)	6993 (21.1%)
15 ≤ time < 20	1360 (4.1%)	1711 (5.2%)	3071 (9.3%)
20 ≤ time < 25	694 (2.1%)	910 (2.7%)	1604 (4.8%)
25 ≤ time ≤ 30	368 (1.1%)	504 (1.5%)	872 (2.6%)

2.2. Data

Due to the lack of a sufficiently large dataset with randomly selected samples containing emergency medical handing information for all types of crashes, the inferred associations between the EMS response time and the odds of death will inevitably be conditional. In fact, such information on less severe crashes has a lower chance of being reported. The 2015 Fatality Analysis Reporting System (FARS) national dataset of the United States was adopted in this study. The dataset is maintained by the National Highway Traffic Safety Administration of the United States (NHTSA), providing a nationwide yearly census of motor vehicle crashes. To be included in FARS, a crash must involve a motor vehicle traveling on a trafficway customarily open to the public and must result in the death of an occupant of a vehicle or a non-occupant, within thirty days of the crash. Therefore, the modeling results will inherently be conditional on the most severe (fatal) traffic crashes. Fortunately, at the person level, a great proportion of the passengers and drivers in these crashes survived, and constitute the comparative group to those killed.

In this dataset, the data are organized on three levels, crash, vehicle and person. In total, there is information provided on 32,166 traffic crashes involving 48,923 vehicles and 80,587 people. Since these crashes were all relatively severe, almost all of the scenes were reached by EMS. Other than the EMS response time, several other variables, including age, gender, seating position of the person and manner of collision of the crash, were adopted to serve as exogenous factors to enhance the modeling performance, as well as to assist statistical inference regarding the EMS response time. Only those cases with EMS response times less than or equal to 30 minutes were included, as the proportion of cases with longer EMS response times was extremely small, and produced unstable results with wide confidence intervals in preliminary statistical analyses. After removing observations with missing or indeterminate values for the variables that were to be used, 33,091 person observations eventually remained. As a scalar variable, the EMS response time had a mean value of 9.198 minutes with a standard deviation of 5.922 minutes. Also as a categorical variable, its descriptive distribution is illustrated in Table 1. For the other categorical variables, we observed that drivers (at 60.8%) made up a greater proportion of the total than the other seating positions (i.e., other front seat, second and after second seat, and not a motor vehicle occupant); “not a collision with a motor vehicle in transport” (44.6%) was the most frequent manner-of-collision (others were front-to-rear, front-to-front, angle, and sideswipe); males (at 65.1%) were more frequently involved than females.

2.3. Additive logistic regression model

The nonparametric additive logistic regression model (Hastie et al., 2009) was adopted to calibrate smooth associations between the EMS response time and the odds of death. Since this study focuses on dichotomous outcomes (death versus survival) for traffic crash victims, it is reasonable to use a binary-choice modeling framework. Eq. (1) shows an ordinary logistic regression model in which the probability of being killed $P(Y = 1)$ is connected to explanatory variables through the logit link function. In terms of statistical inferences, $\exp(\beta_i)$ is exactly the odds ratio of being killed, associated to the corresponding variable $x_i = 1$ versus $x_i = 0$. Thus, a positive β_i indicates that the variable is positively associated with the chance of being killed.

$$\mathrm{logit}[P(Y=1)] = \log\left[\frac{P(Y=1)}{P(Y=0)}\right] = \beta_0 + \beta_1 x_1 + \cdots + \beta_i x_i + \cdots + \beta_p x_p. \tag{1}$$

However, the ordinary logistic formulation assumes a linear influence of the variables, restraining the model's flexibility to explain a continuous variable and further reveal the possible smooth and non-linear associations between the variables of interest. In Eq. (2), a more flexible version of the logistic regression model, also called the additive logistic regression model, is adopted. Conceptually, the linear function $\beta_i x_i$ is replaced by the smoothing function $f_i(x_i)$ with which almost any influencing trend of the EMS response time can be fitted, depending on the elementary smoothing functions chosen.

$$\mathrm{logit}[P(Y=1)] = \beta_0 + f_1(x_1) + \cdots + f_i(x_i) + \cdots + f_p(x_p). \tag{2}$$

Because these smoothing functions could involve a huge number of parameters, the ordinary maximum-likelihood-estimation method would select a set of parameters that completely matched the data, leading to heavy over-fitting. To solve this issue, a penalty term, exerting constraints on the smooth levels of the functions, is adopted as shown in Eq. (3).

$$\begin{aligned} L(f;\lambda) &= \sum_{i=1}^{n} \{y_i \log P(Y=1\mid x_i) + (1-y_i)\log[1-P(Y=1\mid x_i)]\} - \frac{1}{2}\sum_{j=1}^{p} \lambda_j \int \left[f_j''(t)\right]^2 dt \\ &= \sum_{i=1}^{n} \left\{y_i\left[\beta_0 + \sum_{j=1}^{p} f_p(x_{ij})\right] - \log\left[1 + \exp\left(\beta_0 + \sum_{j=1}^{p} f_p(x_{ij})\right)\right]\right\} - \frac{1}{2}\sum_{j=1}^{p} \lambda_j \int \left[f_j''(t)\right]^2 dt \end{aligned} \tag{3}$$

Here, $L(f;\lambda)$ is the penalized likelihood function containing two parts, first, the ordinary log-likelihood function measuring the closeness between the data and the fitted model, and second, the function that penalizes the overall curvature of the smooth function. $\lambda_j \in [0,\infty)$ is a fixed smoothing parameter used to balance the data fitting against the smoothness of the function $f_j(\cdot)$. It can be shown that the optimal $f_i(x_i)$ is a smoothing cubic spline with knots at each unique value of x_i (Hastie et al., 2009). To estimate parameters for the model, back-fitting algorithms can be applied (Hastie and Tibshirani, 1986; Yee and Wild, 1996; Ma and Yan, 2014).

$$\mathrm{logit}[P(Y=1)] = \beta_0 + f_1(x_1) + \cdots + f_{ij}(x_i, x_j) + \cdots \sum^{k\in K} [f_m(x_m) I(x_n = k)] + \cdots + f_p(x_p). \tag{4}$$

Considering interaction terms between two factors, Eq. (4) illustrates the formulation of the model. For two interacting continuous variables, the smoothing function $f_{ij}(x_i, x_j)$ forms a smooth surface, and for a continuous variable interacted with a categorical variable, it could be expected that each level of the categorical variable would have its own smooth function.

One important issue is that several subjects could come from the same crash. In this study, we included every person from every crash. Thus, there might be certain within-group random effects. Thus, we performed tests using a random-effect/mixed-effect model. However, the latter exhibited almost identical results to the fixed-effect model, and worse modeling performance, due to its larger

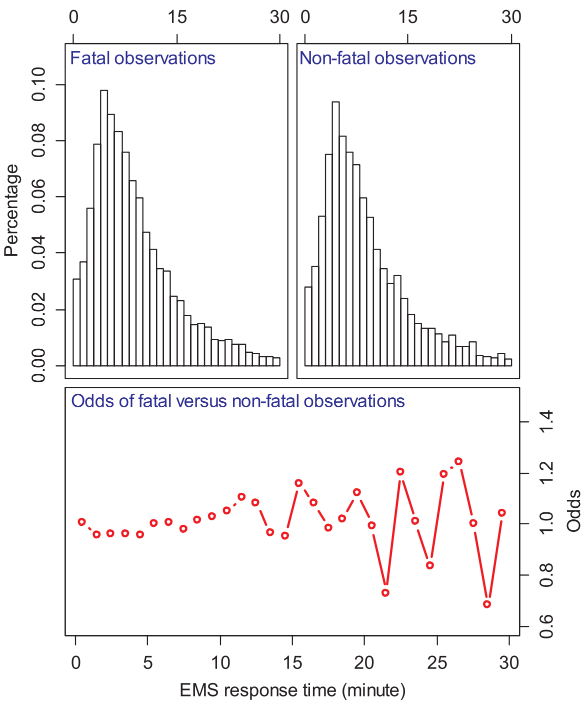

Fig. 2. Percentages of fatal and non-fatal observations under different EMS response times and the corresponding odds.

Table 2
Odds of fatal versus non-fatal observations and the corresponding odds ratios for reference levels of the categorical variables.

Categorical variables	Odds of fatal versus non-fatal observations	Odds ratio to the reference level
Seating position		
Driver*	0.871	1
Other front seat	0.440	0.505
Second and after second seat	0.300	0.344
Not a motor vehicle occupant	10.861	12.470
Manner of collision		
Front-to-rear*	0.415	1
Front-to-front	0.637	1.535
Angle	0.509	1.227
Sideswipe	0.413	0.995
Not collision with motor vehicle in transport	1.227	2.957
Gender		
Male*	0.860	1
Female	0.616	0.716
Age		
age < 20*	0.365	1
20 ≤ age < 40	0.709	1.944
40 ≤ age < 60	0.865	2.371
66 ≤ age < 80	1.254	3.437
age ≥ 80	2.780	7.616
EMS response time		
time < 5*	0.742	1
5 ≤ time < 10	0.758	1.022
10 ≤ time < 15	0.801	1.080
15 ≤ time < 20	0.795	1.071
20 ≤ time < 25	0.763	1.028
25 ≤ time ≤ 30	0.730	0.984

* This category was used as the "reference level" in this study.

Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values. Thus, within-group random effects were not statistically supported by the data.

3. Results

3.1. Effect of EMS response time without controlling for other factors

Fig. 2 illustrates the percentage of fatal versus non-fatal observations under different EMS response times, and the corresponding odds. It can be observed that the distribution of the EMS response time is right-skewed, with the proportions for very long EMS response times smaller. Comparing the numbers of fatal and non-fatal observations for a given EMS response time can give the overall association between the EMS response time and the chance of being killed. In the lower part of Fig. 2, the observed odds of fatal versus non-fatal observations are provided to illustrate the influencing pattern of the EMS response time. It is hard to see the influencing pattern, and therefore statistical tests are needed. It is also worth noting that the trend fluctuates for larger values of the EMS response time. Similar phenomena have also been observed in previous studies (e.g. Pons and Markovchick, 2002), mainly due to small numbers of observations with large response times making it difficult to see a robust trend. Thus, it is necessary and interesting to estimate a smooth influencing pattern of EMS response times based on more advanced statistical models.

For the categorical variables, Table 2 reports the odds of fatal versus non-fatal observations and the corresponding odds ratios, based on reference levels. Regarding the EMS response time, the interval from 10 to 15 minutes is related to the largest odds of death. The odds of death increase consistently with the age of the person. With respect to the seating position, "not a motor vehicle occupant" has the largest odds of death, exhibiting a huge odds ratio (12.470) with respect to the driver. The driver has a larger chance of dying than people in other seating positions inside the vehicle. With respect to the manner of the collision, victims in crashes where there was no collision with other motor vehicles in transport have the largest chance of dying, with an odds ratio of 2.957 with respect to front-to-rear collisions. The results also indicate that female victims have a better chance of survival than male victims.

These results provide important hints regarding the conditional associations between influencing factors and the odds of death in a traffic crash, but the inferences may not be completely valid as the factors could be highly correlated, potentially leading to confounding effects. For example, the observed odds ratio of female to male victims (0.716) is slightly smaller than common sense would suggest. In fact, there would probably be less of a difference between female and male victims' death likelihoods, if we controlled for the fact that males are more likely to be driving than females.

To extract more direct associations between the variables, the following sections adopt the additive logistic regression model to consider the factors comprehensively and, more importantly, to determine smooth influencing patterns of the EMS response time.

Table 3
Estimation results from additive and ordinary logistic regressions.

Explanatory variables	Additive logistic model		Ordinary logistic model A		Ordinary logistic model B	
	Estimate (t-value)	Odds ratio	Estimate (t-value)	Odds ratio	Estimate (t-value)	Odds ratio
Intercept	−1.347 (−23.015)	N/A	−1.338 (−22.888)	N/A	−1.389 (−22.832)	N/A
Seating position (driver as reference)						
Other front seat	−0.645 (−18.765)	0.524	−0.644 (−18.748)	0.525	−0.644 (−18.752)	0.525
Second and after second seat	−0.799 (−19.219)	0.449	−0.799 (−19.227)	0.450	−0.798 (−19.194)	0.450
Not a motor vehicle occupant	2.239 (28.606)	9.383	2.222 (28.404)	9.226	2.235 (28.536)	9.346
Manner of collision (front-to-rear as reference)						
Front-to-front	0.482 (9.723)	1.619	0.486 (9.822)	1.626	0.486 (9.800)	1.626
Angle	0.261 (5.680)	1.298	0.257 (5.582)	1.293	0.264 (5.723)	1.302
Sideswipe	0.038 (0.542)	1.038	0.046 (0.642)	1.047	0.040 (0.557)	1.041
Not collision with motor vehicle in transport	0.988 (22.719)	2.685	0.987 (22.699)	2.683	0.991 (22.769)	2.694
Gender (male as reference)						
Female	−0.147 (−5.582)	0.863	−0.146 (−5.546)	0.864	−0.148 (−5.608)	0.862
Age (age < 20 as reference)						
20 ≤ age < 40	0.357 (8.903)	1.429	0.355 (8.858)	1.426	0.356 (8.868)	1.428
40 ≤ age < 60	0.492 (11.547)	1.636	0.489 (11.466)	1.631	0.491 (11.512)	1.634
66 ≤ age < 80	0.961 (20.188)	2.614	0.956 (20.088)	2.601	0.959 (20.141)	2.609
age ≥ 80	1.960 (25.098)	7.099	1.956 (25.059)	7.071	1.958 (25.066)	7.085
Smooth function of EMS response time	0.017 (8.468)	N/A	N/A	N/A	N/A	N/A
EMS response time (scale variable)	N/A	N/A	0.016 (8.281)	N/A	N/A	N/A
EMS response time (categorical / < 5 as reference)						
5 ≤ time < 10	N/A	N/A	N/A	N/A	0.188 (5.645)	1.207
10 ≤ time < 15	N/A	N/A	N/A	N/A	0.306 (8.062)	1.358
15 ≤ time < 20	N/A	N/A	N/A	N/A	0.371 (7.736)	1.449
20 ≤ time < 25	N/A	N/A	N/A	N/A	0.319 (5.285)	1.376
25 ≤ time ≤ 30	N/A	N/A	N/A	N/A	0.315 (4.049)	1.370
Modeling performance						
AIC	39,610		39,640		39,621	
BIC	39,753		39,757		39,772	

3.2. Marginal effect of the EMS response time

In examining the marginal effect of the EMS response time, all explanatory variables were involved but no interaction terms. The EMS response time was handled in terms of a smooth link function under additive settings. For the other categorical variables (gender, age, seating position, and manner of collision), the relative contribution of each level of the variable was captured by the corresponding coefficient relative to the fixed (at zero) coefficient of the reference level. Table 3 reports the estimated parameters from the proposed additive logistic model and the two ordinary logistic regression models, as well as their modeling performances shown by the AIC and BIC.

The results indicate that the additive logistic model is slightly better than the other two models given its smaller AIC and BIC values. That means treating the EMS response time as a smooth term is beneficial for mining additional information from the data. The three models have similar coefficients for the variables other than the EMS response time. This indicates that the influence of those variables on the death likelihood is unrelated to the settings of the EMS response time. However, the estimated coefficients of the EMS response time are largely different across the models. The additive model in fact produces a huge number of coefficients corresponding to each value of EMS response time; ordinary logistic model A produces just one coefficient; ordinary logistic model B produces several coefficients for different intervals of the EMS response time.

Ordinary logistic model A treats the EMS response time as a scalar variable, corresponding to an assumed linear function. Under such a setting, the model will intrinsically suggest a monotonic relationship (either increasing or decreasing) between the EMS response time and the odds of death in a traffic crash. This reflects an averaged influence. Ordinary logistic model B involves a categorized EMS response time, which is a traditional way to capture nonlinear influences of variables. Instead of the assumed linear function, it provides a step function for the EMS response time. The smooth function of the additive logistic model and the functions of the other two models are presented in Fig. 3. These functions directly reflect the impact of the EMS response time on the victims' death outcome variable.

The additive logistic model illustrates an interesting associative pattern between the EMS response time and the odds of death in a traffic crash, in that, for EMS response times less than or equal to 17 minutes, as the EMS response time increases the odds of death increase, whereas after 17 minutes the trend reverses but with a shallower slope. Such a phenomenon has not been recognized in the previous literature.

However, it is difficult to believe the reversed relationship in the later part of the function. Although we do not yet fully understand the physical mechanism at work here, the bottom line is that common sense would predict a flat function (i.e. zero influence) rather than a negative influence. In fact, some latent influencing factors, not yet documented or difficult to observe, yet highly correlated with the EMS response time, may interfere with our understanding. The urgency/severity level of a traffic crash

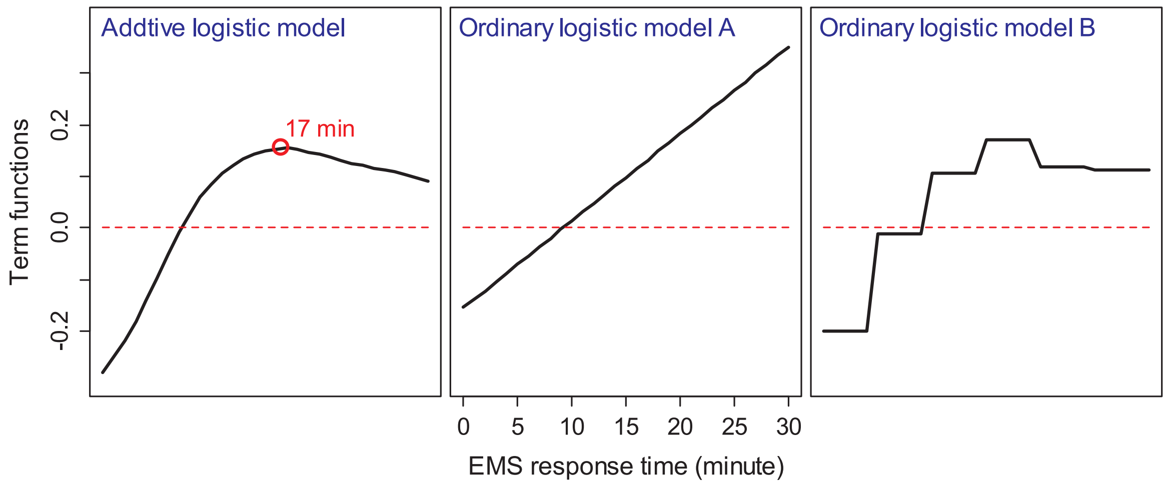

Fig. 3. Term functions showing the EMS response time's relationship with odds of death under the three models.

could be a good example of such a latent variable. It is usually determined based on the oral description of the crash given by the person notifying the police or EMS facility, at the very first stage of the rescue. A very severe crash will be easily identifiable by the notifier, leading to very short response times, while less severe crashes will also be identifiable and given lower priority. There is thus a chance that longer EMS response times are inherently related to less severe crashes, since the dispatching of EMS vehicles will follow priority dispatch codes (Shah et al., 2005; Bandara et al., 2014; Alter et al., 2017). This could result in the observed smaller odds of death for larger EMS response times. Ordinary logistic model B confirms the influencing pattern illustrated by the additive logistic model. As mentioned, ordinary logistic model A is less flexible as it assumes a monotonic relationship between the EMS response time and the odds of death of the victims. It can be used to reflect the averaged influence between variables but is incapable of capturing such a subtle influencing pattern as is found by the other models.

Due to the nature of logistic regression (both the additive logistic model and the two ordinary logistic models), the quantitive impact of the EMS response time also depends on other variables. Thus, there is no fixed smooth function for the actual probability of death in a traffic crash and only the associated term in the link function are fixed for all the samples. To be clear, all three curves in Fig. 3 are the term functions which are useful for understanding the behavioral influence of the EMS response time on the odds of death in a traffic crash, but they are not magnitude-level reflections of the probability of dying in a traffic crash.

One empirical way of handling this issue is to aggregate the impact of a variable across each observation, in which the combinations of all variables are inherently contained. The aggregated impact forms an empirical sensitivity that reflects how the population reacts to hypothetical changes in the EMS response time. Eq. (5) provides a definition of empirical sensitivity S, measuring population-level increments in the mortality probability with respect to systematic increments in the EMS response time. Here, P_i^* is the predicted probability of dying in a traffic crash giving a hypothetical increment in the EMS response time for the observation i and P_i is the corresponding predicted probability without the hypothetical increment.

$$S = \frac{\sum_{i=1}^{n} (P_i^* - P_i)}{n} \tag{5}$$

we considered hypothetical increments of the EMS response time ranging from -5 to 5 minutes. Fig. 4 illustrates the increments in the mortality probability with respect to the increments in the EMS response time. Within the given range, all three models suggest that the mortality probability increases with an increase in the EMS response time, but with different patterns. The additive logistic model exhibits an asymmetric pattern in that a reduction in the EMS response time of a certain amount would save more lives than the deaths that would result from an equal increase in the EMS response time. For example, if the EMS response time systemically increased by 5 minutes, the chance of dying in a traffic crash would increase by 2.1%, while if the EMS response time systemically decreased by 5 minutes, the chance of dying would decrease by 3.0%. Such a pattern also indicates that, as the EMS response time increased, the survival chance would become more stable and less sensitive to changes in the EMS response time, which reflects common sense. However, no such pattern is captured by the other two models. Note that the pattern in the ordinary logistic model A is a curve approaching a straight line within the range of increments in the EMS response time.

Besides the EMS response time, the gender, age, seating position of the victim, and the manner of the collision were also found to have significant impacts on the death likelihood for traffic crash victims. Regarding age, the general results are in line with previous studies (e.g., Xie et al., 2012; Aziz et al., 2013) in that an older person would have a higher chance of losing their life in a road traffic crash.

The estimated odds ratio of female to male victims (0.863) indicates that female victims are less likely to die than males, all other variables being fixed, probably due to gender differences in EMS transport (Weiss et al., 2000), or possibly pre-hospital trauma management protocols expediting the trauma care of female patients (Wahlin et al., 2016). Remember that the observed odds ratio for female victims was 0.716. The model narrows the discrepancy between female and male victims' risk of death in a traffic crash by

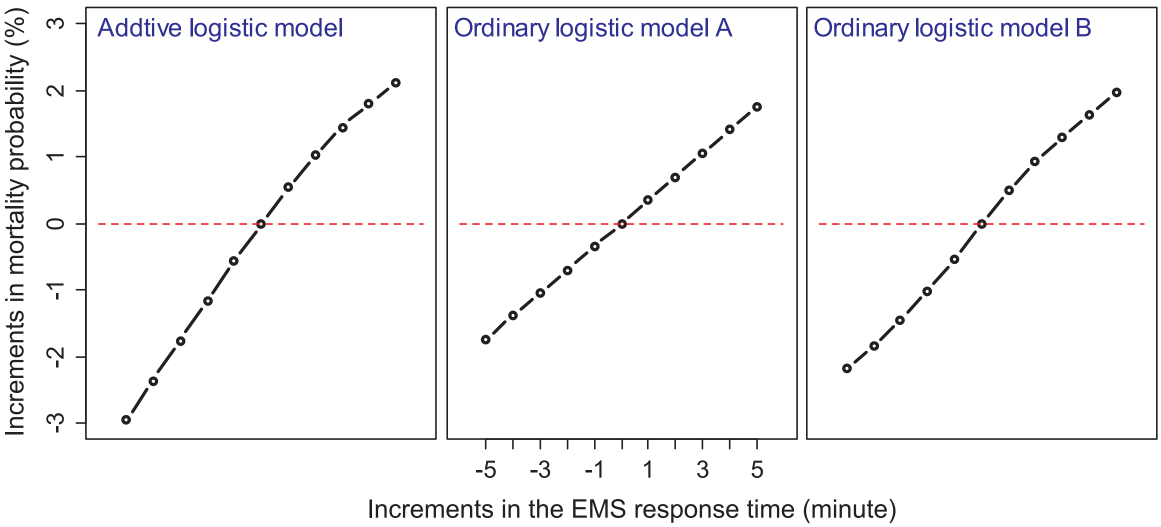

Fig. 4. Sensitivity of mortality probability to the EMS response time.

controlling other factors.

The seating position defines traffic crash victims as either not a motor vehicle occupant (e.g. a pedestrian or cyclist) or by their actual seating position in the vehicle. It exhibits a significant influence on the odds of death, with the chances of dying decreasing as follows: not a motor vehicle occupant, driver, other front seat, and second and after second seat. Victims that were not in a motor vehicle have an odds ratio with respect to the driver of 9.383.

The manner of the collision also demonstrates a significant influence on the chance of death in a traffic crash, the chance decreasing from “not a collision with a motor vehicle in transport”, through front-to-front, angle, sideswipe, to front-to-rear collision.

3.3. Heterogeneous effects of the EMS response time

In fact, different crash-level or person-level characteristics could produce different patterns of influence from the EMS response time. For example, a very serious collision might mean there is a more rapid increase in rates of mortality as EMS response time increases, indicating a shorter “golden time” for the rescue. The modeling settings in previous studies were not able to capture the potential heterogeneous effects of EMS response time with respect to the statuses of other factors. To this end, models with interaction terms between the EMS response time and other factors were established in this study. Table 4 reports the estimation results from these models. Models 1, 2, 3 and 4 involve interaction terms between the EMS response time, and gender, seating position, manner of collision and age respectively. In these models, the EMS response time was also treated as a smooth additive term. Its interaction with a categorical variable will capture heterogeneous influencing patterns for each status of that categorical variable. Fig. 5 illustrates the heterogeneous influencing patterns of the EMS response time.

According to the results from Model 1, we can observe significantly different patterns in the EMS response time’s effect on death probability between male and female victims. For cases with shorter EMS response times (roughly less than twenty minutes), male victims would have a greater chance of dying in a traffic crash, but the trend reverses for cases having longer EMS response times. Such a pattern would be impossible to observe through traditional or non-interaction regression models. Female victims seem to have higher odds of survival than male victims when an EMS vehicle arrives more quickly, probably due to being given priority over males in first-aid rescuing. However, beyond a certain length of EMS response time, the factor most heavily affecting survival chances would probably relate to physical and vitality conditions, in which males probably outperform females.

Regarding the influencing patterns of the EMS response time for different seating positions of the victim, we can observe a complete separation of these smooth functions, indicating a constant ordering of the odds of death with respect to different seating positions, which is in line with the additive model without interaction terms. More interestingly, we found a distinct influencing pattern of the EMS response time for the seating position “not a motor vehicle occupant” in comparison to the seating positions within a vehicle. For the former, the odds of death drop as the EMS response time increases. Such a phenomenon seems to be against common sense, yet it in fact reflects the existence of strong latent influential variables, e.g. the fact that the urgency/severity level of a traffic crash is pre-judged and influences the dispatching of EMS vehicles. Usually, the condition (life-threatening or not) of a non-vehicle-occupant victim (e.g. a pedestrian or a cyclist) can be more accurately estimated, or may even be overestimated. In other words, given the same life-threatening condition, a pedestrian may be treated with a quicker EMS response time than a motor vehicle occupant, resulting in a negative association between the EMS response time and the odds of death. For the other seating positions, the odds of death increase with the increase in EMS response time, until a large EMS response time is reached, which is in line with many previous studies and common sense. The overall effect of the EMS response time calculated by compounding its influences on different seating positions explains the inverted U-shaped smooth function of the marginal effect of the EMS response time as

Table 4
Estimation results from additive logistic regression with interaction terms.

Explanatory variables	Model 1	Model 2	Model 3	Model 4
	Estimate (t-value)	Estimate (t-value)	Estimate (t-value)	Estimate (t-value)
Intercept	−1.305 (−21.795)	−1.372 (−22.822)	−1.088 (−13.065)	−1.391 (−18.437)
Seating position (driver as reference)				
Other front seat	−0.646 (−18.788)	−0.591 (-9.286)	−0.652 (−18.928)	−0.645 (−18.767)
Second and after seat	−0.800 (−19.230)	−0.735 (-9.910)	−0.805 (−19.307)	−0.800 (−19.240)
Not a motor vehicle occupant	2.240 (28.611)	2.610 (19.463)	2.304 (29.272)	2.238 (28.584)
Manner of collision (front-to-rear as reference)				
Front-to-front	0.482 (9.732)	0.480 (9.689)	0.296 (3.123)	0.481 (9.702)
Angle	0.262 (5.684)	0.262 (5.683)	0.182 (2.129)	0.260 (5.654)
Sideswipe	0.037 (0.524)	0.038 (0.535)	−0.020 (-0.148)	0.038 (0.532)
Not collision with motor vehicle in transport	0.989 (22.741)	0.987 (22.696)	0.520 6.378)	0.987 (22.691)
Gender (male as reference)				
Female	−0.280 (−5.795)	−0.148 (−5.610)	−0.144 (−5.475)	−0.147 (−5.596)
Age (age < 20 as reference)				
20 ≤ age < 40	0.358 (8.922)	0.357 (8.916)	0.361 (8.981)	0.381 (5.238)
40 ≤ age < 60	0.494 (11.580)	0.492 (11.530)	0.498 (11.636)	0.581 (7.636)
66 ≤ age < 80	0.963 (20.223)	0.961 (20.191)	0.970 (20.317)	1.001 (11.795)
age ≥ 80	1.964 (25.135)	1.959 (25.080)	1.964 (25.139)	2.120 (15.000)
Smooth function of EMS response time	0.012 (5.128)	0.020 (8.092)	−0.009 (-1.492)	0.021 (4.184)
Smooth interaction of EMS response time				
Female	0.014 (3.287)	N/A	N/A	N/A
Other front seat	N/A	-0.005 (-1.018)	N/A	N/A
Second and after seat	N/A	-0.006 (-1.079)	N/A	N/A
Not a motor vehicle occupant	N/A	-0.051 (-3.611)	N/A	N/A
Front-to-front	N/A	N/A	0.019 (2.362)	N/A
Angle	N/A	N/A	0.005 (0.725)	N/A
Sideswipe	N/A	N/A	0.006 (0.498)	N/A
Not collision with motor vehicle in transport	N/A	N/A	0.048 (6.691)	N/A
20 ≤ age < 40	N/A	N/A	N/A	-0.002 (−0.371)
40 ≤ age < 60	N/A	N/A	N/A	-0.009 (−1.418)
66 ≤ age < 80	N/A	N/A	N/A	-0.004 (−0.551)
age ≥ 80	N/A	N/A	N/A	-0.018 (−1.350)
Model Performance				
AIC	39,601	39,602	39,518	39,614
BIC	39,752	39,771	39,695	39,790

illustrated in Fig. 3.

For crashes involving different manners of collision, the influencing patterns of the EMS response time also vary. Vehicles that do not collide with motor vehicles in transport suffer the highest risk of death to victims, monotonically increasing with the increase in EMS response time.

4. Discussion and conclusions

4.1. Information from the first-order derivative of the smooth function

The smooth function chosen in this study is differentiable and hence its first-order derivative exists. It is interesting to observe the features of the first-order derivative to further investigate the smooth function. Because the smooth function is a smoothing cubic spline with many knots, it is almost impossible to write down its closed form. The numerical first-order derivative is illustrated in Fig. 6.

The first-order derivative reflects the quantitive slope of the smoothness. Inspecting it will help us to understand how quickly the chance of survival drops after the EMS facility has been notified. In this study, we observe that 5.5 minutes is the time at which there is the sharpest change in the rate of influence of the EMS response time on the odds of death. This indicates that the vitality of a victim would fall dramatically 5.5 minutes after notification of an EMS facility. Intuitively, at around 5.5 minutes, a reduction in EMS response time would most increase the chance of survival of the victim. Thus, crashes with an estimated EMS response time of around 5.5 minutes should receive the highest dispatch priority.

4.2. General conclusions and future research directions

The motivation for treating the effect of EMS response times as a smooth function rather than a scalar variable or categorized variable is to identify the elaborate influencing patterns of the EMS response time on the odds of death for traffic crash victims. Doing this allows inspection of any sensitivity in the odds of death at different EMS response times. Based on the 2015 FARS traffic crash

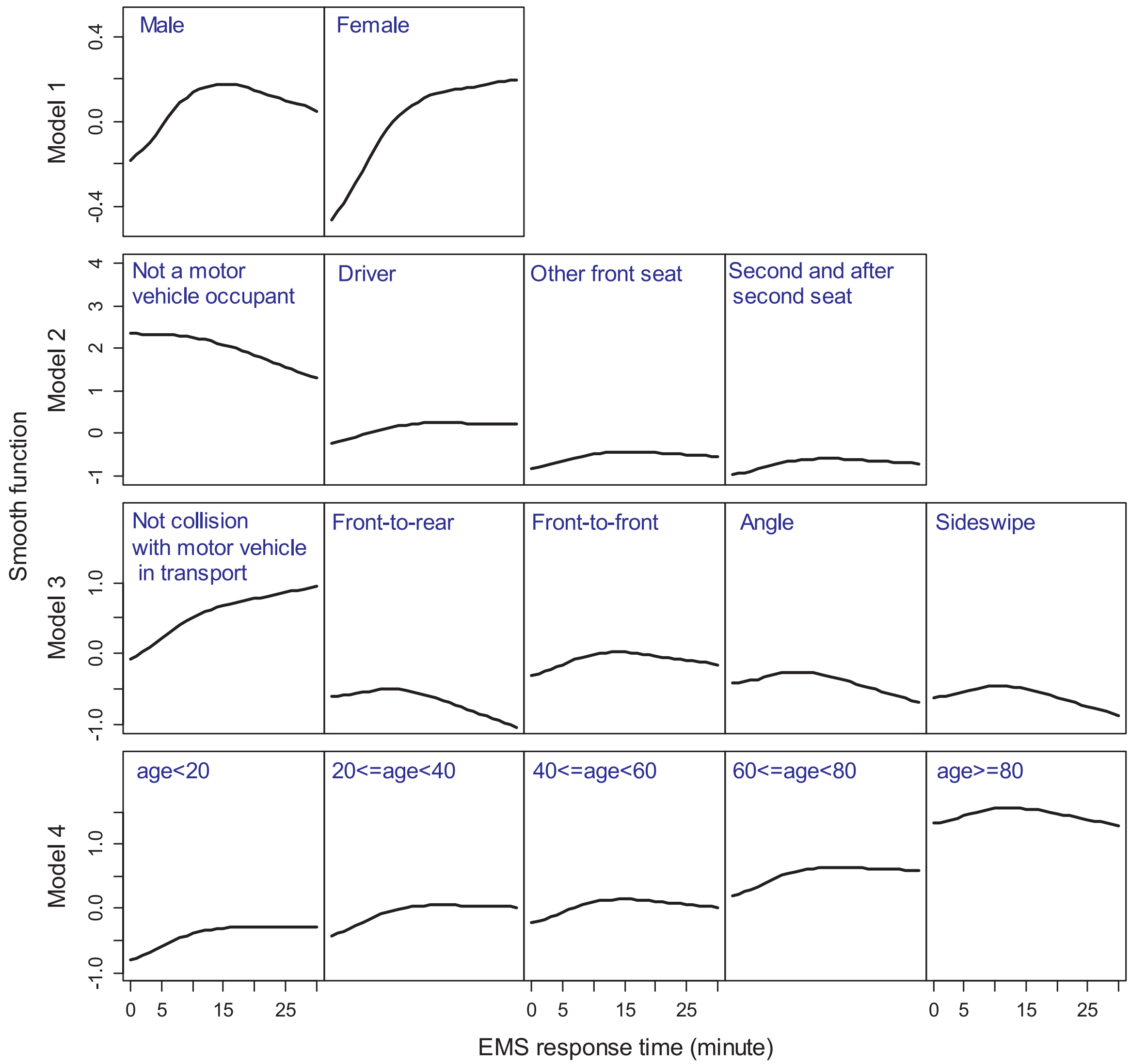

Fig. 5. Heterogeneous effects of the EMS response times with respect to different statuses of exogenous variables.

dataset, two critical EMS response times, namely five minutes and 17 minutes, were identified. The former represents the point at which the fastest decline in the odds of survival occurs, and the latter is just the "gold time" for rescue operations. Under different statuses of other factors, the EMS response time also exhibits heterogeneous influencing patterns, including a negative association with the odds of death. Such results explain certain controversial opinions regarding the relationship between EMS response time and fatality likelihood.

The most crucial limitation of this study is that the adopted dataset only covers observations from fatal traffic crashes. This is because, for minor traffic crashes, the EMS response times are often not reported or EMS are not requested at all, leading to some selection bias in the data. This is also a universally inevitable problem that impedes the consideration of characteristics of the post-crash medical handling when analyzing traffic crash severity. It is difficult to evaluate the influence of selection bias on the results of this study, but it is sufficient to understand the influencing mechanism of the EMS response time on the risk of fatality through the inferred conditional associative relationships. In fact, as just mentioned, the results of this study explain past controversies.

For future studies, it would be interesting to try to alleviate the effect of selection bias using Heckman correlation (Heckman, 1979), with the aid of a supplementary dataset containing a more diverse traffic crash sample. This would require an additional modeling stage to consider the percentage of observations in all types of traffic crashes, and in turn to correct the biased estimations of parameters. Some other methods may have potential for dealing with the endogeneity problem, such as the instrumental variable model, structural equation model, random-parameters model and latent class model.

Wilde (2013) used the distance to the closest agency covering the territory in which the incident occurred as an instrument variable to account for the relation between the outcome and EMS response time. This approach is advanced, because the distance is exogenous while the actual response time is endogenous. It would also be interesting to include some instrument variables and use

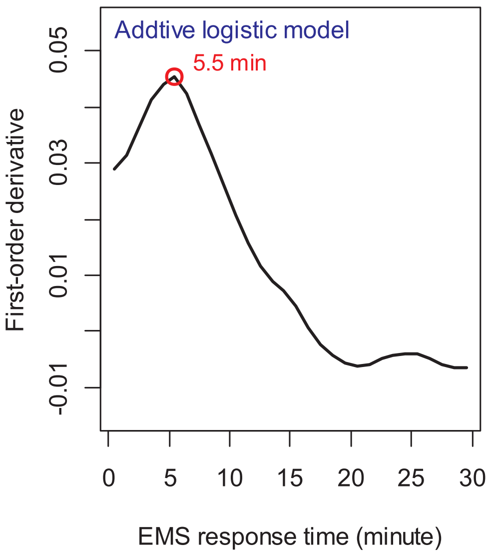

Fig. 6. First-order derivative of the smooth function according to the additive logistic model.

additive models to investigate the smoothness of the relationship between the factors and outcomes of traffic crashes.

Conflict of interest

The authors report that they have no conflicts of interest.

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References

Abdel-Aty, M., 2003. Analysis of driver injury severity levels at multiple locations using ordered probit models. J. Saf. Res. 34 (5), 597–603.
Abdel-Aty, M., Abdelwahab, H., 2004. Modeling rear-end collisions including the role of driver's visibility and light truck vehicles using a nested logit structure. Accid. Anal. Prev. 36 (3), 447–456.
Al-Ghamdi, A.S., 2002. Emergency medical service rescue times in Riyadh. Accid. Anal. Prev. 34 (4), 499–505.
Alter, S.M., Infinger, A., Swanson, D., Studnek, J.R., 2017. Evaluating clinical care in the prehospital setting: is Rapid Emergency Medicine Score the missing metric of EMS? Am. J. Emerg. Med. 35 (2), 218–221.
Amorim, M., Ferreira, S., Couto, A., 2017. Road safety and the urban emergency medical service (uEMS): strategy station location. J. Transp. Health.
Arroyo, A.S., García-Ferrer, A., de Juan Fernández, A., Sánchez-Mangas, R., 2013. Lower posterior death probabilities from a quick medical response in road traffic accidents. J. Appl. Stat. 40 (1), 40–58.
Aziz, H.A., Ukkusuri, S.V., Hasan, S., 2013. Exploring the determinants of pedestrian–vehicle crash severity in New York City. Accid. Anal. Prev. 50, 1298–1309.
Bakke, H.K., Wisborg, T., 2017. The trauma chain of survival-Each link is equally important (but some links are more equal than others). Injury 48 (5), 975–977.
Bandara, D., Mayorga, M.E., McLay, L.A., 2014. Priority dispatching strategies for EMS systems. J. Oper. Res. Soc. 65 (4), 572–587.
Bansal, V., Fortlage, D., Lee, J.G., Costantini, T., Potenza, B., Coimbra, R., 2009. Hemorrhage is more prevalent than brain injury in early trauma deaths: the golden six hours. Eur. J. Trauma Emerg. Surg. 35 (1), 26–30.
Ba, Y., Zhang, W., Wang, Q., Zhou, R., Ren, C., 2017. Crash prediction with behavioral and physiological features for advanced vehicle collision avoidance system. Transp. Res. Part C Emerg. Technol. 74, 22–33.
Blackwell, T.H., Kaufman, J.S., 2002. Response time effectiveness: comparison of response time and survival in an urban emergency medical services system. Acad. Emerg. Med. 9 (4), 288–295.
Brown, D.B., 1979. Proxy measures and accident countermeasure evaluation: a study of emergency medical services. J. Saf. Res. 11 (1), 37–41.
Bunn, T.L., Slavova, S., Robertson, M., 2012. Crash and burn? Vehicle, collision, and driver factors that influence motor vehicle collision fires. Accid. Anal. Prev. 47, 140–145.
Clark, D.E., Cushing, B.M., 2002. Predicted effect of automatic crash notification on traffic mortality. Accid. Anal. Prev. 34 (4), 507–513.
Clark, D.E., Winchell, R.J., Betensky, R.A., 2013. Estimating the effect of emergency care on early survival after traffic crashes. Accid. Anal. Prev. 60, 141–147.
Delmelle, E.M., Rogerson, P.A., Akella, M.R., Batta, R., Blatt, A., Wilson, G., 2005. A spatial model of received signal strength indicator values for automated collision notification technology. Transp. Res. Part C Emerg. Technol. 13 (5), 432–447.
Dinh, M.M., Bein, K., Roncal, S., Byrne, C.M., Petchell, J., Brennan, J., 2013. Redefining the golden hour for severe head injury in an urban setting: the effect of prehospital arrival times on patient outcomes. Injury 44 (5), 606–610.
Funder, K.S., Petersen, J.A., Steinmetz, J., 2011. On-scene time and outcome after penetrating trauma: an observational study. Emerg. Med. J. 28 (9), 797–801.
Gonzalez, R.P., Cummings, G.R., Phelan, H.A., Mulekar, M.S., Rodning, C.B., 2009. Does increased emergency medical services prehospital time affect patient mortality in rural motor vehicle crashes? A statewide analysis. Am. J. Surg. 197 (1), 30–34.
Harmsen, A.M.K., Giannakopoulos, G.F., Moerbeek, P.R., Jansma, E.P., Bonjer, H.J., Bloemers, F.W., 2015. The influence of prehospital time on trauma patients outcome: a systematic review. Injury 46 (4), 602–609.
Hastie, T., Tibshirani, R., 1986. Generalized additive models. Stat. Sci. 1 (3), 297–310.

Hastie, T., Tibshirani, R., Friedman, J., 2009. The Elements of Statistical Learning Data Mining: Inference and Prediction, 2nd ed. Springer, New York, NY, USA.
Heckman, J., 1979. Sample selection bias as a specification error. Econometrica 47 (1), 153–161.
Heestermans, T., van't Hof, A.W., Jurriën, M., van Werkum, J.W., Boersma, E., Mosterd, A., Stella, P.R., van Zoelen, A.B., Gosselink, A.M., Kochman, W., Dill, T., 2010. The golden hour of prehospital reperfusion with triple antiplatelet therapy: a sub-analysis from the ongoing tirofiban in myocardial evaluation 2 (On-TIME 2) trial early initiation of triple antiplatelet therapy. Am. Heart J. 160 (6), 1079–1084.
Hussain, L.M., Redmond, A.D., 1994. Are pre-hospital deaths from accidental injury preventable? BMJ 308 (6936), 1077–1080.
Jaldell, H., Lebnak, P., Amornpetchsathaporn, A., 2014. Time is money, but how much? The monetary value of response time for Thai ambulance emergency services. Value Health 17 (5), 555–560.
Jones, A.P., Bentham, G., 1995. Emergency medical service accessibility and outcome from road traffic accidents. Public Health 109 (3), 169–177.
Jung, S., Qin, X., Oh, C., 2016. Systemwide impacts of emergency medical services resources on freeway crash severity. Transp. Res. Rec. J. Transp. Res. Board 2582, 51–60.
Kidher, E., Krasopoulos, G., Coats, T., Charitou, A., Magee, P., Uppal, R., Athanasiou, T., 2012. The effect of prehospital time related variables on mortality following severe thoracic trauma. Injury 43 (9), 1386–1392.
Lam, S.S.W., Nguyen, F.N.H.L., Ng, Y.Y., Lee, V.P.X., Wong, T.H., Fook-Chong, S.M.C., Ong, M.E.H., 2015. Factors affecting the ambulance response times of trauma incidents in Singapore. Accid. Anal. Prev. 82, 27–35.
Li, M.D., Doong, J.L., Chang, K.K., Lu, T.H., Jeng, M.C., 2008. Differences in urban and rural accident characteristics and medical service utilization for traffic fatalities in less-motorized societies. J. Saf. Res. 39 (6), 623–630.
Ma, L., Yan, X., 2014. Examining the nonparametric effect of drivers' age in rear-end accidents through an additive logistic regression model. Accid. Anal. Prev. 67, 129–136.
Ma, L., Wang, G., Yan, X., Weng, J., 2016. A hybrid finite mixture model for exploring heterogeneous ordering patterns of driver injury severity. Accid. Anal. Prev. 89, 62–73.
MacLeod, J.B., Cohn, S.M., Johnson, E.W., McKenney, M.G., 2007. Trauma deaths in the first hour: are they all unsalvageable injuries? Am. J. Surg. 193 (2), 195–199.
Mannering, F.L., Bhat, C.R., 2014. Analytic methods in accident research: methodological frontier and future directions. Anal. methods Accid. Res. 1, 1–22.
McCoy, C.E., Menchine, M., Sampson, S., Anderson, C., Kahn, C., 2013. Emergency medical services out-of-hospital scene and transport times and their association with mortality in trauma patients presenting to an urban Level I trauma center. Ann. Emerg. Med. 61 (2), 167–174.
Meng, Q., Weng, J., 2013. Uncertainty analysis of accident notification time and emergency medical service response time in work zone traffic accidents. Traffic Inj. Prev. 14 (2), 150–158.
Morales, A., González-Aguilera, D., López, A.I., Gutiérrez, M.A., 2016. A new approach to road accident rescue. Traffic Inj. Prev. 17 (3), 278–283.
Newgard, C.D., Schmicker, R.H., Hedges, J.R., Trickett, J.P., Davis, D.P., Bulger, E.M., Aufderheide, T.P., Minei, J.P., Hata, J.S., Gubler, K.D., Brown, T.B., 2010. Emergency medical services intervals and survival in trauma: assessment of the "golden hour" in a North American prospective cohort. Ann. Emerg. Med. 55 (3), 235–246.
Nicholl, J., West, J., Goodacre, S., Turner, J., 2007. The relationship between distance to hospital and patient mortality in emergencies: an observational study. Emerg. Med. J. 24 (9), 665–668.
Oliver, G.J., Walter, D.P., Redmond, A.D., 2017. Are prehospital deaths from trauma and accidental injury preventable? A direct historical comparison to assess what has changed in two decades. Injury 48 (5), 978–984.
Petzäll, K., Petzäll, J., Jansson, J., Nordström, G., 2011. Time saved with high speed driving of ambulances. Accid. Anal. Prev. 43 (3), 818–822.
Peura, C., Kilch, J.A., Clark, D.E., 2015. Evaluating adverse rural crash outcomes using the NHTSA state data system. Accid. Anal. Prev. 82, 257–262.
Pons, P.T., Markovchick, V.J., 2002. Eight minutes or less: does the ambulance response time guideline impact trauma patient outcome? J. Emerg. Med. 23 (1), 43–48.
Sánchez-Mangas, R., García-Ferrrer, A., De Juan, A., Arroyo, A.M., 2010. The probability of death in road traffic accidents. How important is. a quick medical response? Accid. Anal. Prev. 42 (4), 1048–1056.
Saver, J.L., Smith, E.E., Fonarow, G.C., Reeves, M.J., Zhao, X., Olson, D.M., Schwamm, L.H., 2010. The "golden hour" and acute brain ischemia. Stroke 41 (7), 1431–1439.
Shah, M.N., Bishop, P., Lerner, E.B., Fairbanks, R.J., Davis, E.A., 2005. Validation of using EMS dispatch codes to identify low-acuity patients. Prehosp. Emerg. Care 9 (1), 24–31.
Weiss, S.J., Ernst, A.A., Phillips, J., Hill, B., 2000. Gender differences in state-wide EMS transports. Am. J. Emerg. Med. 18 (6), 666–670.
Wahlin, R.R., Ponzer, S., Lövbrand, H., Skrivfars, M., Lossius, H.M., Castrén, M., 2016. Do male and female trauma patients receive the same prehospital care? An observational follow-up study. BMC Emerg. Med. 16 (1), 6.
Wan, J., Wu, C., Zhang, Y., 2016. Effects of lead time of verbal collision warning messages on driving behavior in connected vehicle settings. J. Saf. Res. 58, 89–98.
Wilde, E.T., 2013. Do emergency medical system response times matter for health outcomes? Health Econ. 22 (7), 790–806.
Xie, Y., Zhao, K., Huynh, N., 2012. Analysis of driver injury severity in rural single-vehicle crashes. Accid. Anal. Prev. 47, 36–44.
Xiong, Y., Tobias, J.L., Mannering, F.L., 2014. The analysis of vehicle crash injury-severity data: a Markov switching approach with road-segment heterogeneity. Transp. Res. Part B Methodol. 67, 109–128.
Yasmin, S., Eluru, N., Bhat, C.R., Tay, R., 2014. A latent segmentation based generalized ordered logit model to examine factors influencing driver injury severity. Anal. methods Accid. Res. 1, 23–38.
Yee, T.W., Wild, C.J., 1996. Vector generalized additive models. J. R. Stat. Soc. Ser. B (Methodol.) 58 (3), 481–493.
Zhu, X., Srinivasan, S., 2011. A comprehensive analysis of factors influencing the injury-severity of large-truck crashes. Accid. Anal. Prev. 43 (1), 49–57.