ANALYSIS OF FATAL TRAFFIC CRASH-REPORTING AND REPORTING-ARRIVAL TIME INTERVALS OF EMERGENCY MEDICAL SERVICES

Jaeyoung Lee, Ph.D., Corresponding Author
Assistant Professor & Safety Program Director
Center for Advanced Transportation Systems Simulation (CATSS)
Department of Civil, Environmental, and Construction Engineering
University of Central Florida
Orlando, FL 32816, United States
Phone Number: (407) 666-0472
Fax Number: (407) 823-3315
Email: Jaeyoung@knights.ucf.edu

Mohamed Abdel-Aty, Ph.D., P.E.
Pegasus Professor & Chair
Department of Civil, Environmental, and Construction Engineering
University of Central Florida
Orlando, FL 32816, United States

Qing Cai, Ph.D.
Postdoctoral Research Associate
Department of Civil, Environmental, and Construction Engineering
University of Central Florida
Orlando, FL 32816, United States

Ling Wang, Ph.D.
Assistant Professor
College of Transportation Engineering
Tongji University
Shanghai 200000, China

Postdoctoral Research Associate
Department of Civil, Environmental, and Construction Engineering
University of Central Florida
Orlando, FL 32816, United States

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ABSTRACT

Emergency Medical Services (EMS) play a vital role in the post-crash effort to reduce fatalities by providing first-aid and transportation to medical facilities. This study aims to analyze the time required for crash reporting and EMS arrival in fatal traffic crashes and to identify relevant crash, roadway, environmental and zonal socio-economic factors. The time required for EMS reporting and arrivals were calculated by location type (urban or rural) and roadway functional classification using Florida data. Subsequently, a variety of duration models were estimated to reveal contributing factors for the crash-reporting and reporting-arrival intervals. Although about 90% of fatal crashes are reported to EMS within ten minutes in both urban and rural settings, EMS average reporting time in rural areas (4.5 min) is greater than in urban areas (3 min). Moreover, freeways require longer time for EMS arrival (8.3 min) compared to conventional roadways (6.8 min). It was shown that the log-logistic and gamma models perform the best for the crash-reporting and reporting-arrival intervals, respectively. The modeling results reveal that both EMS reporting and arrival times are related to the crash, roadway, environmental, and socio-economic factors. The key findings indicate that EMS reporting and arrival times differ significantly according to the urban/rural designation and road functional classification, and that they have statistically significant relationship with various factors. It is expected that the findings from this study can be used to develop effective and practical strategic plans to minimize EMS reporting and arrival time and, therefore, decrease the likelihood of fatalities.

Keywords: EMS, emergency medical service, reporting time, response time, duration model

INTRODUCTION

According to the United States National Highway Transportation Safety Administration (NHTSA), close to 30,000 people are killed from traffic crashes every year *(1)*. In 2014, slightly more than 10 out of every 100,000 of the population were killed from traffic crashes, which indicate that traffic crashes are one of the major public health concerns. Over the last several decades, many efforts have been made to reduce traffic fatalities. One of the efforts is to quickly and efficiently dispatch Emergency Medical Services (EMS) to the crash scene. EMS has played a vital role in reducing fatalities by providing first-aid and transportation to medical facilities as one of the post-crash countermeasures.

According to Clark et al. *(2)*, the majority of deaths caused by traffic crashes happen before the patient has arrived to a hospital, indicating that efficient EMS can reduce the impact of traffic crashes. Especially, EMS has been proven to be effective to minimize the fatality rates *(3, 4)*. In general, the time interval between crash occurrence and reporting (T1) and the time interval between reporting and EMS arrival on the scene (T2) are the two major factors for EMS *(2, 3, 5, 6)*. Several studies investigated the relationship between the outcome of traffic crashes and the time intervals (i.e., T1 and T2). Castrén et al. *(7)* found that fatalities would be reduced by 6% as T1 is reduced by 1 minute. Also, Sánchez-Mangas et al. *(4)* uncovered that 10 minutes reduction in T2 can decrease the probability of traffic fatalities by one-third.

Despite of the importance of rapid EMS response, only few studies have explored the contributing factors for the time required for reporting and arrival. Brodsky *(3)* explored the factors for delays of reporting time of EMS in traffic crashes. Three explanatory variables, population density, traffic density, and hour of day, were tested for association with an extremely delayed reporting time using logistic regression. Other factors, such as crash, road type, and severity of injury, showed little association with delays. The author also found that notification delays are likely to be accompanied by longer ambulance response time as ambulance stations cover broad areas in remote counties. Yasunaga et al. *(8)* analyzed the time between emergency call and ambulance arrival using population density for cardiac arrest cases. The authors found that the mean call-response intervals in low-density and high-density were 9.3 and 6.2 minutes, respectively. The distribution of EMS centers was almost proportional to the size of the population. EMS resource allocation according to population size may cause disparities in response times. Increasing the number of ambulances could decrease call-response intervals across large, sparsely populated areas. Evanco *(9)* and Gonzalez et al. *(10)* identified that longer T1 and T2 can be observed in the crashes that occurred in rural areas. Brodsky *(11)* found that crashes occurring during nighttime and on interstate highways need more time to be reported. In the study of Meng and Weng *(12)*, it was shown that crashes happening on holidays and those with poor light condition may have longer T1. Meng and Weng *(12)* and Yasmin et al. *(13)* commonly found that the time of crash occurrence, road type, holiday, and weather were found to be significant factors for T2.

Nevertheless, these studies attempted the limited number of variables to explain EMS reporting and arrival time, such as crash characteristics, population density, etc. Therefore, this study aims to analyze the time required for EMS reporting and dispatch in fatal traffic crashes using various explanatory factors including crash, roadway, environmental, and zonal socio-economic factors using duration models. Also, several suggestions to shorten EMS reporting and arrival time intervals are provided based on the modeling results.

METHODS

Study Design

The research team defined the time interval between crash occurrence and notification to EMS as T1 (i.e., crash-reporting interval); and the time interval between the notification to EMS and EMS arrival on the scene as T2 (i.e., reporting-arrival interval) as shown in Figure 1. The overall average crash-reporting and reporting-arrival intervals were calculated and then the average crash-reporting and reporting-arrival intervals by geographic locations (urban/rural) and roadway functional classifications were computed. Furthermore, two duration models were developed to identify significant factors for crash-reporting and reporting-arrival intervals. Hazard-based duration models have been extensively applied to the public health, medical/biometrics, industrial, and transportation engineering fields. The variable of interest in duration models is survival time that elapsed from the beginning of an event until its ending. In this study, crash-reporting and reporting-arrival intervals were used as two targets of the duration models. The distributional form of the error term determines the duration regression model. Five distributions including exponential, gamma, log-logistic, lognormal, and Weibull were attempted for crash-reporting and reporting-arrival intervals. The models with the best fit were determined as the best models and utilized to reveal significant factors for the reporting and arrival times, respectively.

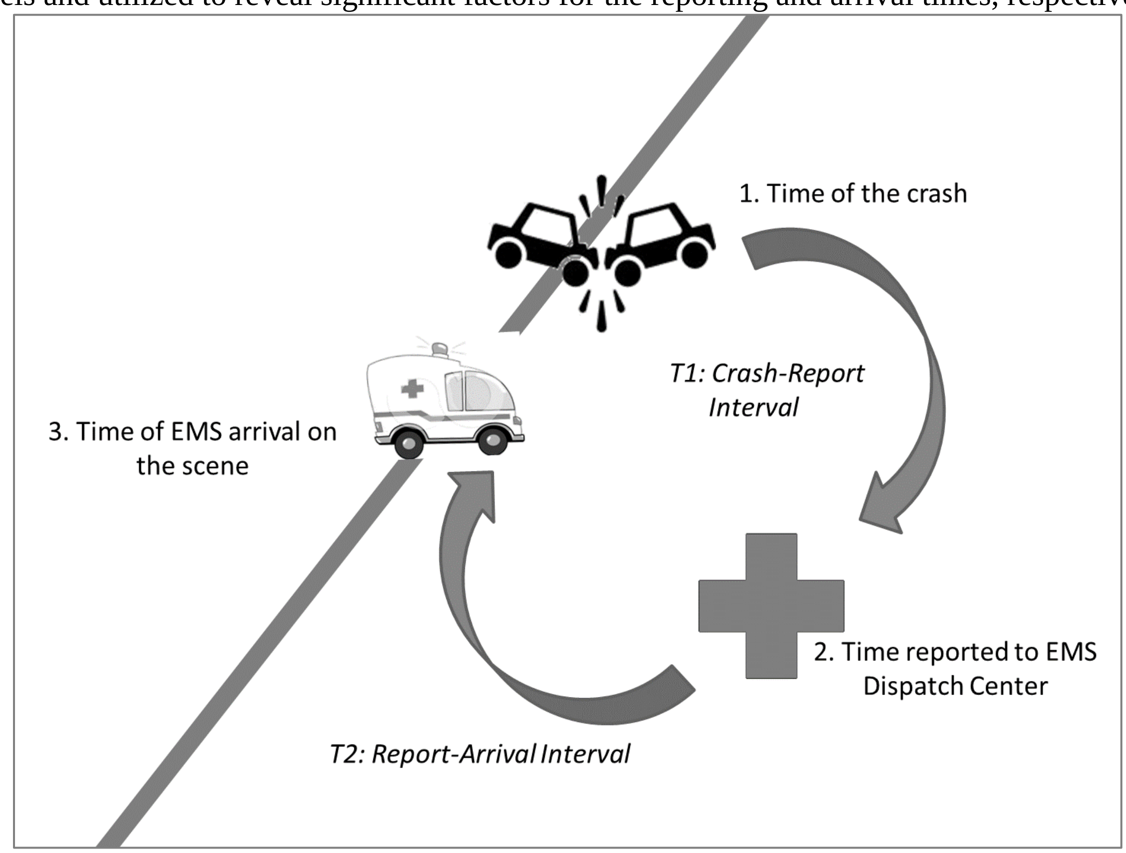


FIGURE 1: Model Estimation Process of the Integrated Approach

Study Population and Data

In order to achieve the objectives of this study, various data were collected from multiple sources. Six years of fatal crash and associated data (2005-2010) in Florida were collected from the FARS (Fatal Analysis Reporting System). These include information of crash location, time, occupant(s), roadway functional classification, light conditions, lane counts, weather, and so forth. Traffic Analysis Zones (TAZ)-based data were collected from the Florida Department of Transportation such as employment, school enrollment, car-ownership, traffic volume, roadway density, et cetera. Furthermore, population and commuter characteristics data were obtained from the U.S. Census Bureau. Lastly, land-use data (i.e. agriculture, industry, mining, public, residential land-use, etc.) were acquired from the Florida Department of Revenue. The collected data were processed for exploratory analysis and developing duration models. The prepared data are summarized in Table 1.

Duration Modeling

The author adopted a duration model to estimate the two target variables: T1, the interval between crash occurrence and reporting; and T2, the interval between crash reporting and EMS arrival. Hazard-based duration models have been used in the fields of biometrics, economics, marketing, and industrial engineering fields as a means of determining causality in duration data and also applied in the transportation field. In the transportation field, duration models have been used in crash analysis *(14, 15)*, travel behavior *(16-19)*, car ownership *(20-22)*, travel delay *(23-25)*, and highway visibility *(26)*. Both Nam and Mannering *(14)* and Chung *(15)* explored the incident durations using hazard-based duration models. In this study, the authors adopted the duration model for investigating the crash-reporting and reporting-EMS arrival time intervals. The variable of interest in a duration model is the survival time that elapsed from the beginning of an event until its end. In this study, duration time can be regarded as the duration that starts when a crash occurs and ends when it is reported (T1). Also, it can be considered as the waiting duration that starts when the crash is reported and ends when EMS vehicle arrives on the crash scene (T2). Therefore, a duration model is appropriately used in this study. To the authors' best knowledge, hazard-based duration models have not been used for EMS reporting or dispatch time analysis. For more detailed information for failure rate or hazard function, please refer to Bhat *(16)*. The most commonly used approach to model duration data is the proportional hazard model. The proportional hazard models for duration data usually assume that the explanatory variables take a constant proportional effect on an unspecified baseline hazard function. Although this assumption may relieve the estimation efforts of the model, it may not be applicable when the constant proportional assumption is violated.

TABLE 1: Descriptive Statistics of the Prepared Data

Category	Variables	Mean	Stdev	Min	Max	Source
Target variables	T1: Crash-Reporting Interval	3.642	8.252	0	120	NHTSA FARS
	T2: Reporting-Arrival Interval	7.055	4.919	1	104	
Person	Number of killed persons in the crash	1.103	0.378	1	7	
	Number of total persons in the crash	2.636	1.888	1	57	
	Proportion of killed persons in the crash	0.560	0.288	0.018	1	
	Whether all crash-involved persons were killed	0.265	0.441	0	1	
Traffic	Log (vehicle-miles-traveled per square mile)	9.235	2.065	0	15.373	FDOT
	Proportion of heavy vehicle traffic	0.074	0.053	0	0.428	
Functional classification	Freeway/expressway	0.167	0.373	0	1	NHTSA FARS
	Arterial road	0.465	0.499	0	1	
	Collector	0.004	0.066	0	1	
Roadway	Lane counts	2.400	0.849	0	9	
	curve	0.186	0.389	0	1	
	Log (road length per square mile)	1.772	0.915	0	7.823	FDOT
Location	intersection	0.316	0.465	0	1	NHTSA FARS
	interchange	0.014	0.119	0	1	
	ramp	0.011	0.105	0	1	
	Urban (vs. rural)	0.591	0.492	0	1	
Driver action	Hit-and-run involved	0.060	0.237	0	1	
Environment	Rain	0.062	0.242	0	1	
	Fog	0.011	0.106	0	1	
	Wet pavement	0.112	0.315	0	1	
Lighting condition	Dark without lighting	0.286	0.452	0	1	
	Dark with lighting	0.277	0.448	0	1	
	Dawn	0.019	0.138	0	1	
	Dusk	0.024	0.152	0	1	
Land-use	Proportion of agriculture areas	0.109	0.238	0	0.994	FDOT
	Proportion of industrial areas	0.020	0.069	0	0.963	
	Proportion of institutional areas	0.020	0.063	0	0.986	
	Proportion of mining areas	0.001	0.016	0	0.537	
	Proportion of public areas	0.056	0.125	0	1	
	Proportion of recreational areas	0.029	0.094	0	0.929	
	Proportion of residential areas	0.178	0.229	0	1	
	Proportion of retail and office areas	0.048	0.100	0	1	
Car-ownership	Proportion of family with no vehicle	0.072	0.075	0	0.73	
	Proportion of family with 2 or more vehicles	0.540	0.163	0	1	
Socio-demographic	Log (population density)	6.473	2.027	0	10.837	
	Log (employment density)	5.572	2.232	0	12.074	
	Log (school enrollment density)	3.260	2.969	0	11.856	
	Proportion of industrial employments	0.207	0.237	0	1	
	Proportion of commercial employments	0.281	0.207	0	1	
	Proportion of service employments	0.505	0.234	0	1	
Commuter	Proportion of commuters using car	0.896	0.068	0	1	
	Proportion of commuters using public transit	0.020	0.037	0	0.549	
	Proportion of commuters using bicycle	0.006	0.013	0	0.234	
	Proportion of commuters who walk	0.016	0.025	0	0.437	
	Proportion of people working at home	0.045	0.036	0	0.807	

An alternative approach is the accelerated hazard model, which is mainly used in reliability theory and industrial experiments. In our study, a parametric hazard approach is adopted because its hazard function can be flexibly chosen. In the accelerated hazard model, the natural logarithm of the duration time, log t, is expressed as a linear function of the covariates, yielding the linear model as following Equation (1):

$$\ln(t_j) = X_j\beta + \varepsilon_j \tag{1}$$

where X_j is a vector of covariates, β is a vector of regression coefficients, and ε_j is the error with density f(ε). It is noted that $(t_j + 1)$ was used for T1 instead of (t_j) in the equation as there are excessive zero values in T1, which means the crashes are reported within one minute.

The distributional form of the error term determines the regression model. If we let *f(ε)* be the logistic density, the log-logistic regression is obtained. If we let *f(ε)* be the standard normal density, the lognormal regression is obtained. Setting *f(ε)* equal to the extreme-value density yields the exponential and the Weibull regression models. Several parametric distributions can be assumed including exponential, gamma, log-logistic, log-normal, and Weibull. These five types of models were developed of which the best models were determined based on Median Absolute Deviation (MAD), which is the mean of absolute differences between predicted and observed values.

RESULTS

Explanatory Analysis of Crash-Reporting and Reporting-Arrival Intervals

Overall 11,071 fatal crash cases were used in this study. The crash-reporting (T1) and reporting-arrival (T2) intervals were explored and the results are shown in Tables 2-3, respectively. Figure 2 shows the distributions of T1 and T2. It was revealed that the overall average crash-reporting T1 and T2 are 3.64 and 7.05 minutes, respectively. Nearly 95% of fatal crashes were reported within 10 minutes and EMS arrive on the crash scene within 10 minutes in 84% of the cases. Only 15% of fatal crashes need 10 to 20 minutes for EMS arrivals. Nevertheless, there is a variance in crash-reporting and reporting-arrival intervals by geographic locations (urban/rural) and roadway functional classifications (freeway/expressway, conventional road, etc.). Thus, the research team analyzed crash-reporting and reporting-arrival intervals by these locations and roadway functional classifications. It was shown that average crash-reporting intervals in the urban and rural areas are 3.03 and 4.53 minutes, respectively. Eighty percent of fatal crashes are reported within 5 minutes in the rural areas whereas almost 90% are reported within 5 minutes in the urban area. In the rural areas, only 27% of EMS arrive on the scene within 5 minutes while 56% in the urban areas need 5 minutes for EMS arrival on the scene after the notification. In case of average crash-reporting and reporting-arrival intervals by roadway functional classifications, there is no considerable difference in the average crash-reporting interval on the freeway/expressway (3.82 min) and conventional road (3.61 min). In contrast, the average reporting-arrival interval on the freeways/expressways (8.25 min) is longer than that on the conventional roads (6.82 min).

TABLE 2: Descriptive Statistics and Distribution of Crash-Reporting Interval (T1)

(a) Descriptive statistics

Location Type	N	Mean	Stdev	Q1	Q2	Q3	Q4
Overall	11071	3.642	8.252	1	2	4	120
Urban	6546	3.027	7.555	0	1	3	120
Rural	4525	4.533	9.094	1	2	5	120
Freeway/expressway	1846	3.819	6.974	1	2	4	115
Conventional road	9225	3.607	8.484	1	2	4	120

*Q1, Q2, Q3, and Q4 stand for First, Second, Third, and Fourth Quartiles, respectively.

(b) Distribution

Required time	Overall	Urban	Rural	Freeway /expressway	Conventional road
5 min or less	79.8%	84.3%	73.2%	75.7%	80.6%
5-10 min	14.1%	11.4%	18.1%	17.3%	13.5%
11-15 min	2.79%	1.85%	4.15%	3.47%	2.66%
15-20 min	1.06%	0.73%	1.52%	1.57%	0.95%
21-25 min	0.43%	0.31%	0.62%	0.76%	0.37%
26-30 min	0.32%	0.24%	0.42%	0.27%	0.33%
More than 30 min	1.50%	1.17%	1.99%	0.93%	1.59%

TABLE 3: Descriptive Statistics and Distribution of Reporting-Arrival Interval (T2)

(a) Descriptive statistics

Location Type	N	Mean	Stdev	Q1	Q2	Q3	Q4
Overall	11071	7.055	4.919	4	6	9	104
Urban	6546	5.824	3.879	4	5	7	72
Rural	4525	8.836	5.664	5	8	11	104
Freeways/expressways	1846	8.246	4.687	5	7	10	65
Conventional roads	9225	6.816	4.930	4	6	8	104

*Q1, Q2, Q3, and Q4 stand for First, Second, Third, and Fourth Quartiles, respectively.

(b) Distribution

Required time	Overall	Urban	Rural	Freeway /expressway	Conventional road
5 min or less	30.4%	39.5%	17.3%	16.7%	33.2%
5-10 min	49.0%	49.7%	48.0%	52.8%	48.3%
11-15 min	14.4%	8.36%	23.1%	22.3%	12.8%
15-20 min	3.91%	1.50%	7.40%	5.85%	3.52%
21-25 min	1.29%	0.43%	2.54%	1.30%	1.29%
26-30 min	0.47%	0.23%	0.82%	0.60%	0.44%
More than 30 min	0.53%	0.28%	0.85%	0.45%	0.45%

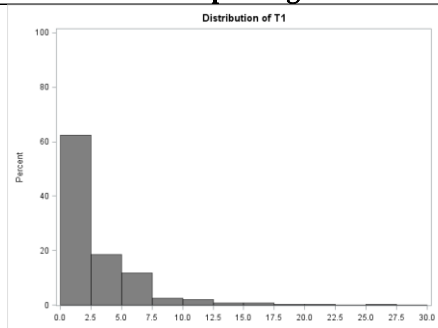
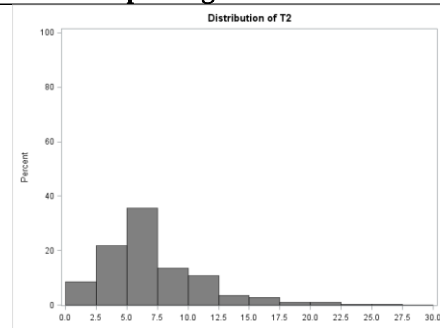
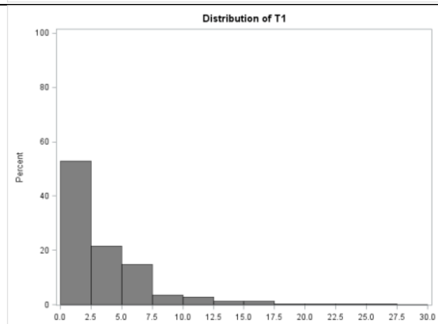
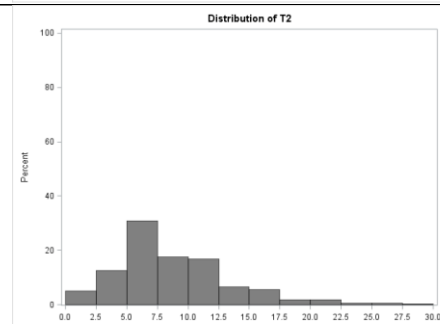
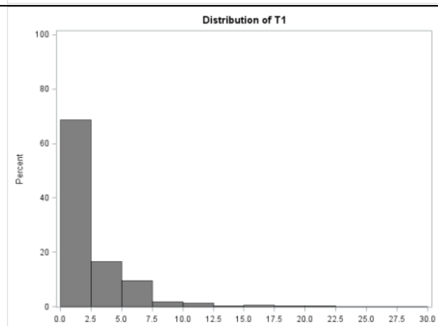
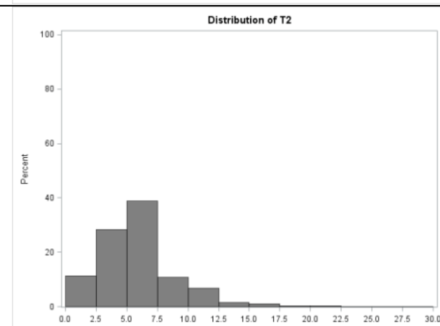
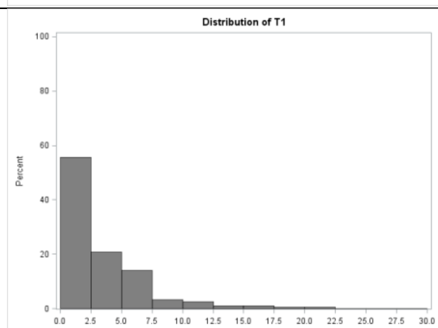
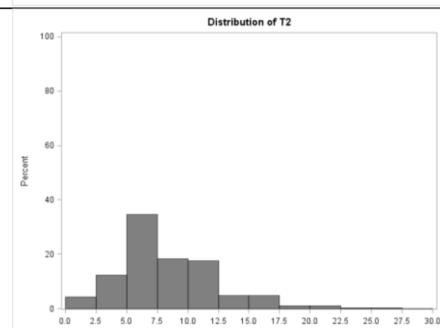
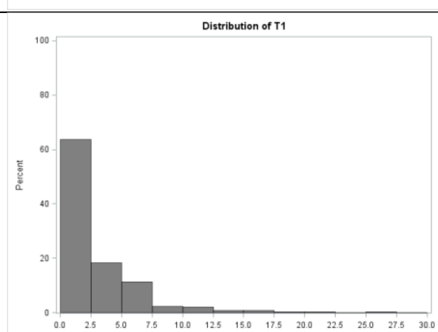
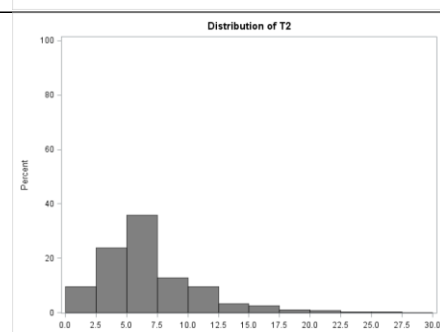
Road class	T1: Crash-Reporting Interval	T2: Reporting-Arrival Interval
Overall		
Urban		
Rural		
Freeway		
Conventional Roads		

FIGURE 2: Histogram of Crash-Reporting (T1) and Reporting-Arrival (T2)

Modeling Results

Table 4 summarizes the median absolute deviation (MAD) values of the estimated models. It was found that log-logistic and gamma performed the best for crash-reporting (T1) and reporting-arrival intervals (T2), respectively. Still no considerable difference was observed in these MAD values. It implies that the other models perform equally well as the best models. For instance, the MAD of the log-normal model for T1 (2.886) is almost same as that of the log-logistic model (2.884). Similarly, the MAD of the log-logistic model for T2 (2.741) is nearly equal to that of the gamma model (2.740). Also, the significant variables were almost identical. Thus, it is possible that the best models in this study may be replaced if different dataset is used. Table 5 summarizes the modeling results for T1 and T2 with the smallest MAD, the modeling results will be discussed in the following section.

TABLE 4: Comparison of Median Absolute Deviation (MAD) Values between the Models

Model	**T1: Crash-Reporting Interval**	**T2: Reporting-Scene Arrival Interval**
Exponential	2.914	3.053
Gamma	2.894	**2.740**
Log-Logistic	**2.884**	2.741
Log-normal	2.886	2.751
Weibull	2.918	2.743

TABLE 5: Modeling Results

Category	Variable	Log-logistic model for T1: Crash-Reporting Interval			Gamma model for T2: Reporting-Arrival Interval		
		Estimate	Std. Err.	p-value	Estimate	Std. Err.	p-value
-	Intercept	1.4145	0.0388	<.0001	1.7844	0.0767	<.0001
Person	Whether all crash-involved persons were killed	0.0527	0.0180	0.0033	0.0728	0.0122	<.0001
Traffic	Log (vehicle-miles-traveled per square mile)	-0.0112	0.0046	0.0151	-	-	-
	Proportion of heavy vehicle traffic	-	-	-	1.1596	0.1181	<.0001
Functional classification	Freeway/expressway	0.1698	0.0238	<.0001	0.2299	0.0150	<.0001
	Arterial road	0.0376	0.0181	0.0380	-	-	-
	Collector	-	-	-	-	-	-
Roadway	Lane counts	-	-	-	-0.0192	0.0065	0.0032
	Curve	0.0845	0.0200	<.0001	-	-	-
	Log (road lengths per square mile)	-	-	-	-0.1035	0.0088	<.0001
Location	Intersection	-0.0861	0.0176	<.0001	-0.0748	0.0125	<.0001
	Interchange	-	-	-	-0.1103	0.0441	0.0124
	Urban (vs. rural)	-0.1457	0.0201	<.0001	-0.2190	0.0127	<.0001
Driver action	Hit-and-run involved	0.0835	0.0325	0.0102	-	-	-
Lighting condition	Dark without lighting	0.1970	0.0183	<.0001	0.0676	0.0122	<.0001
	Dark with lighting	0.0555	0.0190	0.0035	-	-	-
	Dawn	0.1348	0.0542	0.0129	0.1300	0.0378	0.0006
Land-use	Proportion of agriculture areas	-	-	-	0.1349	0.0252	<.0001
	Proportion of public areas	-	-	-	0.1546	0.0427	0.0003
	Proportion of residential areas	-0.1669	0.0363	<.0001	0.0837	0.0291	0.0040
Car-ownership	Proportion of family with 2 or more vehicles	-	-	-	0.1579	0.0356	<.0001
Socio-demographic	Log (employments per square mile)	-0.0444	0.0051	<.0001			
	Log (school enrollments per square mile)	-0.0064	0.0029	0.0270	-0.0097	0.0021	<.0001
Commuter	Proportion of commuters using car	-	-	-	0.2046	0.0809	0.0114
	Proportion of commuters who walk	-0.7213	0.2893	0.0127	-	-	-
Log-logistic parameter	Scale	0.4412	0.0035	-	-	-	-
Gamma parameters	Scale	-	-	-	0.5451	0.0037	-
	Shape	-	-	-	0.2829	0.0173	-
Median Absolute Deviation (MAD)		2.884			2.740		

DISCUSSION AND CONCLUSIONS

It should be noted that the modeling results do not imply a cause-effect relationship but association only. The log-logistic model revealed many significant factors for T1 (Table 5). First of all, 'Whether all crash-involved persons were killed' has a positive effect on T1, which indicates that T1 would be significantly prolonged if all crash-involved people died. If any person survived from the crash and is conscious, this person can report the crash; however, there would be no one to report the crash if all crash-involved people died or were unconscious at the scene. On the other hand, it is also possible that the prolonged T1 resulted in deaths of all crash-involved persons. 'Log (vehicle-miles-traveled per square mile)' is the variable that shows the intensity of traffic volume in a unit area. It is noted that the traffic volume density is not of the roadway where the crash occurred. As the variable was processed from TAZs, it shows the traffic volume density of the zone. The traffic volume density variable has a negative coefficient, which implies that the area with larger volume density can quickly detect and report a crash as there are more drivers and people. Along with the traffic volume density, there are several conditions that a crash can be reported promptly such as 'Intersection', 'Urban (vs. rural)', 'Proportion of residential areas', 'Log (employments per square mile)', 'Log (school enrollments per square mile)', and 'Proportion of commuters who walk'. Furthermore, 'Hit-and-run involved' has a positive relationship with T1. Many hit-and-run crashes occur where the driver believes that he or she would not be noticed by others. Thus, the crashes happening in such areas are less likely to be reported promptly. Two functional classification variables, 'Freeway/expressway' and 'Arterial road' are positively associated with T1. It shows that crash occurrence on the roadway of higher classification (i.e., freeway/expressway and arterial) may need more time to be reported compared to collectors and local roads. 'Curve' is positively correlated with T1. It may be because the crashes occurring on the curve section are less likely to be detectable than those on the straight section. Moreover, all dark conditions were found to have a positive association with T1. It is interesting to note that the dark condition without lighting has the largest effect, the dawn condition is the second largest, and the dark condition with lighting has the smallest effect. It may infer that it is possible to reduce the crash-reporting interval by installing more lighting in key locations.

Moreover, many significant factors were found from the gamma model for T2 as shown in Table 5. 'Whether all crash-involved persons were killed' was also significant as in the T1 model. It is as expected because if all crash-involved persons died from the crash it would be difficult to find the exact crash location, which may considerably delay T2. Several variables indicating that they are located in suburban or rural areas are found to have a positive relationship with T2, including 'Proportion of heavy vehicle traffic', 'Proportion of agriculture areas', 'Proportion of public areas', 'Proportion of residential areas', 'Proportion of family with 2 or more vehicles', and 'Proportion of commuters using car'. The result showed that crashes happening in suburban or rural areas need more time for EMS arrival. On the other hand, there are three factors representing urban areas including 'Log (road lengths per square mile)', 'Urban (vs. rural)', and 'Log (school enrollments per square mile)'. Since these three variables have negative coefficients, it can be interpreted that the urban areas require shorter time for EMS to arrive. 'Freeway/expressway' has a positive sign, which implies more time would be required for EMS dispatch. Because freeways and expressway are full access controlled roadways EMS vehicles can only access from ramps, which results in extended T2. Regarding the lighting condition, both

'Dark without lighting' and 'Dawn' is positively related to T2. It would be very hard to detect precise crash locations under such dark environments. It was also shown that shorter T2 is observed at 'Intersection' and 'Interchange'. It is possible that it is because these locations are easier to access. Lastly, 'Lane counts' has a negative relationship with T2. It suggests that multilane highways have shorter T2 compared to two-lane highways.

It is anticipated that the findings from this study can be used to develop effective and practical strategic plans to minimize EMS reporting and dispatch time and, therefore, decrease the possibility of fatalities. In order to reduce the crash-reporting interval (T1), the following policies or countermeasures may be suggested:

- Conduct frequent patrols on non-local roads with less traffic volume, particularly during the nighttime. Systems as OnStar and in the future connected vehicles technology could lead to improvement of T1.
- Install emergency phones in the area not covered by cell phone networks in rural areas.
- Pay attentions to the areas with less populations, employments, and school enrollments.
- Install more lights at key locations.

The following policies or countermeasures may be effective to reduce the reporting-arrival (T2) interval:
- Install sufficient EMS facilities especially in rural areas.
- Install emergency access ramps for freeway/expressway in the urban areas.
- Use optimized paths to crash locations considering land-use characteristics along with real-time traffic information.
- Implement a signal pre-emption technology widely to allow EMS vehicles right-of-way to pass intersections more safely and promptly.

The strength of this study is that the authors have applied hazard-based duration models for EMS crash-reporting and reporting-arrival intervals, which has not been adopted until this point. As a result, many factors have been revealed in this study. It is expected that the findings from this study can be used to develop effective and practical strategic plans to minimize EMS reporting and arrival time and, therefore, reduce permanent injuries and fatalities from traffic crashes. Another strength of this study is that data from multiple sources were used including the FARS, the Florida Department of Transportation, the U.S. Census Bureau, and the Florida Department of Revenue. Nevertheless, this study is not without limitations. For example, the authors was able to collect fatal crashes only. If non-fatal crash data are available, it is possible that the severity level of crashes has a significant influence on the EMS time. Furthermore, there are only three EMS-related variables that are provided from the FARS database: (1) Notification Time EMS; (2) Arrival Time EMS; and (3) EMS Time at Hospital; however, the third variable have too many missing values and the arrival-hospital duration could not be analyzed. It would be ideal if the EMS response level information were available such as lights, sirens, etc. but they were not available. Lastly, this study analyzed only duration time with factors; however, did not correlate failure rate function or hazard function, which can be meaningful. These limitations need to be addressed and overcome in the future studies.

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