Research Article

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Survival Analysis of the Sick and Injured in the Era of Pre-Hospital Care in the Upper East Region of Ghana

Marcellinus Moabom[1]*, Peter Akayuure[2], Anuwoje Ida L. Abonongo[1] and Albert Luguterah[1]

[1]*C. K. Tedam University of Technology and Applied Sciences, Navrongo (CKT-UTAS), National Ambulance Service-Ghana*

[2]*University of Education Winneba Ghana*

***Corresponding Author**

Marcellinus Moabom, C. K. Tedam University of Technology and Applied Sciences, Navrongo (CKT-UTAS), National Ambulance Service-Ghana.

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Abstract

An emergency occurrence is an uncertain event, and the risk of losing a single soul or life is a concern to many health managers and other related healthcare agencies. Over the past few years, many health concerns have focused on bridging the gap between patients and their caregivers. In this regard, the research interest is to perform a survival analysis of the sick and injured in the era of pre-hospital care in the Upper East Region, and the method used was survival analysis for the occurrence of life events. A total of four thousand, five hundred and sixty-two (4,562) patients were involved, covering 18 operational months. The results showed that there was a higher probability of a patient surviving within the first ten minutes than in the last 30 minutes to an hour. The study found that an EMS-transported patient has a 97.58% chance of surviving given that the incident has not occurred beyond 10 minutes of onset and a 94.53% survival rate for persons whose incident occurred between 30 and 60 minutes from the onset, which is below the average survival rate of 94.98%. The Gamma AFT model fits the survival dataset well and has better predictive power than any other distribution under the AFT model. The study concludes that the survival of pre-hospital patients is higher within the first 10 minutes, as are patient location, incident type, age of the patient, and other factors that affect patient survival. Patient location is of essence to their survival, the study recommends ambulances be stationed at vantage points to facilitate prompt response to patient location.

Keywords: EMS, Pre- Hospyal Care, PIMS, NAS, Obs and Gynaec, RT, WHO, AFT

Abbreviations

EMS: Emergency Medical Service
Pre-Hospital Care: Out-of-Hospital Emergency Care
PIMS: Pre-Hospital Information Management System
NAS: National Ambulance Service
Obs and Gynaec: Obstetrics and Gynecology
RT: Response Time
WHO: World Health Organization.
SCPH: Survival Cox Proportional Hazard
AFT: Accelerated Failure Time

1. Introduction

Emergency Medical Service (EMS) is the single most important and efficient means of saving lives in the country. It solves and bridges the gap between casualty, victim, and patients and their caretakers at the health care facility [1]. Emergency medical service is sometimes referred to as "pre-hospital care, known in some countries as emergency rescue service," or "out-of-hospital emergencies where there are no doctors or other healthcare professionals.

The emergency medical system, just like other emergency response systems around the world, is the first health care provider to be at the scene of an accident or other disaster. In 2021, there was a projected road traffic fatality rate of 31850, which represents a 10.5% increase from the previous year, and 31785 other recorded injuries between January and December of 2022, representing a 0.2% decrease in fatalities [2].

The fear of everyone in this world is how we lose innocent lives daily. The moment an emergency occurs, the next step is to determine how the victim or patient is going to meet the healthcare professional and by what means. Similarly, in the case of a sudden collapse victim or accident victim, what happens next is whether they will survive or not, and this is dependent on the means and the care they received at that critical moment. In all these cases, on-scene care is needed for the care and transport. The survival rate of victims or patients who suffer various degrees of injuries and ailments at the scene outside the hospital without any intervention or care cannot be quantified.

In a country like Ghana, the majority of deaths recorded are due to time-sensitive conditions, which are either the result of inadequate pre-hospital care, the unavailability of transport, or both [3]. The survival rate of victims or patients is dependent on the prompt response to the scene outside the hospital. The delay in response could be due to the nature of our country's roads, which are considered an inhibitor for prompt response in rural areas, and in the rainy season, the roads get worse and are sometimes unmotorable. Transporting a trauma victim to a definitive care unit or advanced care within 60 minutes of the injury is the top priority of emergency care providers. The taught, and practised for curative health over the last three decades is that injury outcomes should improve with reduced time to a definitive care centre [4]. Pre-hospital care has become an obvious point where critical research needs to be conducted to ascertain the patient's survival or otherwise. Another point or problem is that there is a lack of contextual knowledge among researchers engaging in pre-hospital care research. Therefore, the study seeks to use the pre-hospital care survival date to find the prognostic factors associated with the survival data.

The general objective of this study is to determine the prognostic factors associated with the survival time of patients:

- to estimate the survival rate of emergency patients transported within the 10-minute time frame.
- to determine the hazard rate of emergency patients transported within the 10-minute time frame.
- to compare the survivorship probability of patients for different categories of the independent variables.
- to examine the influence of prognostic factors associated with survival time.
- to determine the appropriate model suitable for the dataset.

Emergency conditions and injuries are the major causes of deaths and disabilities worldwide. The prompt response in many of these cases leaves much to be desired. Prevention is good, but when emergencies occur, a rapid medical response is required.

Out of the hospital, emergency care delivery is critical to Ghana's healthcare service and emergency response system, providing treatment and transport to millions of sick and injured individuals in the country. Research conducted by Norman et al. (2012) noted that the inadequacies of the hospital system in responding to emergencies raise serious public health concerns [5]. The biggest challenge facing hospitals in their emergency intervention is the lack of pre-emergency and emergency preparedness plans as well as the coordination of the hospital's response mechanisms [6]. According to the study, Ghana's emergency medical service remains a serious developmental and public health concern for both pre-hospital and healthcare facility-based support. Some Ghanaians have a negative perception of emergency medical services, specifically ambulance care operations [7]. Pre-hospital care saves patients who would have otherwise died at the accident site [8]. The survival of any emergency victim or patient is time bound, that is from the time the incident occurred to the time the patient reaches the definitive care unit or treatment unit. Research by Constantine (2016), suggested that surviving for 30 days after a witnessed Oklahoma Health Care Authority (OHCA) incident decreases as ambulance response times increase [9].

Davis, et al., (2003), noted that people who suffer a traumatic injury or acute illness in cities are far more likely to die in an out-of-hospital situation, even if the response time is short unless trained EMS professionals are accompanied to manage the critical cases [10]. The study concluded that response time is widely dependent on the location where the incident occurs and the number of trained professionals on board for the survival of the patients. Similarly, Mohammed-Najeeb, used the chi-square test on response time for trauma patients in a retrospective cross-sectional study [11, 12]. According to the study findings, over 98% of trauma patients survived, and their response time was 8 minutes. The majority of the studies reviewed in the literature focused on response time rather than patient survival and risk.

1.1 Research Design and Data Type

The study's structural framework is a retrospective quantitative study, and the study population includes all types of emergency cases, such as trauma, medical, gynaecological, and so on, that have been transported to the health care facility for treatment within the region and beyond. This covers the Upper East Region from 2021 to 2022 (one and a half years). The data is secondary data extracted from the National Ambulance Service Pre-Hospital Information Management System (NAS -PIMs) database from February 4, 2021, to July 31, 2022 (18 months).

When we have some information about a subject's event time but do not know the exact event time, we use censoring to protect the current data. Censorship is also known as "incomplete data [13]. Three (3) types of censoring may occur: right, left, and interval censoring, and they are classified under the three reasons listed below as the reasons why censoring may occur.
(i) A person who does not witness the event before the study concludes, thereby missing out on the golden hour.
(ii) A person or persons whose information was lost to follow-up during the study period.
(iii) A person withdraws from the study.

1.2 Inclusion and Exclusion Criteria

All patients, regardless of age, gender, health-related condition, whether stable or not, and whether or not they are conscious or not treated or transported are included irrespective of location. It should be noted that the number of times the patient is transported does not matter but must be considered.

2. Data Analysis Method

The study used the Kaplan-Meier, log-rank test, Cox proportional hazard regression, and accelerated failure models for analysis.

Survival analysis is a study of survival data (time to event outcome). Survival analysis is a branch of statistics that studies how long it takes for an event to occur. The term "survival analysis" refers not only to analysing time until death but also to a wide range of events [14];
(i) Estimate the lifespan of a particular population under study also called "Time to event" analysis.
(ii) Compare time to the event between groups.
(iii) Assess the relationship of covariates on time to event.
The survivorship function, probability density function, and hazard function are the three major functions that govern the survival analysis. The survival function S (t) is defined as the likelihood that an individual will live longer than the time (t). As a result, the probability that the outcome event will not occur up to a specific point in time, including the time point of observation (t).

Hazard is a rate rather than a probability per unit of time. It is always nonnegative that is equal to or greater than zero and has no upper bound. The hazard function has four distinguishable graphs, identified by their pattern or shape over time:
(i) A hazard function can be constant over time
(ii) A hazard function is increasing over time.
(iii) A hazard function is decreasing over time.
(iv) A hazard function can be a bathtub (first decreasing and then increasing over time or it can be an upside-down bathtub (unimodal))

2.1 Kaplan Meier Estimate (Product Limit)

Kaplan-Meier is a non-parametric (based on no underlying distribution) statistic that estimates the likelihood that an individual or a population will "survive" a given time (t) [15]. Even if some of the data is censored, the Kaplan-Meier estimator provides an estimate of the S (t) at all time points. Product limit estimators are another name for Kaplan-Meier estimates. The incident rate as a function of time is calculated by observing the order of time until the event occurs. The Kaplan-Meier method employs two variables: observation period and occurrence or non-occurrence. At each occurrence of the event, the incidence rate is calculated, and the survival curve is estimated.

2.2 Cox Proportional Hazard Model

The Cox proportional hazard model is a linear model for the log of the hazard ratio that assumes an exponential model, a Weibull model, or any other specific parametric model. Because no assumptions are made about the shape of the baseline hazard function, the Cox proportional model is semi-parametric.

2.3 Accelerated Failure Time (AFT) Model

An AFT model is any model that measures the direct effect of explanatory variables on survival time rather than a hazard. It also describes the relationship between the set of covariates and the survival probabilities. The AFTM includes a failure time (T) and a linear regression model based on log-transformed T.

2.4 Model Selection Criteria

The process of model selection has several approaches. It combines the knowledge of science, trial and error, common sense, automated variable selection procedures (forward selection, backward selection, stepwise selection), measures of explaining variation, information criteria (Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), etc.). dimension reduction.

3. Results

The results consisted of 4562 patient records studied, which comprised 44.41% (2026) of males and 55.59% (2562) of females of the total case count. Also, there were 33.80% (1542) of medical cases, 31.37% (1431) of trauma cases, 31.17% (1422) of obstetric and gynaecological cases, 1.34% (61) of paediatric cases, and 0.15% (7) of them were psychiatric cases. However, about 2.17% of the cases were unknown. The overall death cases were 5% of the cases attended to; however, these included cases either before arrival, en route, or on arrival over the period. The study has patients as young as a day old and as old as 100 years of age.

The survival of patients, be they sick or injured, is subject to the probability that the patient will either survive before he or she gets to the hospital to see a doctor or will die within the golden one-hour period. The study, therefore, estimated the survival rate and its corresponding hazard estimate. The probability of a person surviving for at least 10 minutes is 0.9758. Also, the probability of the person surviving for at least 20 minutes is 0.9476; 30 minutes or less is 0.9193; and finally, above 30 minutes, the survival rate is 0.6483, as shown in both the K-M plot and the life table

In the Kaplan-Meier survival estimate plot in Figure 1, there is a step function with discontinuities at the observed failure time in a graphical form or presentation. Similarly, in the Kaplan-Meier graph, estimate from time zero to the sixty-sixth minute. Figure 1 shows that at time zero, the probability of a patient (sick or injured) surviving past that time immediately after the incident had occurred is one (1), but its rate gradually decreases as the time increases to 60 minutes, which is referred to as the golden one (1) hour," to 0.648. This is a stepwise increase, or the survival is diminished, indicating an inverse relationship between the probability of the rate of survival and the survival time (t). The K-M hazard plot indicates the probability that a patient (sick or injured) will die at time t. The Kaplan-Meier hazard plot increases with increasing time. Figure 2 below shows the plot of the Kaplan-Meier Hazard Curve. From the plot, the hazard at time zero, h(t=0), is zero(0), and the hazard then increases with increasing time, and h(t=60) 1, 1 or approximately. This means that as the time and its corresponding hazards increase, the risk of the sick or injured dying between time zero (0) and the first 10 minutes is 2.42% and 35.17% at the 60th minute, or the golden one-hour mark. In Life Table 1, it is indicated that the survival rate for patients who survive the first 10 minutes is 0.9758, the corresponding hazard or failure rate for the same period is 0.0034, and the cumulative hazard is 0.0242. Also, between 11 and 20 minutes, the survival rate reduced to 0.9476 with the increase in time, the cumulative hazard increased to 0.0807, and the hazard for patients (sick or injured) with an onset exceeding 30 minutes had a hazard of or probability of dying at 0.3517.

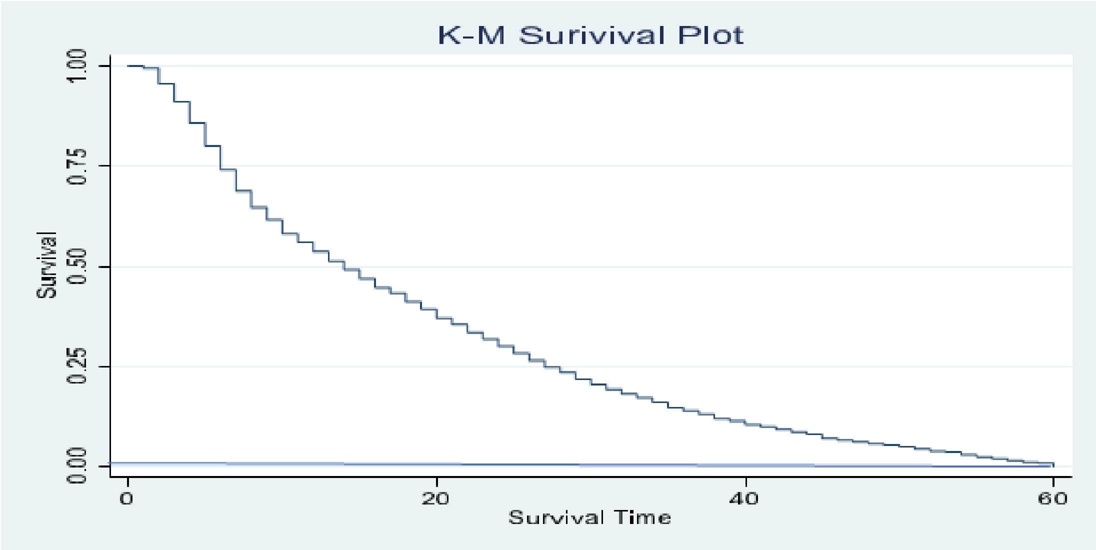

Figure 1: Kaplan -Meier Survival Plot

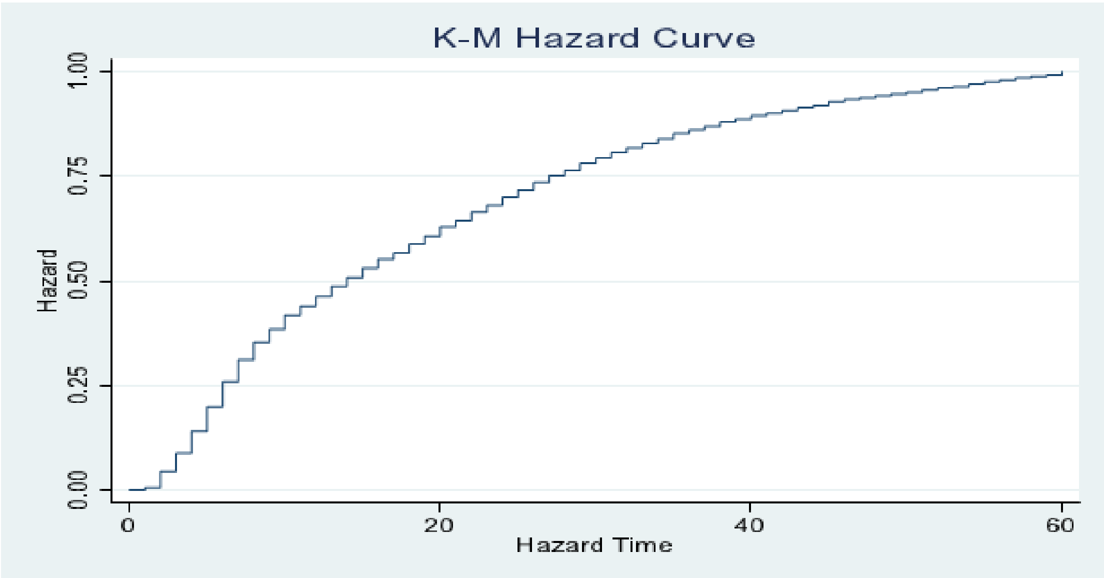

Figure 2: Kaplan-Meier Hazard Plot

Interval	Interval	Beg. Total	Deaths	Lost	Survival	Std. Er	[95%Conf.Int]	
1	2	4562	3	25	0.9993	0.000	0.998	0.9998
5	6	3897	14	262	0.9914	0.002	0.988	0.9948
10	11	2750	9	153	0.9758	0.003	0.970	0.9815
15	16	2162	7	101	0.9604	0.004	0.956	0.9679
20	21	1704	5	96	0.9476	0.004	0.938	0.9566
25	26	1284	2	77	0.9359	0.005	0.925	0.9452
30	31	921	4	56	0.9193	0.006	0.906	0.9310
35	36	664	3	53	0.9025	0.008	0.886	0.9167
40	41	455	1	34	0.8767	0.010	0.856	0.8950
45	46	321	2	38	0.8640	0.011	0.840	0.8848
50	51	210	0	16	0.8567	0.012	0.830	0.8792
55	56	113	1	19	0.8261	0.018	0.787	0.8586
60	61	30	2	28	0.6483	0.070	0.494	0.7661

Table 1: Life Table for Sick and Injured Survival

Fitting a reduced AFT gamma model for the prediction of gender, age group, patient location, and incident type Generally, age group was significant at the 5% level of significance, and with variable patient location, where the patient is located matters a lot statistically, as shown in Table 7.

In determining the best model, the parametric survival model (proportional hazard model) failed the proportionality assumption using the Cox model based on the global test as in Table 5. The AFT model (AFTM) estimates the variables within the model at a 5% significant level. In Table 8, the Gamma model is considered the best model for the survival data since the Gamma model's BIC and AIC results are the least among the rest. The scale parameter, when >1, indicates that the hazard decreases with time. 0.5 1, the hazard is increasing at an increasing rate. The gamma AIC and BIC values were the best among the rest, with the lowest values of 11700.81 and 11745.79, respectively, and the highest log likelihood value of -5843.4059.

The null hypothesis for a log-rank test is that the groups have the same survival probabilities. Table 2 tests the various variables against the critical time; gender is not statistically significant in the first 30 minutes of an emergency but is significant when the time exceeds 30 minutes. Also, the age group is statistically significant in the first 10 minutes of incidence. However, beyond 10 minutes, it indicates that they are not significant. There is, however, statistical significance when the critical time increases beyond 30 minutes. The incident type is the same and has the same statistical significance as the age group. More so, patient location has statistical significance for 10 minutes of incident or below and is not significant for any time above 10 minutes. In the overall test of equality in Table 2, both the log-rank and Cox regression tests were found to be significant for only gender (sex) but not for age group or patient location. The incident type was not significant for log-rank but was significant for the Cox regression.

	Case Response Time (CRT)							
	≤10Min		**11-20Min**		**21-30Min**		**31-60Min**	
Variable	**Observe**	**Expect**	**Observed**	**Expect**	**Observe**	**Expect**	**Observe**	**Expect**
Gender								
Male	931	913.02	363	362.8	274	287.9	309	340.3
Female	960	977.98	560	560.3	432	418.1	504	472.7
Total	1891	1891	923	923	706	706	813	813
Chi-sq	0.96		0.00		1.56		5.63	
P-value	0.3262		0.9842		0.2119		0.0177	
Age Group								
below 1	130	126.79	86	93.98	75	67.75	72	66.78
1-14	131	142.53	77	80.71	68	77.58	57	64.51
15-29	802	736.13	364	363.9	284	285.2	333	303.3
30-44	495	491.68	224	211.4	151	137.9	199	209.2
45-60	168	184.36	79	70.49	63	62.72	72	85.56
Above 60	164	206.59	93	102.5	65	74.84	80	83.63
Unknown	1	2.91	-	-	-	-	-	-
Total	1891	1891	923	923	706	706	813	813
Chi-sq	27.37		4.85		6.31		7.92	
P-value	0.0001		0.4346		0.2769		0.1605	
Trauma	752	695.46	244	254.0	150	152.3	182	207.9
Medical	597	648.79	320	329.5	250	256.4	281	284.7
Ob and G	494	485.05	323	308.4	269	252.6	317	291.2
Paediatric	21	28	6	7.95	12	17.13	15	13.14
Psychiatry	1	1.52	1	0.09	3	1.33	2	1.96
Others	26	32.18	29	22.96	22	26.23	16	13.88
Total	1891	1891	923	923	706	706	813	813
Chi-sq	17.17		14.23		7.54		6.97	
P-value	0.0042		0.0142		0.1837		0.2220	
Patient Location								
Hospital	1305	1414.6	783	800.18	656	657.8	758	762.6
Roadside	506	382.79	91	80.63	24	22.68	23	20.33

Residence	52	70.74	39	31.74	21	20.09	28	25.01
Industrial	4	2.94	1	0.67	-	-	-	-
Recreation	4	4.07	2	1.27	-	-	-	-
Others	20	15.89	7	8.51	5	5.4	4	5.08
Total	1891	1891	923	923	706	706	813	813
Chi-sq	75.02		5.62		0.21		1.06	
P-value	0.00		0.3453		0.9765		0.7877	

*At a 5% significant level

Table 2: Log-Rank of CRT against Incidence Type, Gender, Age Group

The estimated contributions of age group, gender, and patient location variables were insignificant, but the global test for the overall variable failed at the same significant level as seen in Table 3 and 4 at a 5% level of significance.

Variable		Log-Rank Test		Cox Regression Test		
	observed	Chi-square	P-value	Relative Hazard	Chi-square	P-value
Gender	4333	0.92	0.3375	1	0.69	0.4061
Age Group	4333	28.41	0.0001	1	21.23	0.0017
Incidence Type	3502	13.45	0.0195	1	10.13	0.0717
Patient Location	4333	75.02	0.0000	1	43.60	0.0000

Table 3: Testing for equality using Log-Rank and Cox Regression Test

Variables	Coef.	Std. Err.	z	P-value	[95% Conf. Interval]	
Patient Location	0.200979	0.019573	10.27	0.000	0.162616	0.239343
Age Group	-0.03445	0.011832	-2.91	0.004	-0.05764	-0.01126
Incident Type	-0.09082	0.017789	-5.11	0.000	-0.12568	-0.05595
Gender	0.029686	0.034762	0.85	0.393	-0.03845	0.097818
Log likelihood = -32303.72 chi-square= 123.45 P-value = 0.0000						

Table 4: Cox Proportional Hazard

The Global test for the proportionality assumption of the Cox model was violated, so an Accelerated Failure Time model was fitted to determine the relationships between covariates and the dependent variable (Table 5). Five distributions were used: Weibull, Logistic, Gamma, Exponential and Lognormal in Table 6. The Weibull AFT model had gender insignificant at an alpha level of 0.05, while the exponential AFT model had patient location, incident type and age group being significant while the gender was statistically insignificant at a 5% significant level. The lognormal AFT model had patient location, incident type and age group being statistically significant whereas gender was statistically insignificant.

Variable	Rho	Chi-square	P-value
Patient Location	-0.06818	13.89	0.0002
Age Group	0.00399	0.07	0.7982
Incident Type	0.08301	31.38	0.0000
Gender	0.01886	1.54	0.2140
Global test		70.60	0.0000

Table 5: Testing of Proportional-Hazards Assumption

Variable	Coef.	Std. Err.	Z	P>z	[95% C. Interval]	
Gender	-0.0086	0.0298	-0.29	0.773	-0.0670	0.0498
Patient Location	-0.2082	0.0187	-11.11	0.000	-0.2450	-0.1715
Incident Type	0.0982	0.0151	6.52	0.000	0.0687	0.1277
Age Group	0.0281	0.0103	2.74	0.006	0.0080	0.0483
Constant	2.7354	0.0647	42.28	0.000	2.6086	2.8623
/lnsigma	-0.1430	0.0128	-11.21	0.000	-0.1679	-0.1180
/kappa	0.4031	0.0493	8.18	0.000	0.3065	0.4998
Sigma	0.8668	0.0111			0.8454	0.8887
Log likelihood =	-5843.4059	Chi2(4) = 188.53		Prob > chi2= 0.0000		

Table 6: Generalized Gamma AFT

Fitting a reduced AFT gamma model for the prediction of gender, age group, patient location, and incident type Generally, age group was significant at the 5% level of significance, and with variable patient location, where the patient is located matters a lot statistically, as shown in Table 7.

Variable	Coef.	Std. Error	Z	P-value	[95%ConfInterval]	
Age Group	0.0215	0.0101	2.12	0.034	0.0016	0.0413
Gender						
Female	-0.0206	0.0317	-0.65	0.516	-0.0827	0.0415
Patient Location						
Roadside	-0.9473	0.0432	-21.91	0.000	-1.0321	-0.8626
Residence	-0.0178	0.0709	-0.25	0.802	-0.1568	0.1212
Industrial	-1.02236	0.3685	-2.77	0.006	-1.7446	-0.3001
Recreational	-0.87512	0.3370	-2.60	0.009	-1.5355	-0.2147
Others	-0.45075	0.1413	-3.19	0.001	-0.7277	-0.1738
Incident Type						
Medical	-0.12566	0.0374	-3.36	0.001	-0.1990	-0.0523
Obs and Gynae	-0.06012	0.0442	-1.36	0.174	-0.1468	0.0266
Paediatric	0.13046	0.1171	1.11	0.265	-0.0991	0.3600
Psychiatric	0.3667	0.3189	1.15	0.250	-0.258	0.9917
Others	0.0409	0.0901	0.45	0.650	-0.136	0.2175
Constant	2.9223	0.0443	65.95	0.000	2.8354	3.0091
/lnsigma	-0.1950	0.0129	-15.1	0.000	-0.220	-0.1696
/kappa	0.4766	0.0456	10.44	0.000	0.3872	0.5661
Sigma	0.8228	0.0107			0.8022	0.8440

Table 7: Gamma AFTM Reduced Comparison

In determining the best model, the parametric survival model (proportional hazard model) failed the proportionality assumption using the Cox model based on the global test. The AFT model (AFTM) estimates the variables within the model at a 5% significant level. In Table 8, the Gamma model is considered the best model for the survival data since the Gamma model's BIC and AIC results are the least among the rest. The scale parameter, when >1, indicates that the hazard decreases with time. 0.5 1, the hazard is increasing at an increasing rate. The gamma AIC and BIC values were the best among the rest, with the lowest values of 11700.81 and 11745.79, respectively, and the highest log likelihood value of -5843.4059.

AFT Model	Log-likelihood	ll(null)	ll(model)	AIC	BIC
Weibull	-5907.414	-5977.86	-5907.414	11826.83	11865.38
Exponential	-6102.085	-6153.73	-6102.085	12214.17	12246.30
Log-normal	-5877.945	-5983.74	-5877.939	11767.88	11806.43
Log-logistic	-5990.636	-6117.21	-5990.636	11993.27	12031.82
Gamma	-5843.4059	-5937.67	-5843.406	11700.81	11745.79

Table 8: AFT Models Analysis Comparison using AIC and BIC

4. Discussion of Results

In this study, participants, comprising both males and females and covering all age categories, were treated on scene and cared for en route to the health centre by the EMS team in the Upper East Region of Ghana.

The study employed several statistical tools like Kaplan-Meier, Cox proportional hazard, and the accelerated failure time model to appropriately explain the survival dataset and the survival probabilities in Table 1. It was observed that patient survival was a time-sensitive one; once the person was sick or injured, the longer the time spent, the smaller the probability of survival, and the approach supports Dessu et al. [16].

The first 10 minutes of an incident in an out of hospital activities are crucial for proving live-saving interventions, setting the tone and expectations, for patient care and communication and ensuring that medical care is effectively delivered to the sick or injured, are statistically significant, and this is evident in the patient location, type of incident, and age group [17]. In the life table analysis, the survival of the patient at 10 minutes, and the corresponding hazard rate.

In determining the relationship between the study variables and the critical time, gender was not statistically significant for the first 10 to 30 minutes of the incident, meaning that there was not enough evidence to show that gender is a good indicator for the survival of patients within the first 10 to 30 minutes of an emergency, but it is significant when the time exceeds 30 minutes. Also, the age group is statistically significant for the first 10 minutes of incidence but is not significant beyond the 10 minutes. Statistical significance when the critical time increases beyond 30 minutes. The incident type is the same and has the same statistical significance as the age group. The patient location was statistically significant for 10 minutes of incident or below and not significant for any time above 10 minutes. The model evaluation of the Cox proportional hazard model proves that the proportionality assumption was partly satisfied, but the overall test using the global test score reveals there was no significant difference in the survival of patients.

The study, however, further considered the Accelerated Failure Time Model (AFT), which showed that the AFT (Gamma) model was the best predictor for the emergency medical service survival time data of the Upper East Region, as affirmed by residual graphs of deviance, Cox Snell, and martingale, and confirms the study conducted by Nawunbeni et al. [18].

5. Conclusion

This study included a statistical analysis of the factors influencing survival in any emergency within the pre-hospital setting for 4562 patients. The Cox model revealed that gender, patient location, incident type, and age or age group were significant predictors of patients surviving beyond the critical time. The study discovered that the Cox proportional assumption was not met; thus, the Cox model cannot be used adequately for pre-hospital survival data. The accelerated failure time model (parametric) was then used to account for the covariate hazards' variability. It was evident that the gamma distribution proved to be the best in determining the chances of survival of sick or injured in the pre-hospital setting. An investigation into the prognostic factors for the survival of sick and injured patients by the Gamma model evidenced at a 95% confidence level (significance at 5%) that the significant prognostic factors for pre-hospital care patients were where the sickness occurred, the accident or road traffic crash occurred, and the age of the respondent. The study, therefore, concludes that:

(i) The survival rate of the pre-hospital patients is 0.9758, or 97.58 percent, given that the time has not exceeded 10 minutes.
(ii) The hazard rate of the pre-hospital care patients is 0.0242, or 2.42 percent.
(iii) The survival and hazard rates of patients in the pre-hospital setting are significantly affected by the time taken to receive care from the onset of the incident or illness.
(iv) The patient location, incident type, and age of the patient, whether sick or injured, significantly affect the survival rate of out-of-hospital patients.
(v) The Gamma model is the best-fitted model for the pre-hospital care survival dataset.

Recommendations

The following recommendations are made based on the outcome of the study:
(i) Public education is recommended to improve the survival rate of 97.58% for injured or sick people because survival depends greatly on the earliest time to enhance a better outcome.
(ii) Patient age affects the survival of out-of-hospital emergency patients; therefore, the study recommends that victims or patients should be handled based on their ages.
(iii) Since at time zero, the hazard rate is zero, the study recommends that steps be taken by National Ambulance Service, etc to reduce the time between the time the incident happens and the time the patient first receives treatment to further reduce the risk.
(iv) Patient location is of essence to their survival, the study recommends ambulances be stationed at vantage points to facilitate prompt response to patient location.
(v) The Cox model did not work so well with the out-of-hospital care settings; the study recommends further investigating using the AFT model for prehospital care data.

The study, however, could not assess the quality of care in the prehospital setting and hence recommend future research into the quality of care.

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