Modeling Hospital Admission Counts at the State Specialist Hospital Maiduguri, Borno State.

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Abstract : *Services and infrastructure such as health, education, water, security etc. provided by the government and other independent providers are usually scarce and in great demand by the public. Pressure due to over dependence on the limited resources by the ever growing population due to the influx of internally displaced persons into Maiduguri has resulted in great dissatisfaction and sometimes wastages of the resources. The ultimate goal of this paper is to model hospital admissions of in-patients at the State Specialist Hospital Maiduguri, Borno State to understand the nature of dependencies of the categories of the factors on the available facilities in terms of length of bed occupancy using socio-demographic factors. Hospital records of 1418 of in-patients who were diagnosed, admitted, treated and officially discharged from 2011-2015 were studied and modeled using descriptive statistics and Generalized Poisson regression. The results obtained shows clearly how the services are demanded and consumed by the different categories of the variables considered. The results showed that gender differences, employment and age categories have significant impact on the admission rate and the length of stay by patients on admission.*

Keywords: *Admission rate, Internally Displaced Persons, Generalized Poisson Regression, Socio-Demographic Variables, Bed occupancy.*

I. Introduction

Healthcare and hospital Services provided by Government and other independent service providers are usually scarce and in great demand by the public. Towns and cities with health facilities have seen increasing number of patients over the years thereby putting too much pressure on the limited resources. Health services in Nigeria generally have been under great pressure due to unmatched population growth to the limited available facilities. Borno state in particular has seen increase in population in some local government headquarters more especially in Maiduguri, the state capital which has received large number of internally displaced persons (IDPs) due to the activities of insurgent in North-East of Nigeria. The sudden increase in population has put too much pressure on infrastructure and services such as the limited health facilities and services in the state capital. Hospital admissions increased dramatically from 2009 when the insurgency that forced many surrounding villages and towns to abandon their habitat and relocated to Maiduguri begun. According to available records at the state specialist hospital, 44, 871 patients were diagnosed, admitted, treated and officially discharged from 2011-2015. This figure excludes out-patients and those who left the hospital without being officially discharged. The over dependence on the health facilities provided by the government calls for better understanding of the population structure so that a good plan can be put in place to ensure effective utilization of the limited resources. Since health care services plays crucial role in people’s everyday life, it is therefore pertinent to develop robust procedure that guarantees maximum utilization of the limited facilities and services such as bed space utilization in hospitals.

In modeling the limited bed spaces for effective utilization, hospital admissions were considered where the outcome of interest is count data. The distribution of the number of admissions per age group, sex, occupation and educational status is presented. The discharge rate of patients was also modeled to determine which group stay longer on admission. The standard frame work for explaining the relationship between the outcome variable and a set of explanatory variables for count data includes the Poisson and negative binomial regression models; however, the basic Poisson regression model requires that the conditional variance of the outcome be equal the conditional mean a condition that rarely holds in many real life situation..

Hospital admissions and discharge rates are count data which could be modeled using Poisson distribution under the assumption that the sample mean and sample variance are almost equal, but this assumption rarely holds in many real life situations as the data may either be over or under dispersed. We then use generalized Poisson regression model to model hospital admissions and discharges at the State Specialist Hospital Maiduguri considering the socio-demographic factors of the patients. The need for better health care services by both patients and the general public, calls for effective management of the limited available resources. Understanding the distributional structure of the admission rate and the length of stay for each category of patients will help in managing the limited resources for effective utilization.

Patients and their relatives are the only source of data for information on the dignity and respect with which they are treated and the best source of information on patient education and pain-management (Cleary, 2003). Assessment, monitoring and exploration of patient's complaints and satisfaction provide an indicator of the quality of health care delivery which invariably leads to clinical care improvement strategies (Vuori, 1991; Leino and Vuorenheimo, 1992; Bendall and Power, 2001). Count data such as road accidents, schools' enrollment, deaths, etc. has been effectively modeled using Poisson distribution. Different approaches has been adapted in modeling health care services in many countries, however it is extremely difficult to generalize such models which have worked somewhere to data obtained from different countries due to the variations in the various factors associated with health care services and facilities in different countries (Fletcher *et al*., 2006).

II. The Poisson Distribution

Poisson distribution is a discrete probability distribution that expresses the probability of number of events occurring in a fixed period of time, interval, area or volume with known average rate of occurrence, where the counts occurs independent of the time since the last event. It is used to describe count data as a function of a set of predictor variables, and it has been extensively used in epidemiological studies to investigate the incidence and mortality of chronic diseases, for modeling causes of accidents in different parts of the world, and other events which has counts as outcomes. The Poisson distribution can be derived as a limiting case of the binomial distribution and it is applicable to systems with a large number of possible events, each of which is rare as in nuclear decay of atoms. With λ the expected number of occurrences in a given interval, the probability of recording exactly k occurrences (k being a non-negative integer, k = 0, 1, 2 ...) in the specified interval can be estimated by;

$$f(k,\lambda) = \lambda \mathrm{k} \ \frac{e^{-\lambda}}{\mathrm{k!}} \qquad (2.1)$$

where k is the number of occurrences of an event with probability function given by $f(k,\lambda)$, and λ is a positive real number which is equal to the expected number of occurrences in the given interval. The parameter λ represent the *mean* number of occurrences and it is the same as the variance of the distribution

$$\sigma_k^2 = (k^2) - [(k)]^2 = \lambda. \qquad (2.2)$$

Thus, the number of observed occurrences fluctuates about the mean λ with a standard deviation

$$\sigma_k = \sqrt{\lambda}\,. \qquad (2.3)$$

However the assumption of $mean\ (\lambda) = variance\ (\lambda)$ is not always satisfied as the data could be over or under dispersed making the Poisson distribution not suitable for modeling such data, hence the need for a distribution that can handle this short comings.

2.1 Poisson Regression

Poisson regression analysis is a technique used to model dependent variables that describe count data as a function some predictor variables (Cameron and Trivedi, 1998). The Poisson regression model has found application in wide range of fields in experimental and observational studies; ranging from the Medical Sciences, Economics, Demography, Psychology, Herd management, animal health in domestic and wild animals, control of infectious diseases, and in the analysis of data from multidisciplinary studies (Cameron and Trivedi, 1998; Gardener, 1995; Famoye, 1993; Fletcher *et al*., 2006). It can also be used as an alternative to the Cox model for survival analysis when hazard rates are approximately constant during the observation period and the risk of the event under study is small as in the case of road accidents (Miauo and Lum, 1993; Miauo, 1994), however it is not suitable for aggregated data.

Other works that made application of the Poisson regression include; Miauo and Lum (1993) who evaluated the statistical nature of the two conventional linear regression models commonly used for modeling road accidents, where the models fails to adequately describe the distributional characteristics of road accidents data in terms of randomness, non-negative outcome and, the discrete and count properties of the event. Miauo (1994) used Poisson and Negative Binomial regressions for the distributional properties of accident data. However, one should be more cautious in the use of Poisson and the negative binomial since the estimation of the various parameters could be misleading (Miauo, 1994).

The Poisson model overcomes some of the problems associated with normal model, first, it has a minimum value of 0 and it predicts only non-negative values. This makes it ideal for a distribution in which the mean or the most typical value is close to 0. Secondly, it is fundamentally skewed where the data is characterized with long 'right tail' making it most appropriate for counts of rare events. Thirdly, using maximum likelihood method for the estimation of parameters gives unbiased estimates, with the exception of slight rounding error. Fourth, the Poisson model generally gives better estimate in count data. The problem of over- or under-estimation can be addressed with Poisson distribution as it has lower total error than the normal model and this desirable statistical property makes it very useful for predicting hospital admissions and discharge counts.

2.2 Generalized Poisson (GP) Regression Model

With the shortcomings of the Poisson distribution in handling over or under dispersed count data, generalized Poisson distribution can be used to effectively address these problems (Famoye, 1993; Wang & Famoye, 1997). The GP has a dispersion parameter *a* like the Negative Binomial distribution and the probability mass function for the generalized Poisson distribution is given by;

$$P(X=x)=\theta^{x}(1+ax)^{x-1}e^{-\theta(1+ax)}/x!,\; x = 0, 1, 2, ..$$

(2.4)

where $\theta > 0$ and a can take up any variable (negative or positive). The mean and variance of the above model are respectively given by $\mu=\theta/(1-a\theta)$ and $\sigma^2=\theta/(1-a\theta)^3$. Suppose the mean of the GP distribution depends on some independent variables x_i, then $\mu(x)$ can be written as;

$$\mu(x_i)=\theta/(1-a\theta)\Rightarrow\theta=\mu(x_i)/[1+a\mu(x_i)].$$

(2.5)

and therefore the generalized Poisson regression model can be written as;

$$\text{d}\,P(Y=y_i\mid x_i)=\left(\frac{\mu(x_i)}{1+a\mu(x_i)}\right)^{y_i}\frac{(1+ay_i)^{y_i-1}}{y_i!}\exp\left[\frac{-\mu(x_i)(1+ay_i)}{1+a\mu(x_i)}\right],\; y_i = 0, 1, 2, \ldots$$

(2.6)

The mean and variance of the generalized Poisson regression model are respectively given by

$$E(Y)=\mu(x_i) \text{ and } V(Y)=\mu(x_i)[1+a\mu(x_i)]^2.$$

The GP reduces to the Poisson when $a = 0$ and the dispersion factor var (Y_i)/E(Y_i) = $(1+a\mu_i)^2$. If $a > 0$, then var (Y_i) > E(Y_i) and the GP will model count data with over-dispersion. Similarly, when $a < 0$, then var (Y_i) < E(Y_i) and the GP will in this case be modeling under-dispersed count data.

III. Study Design and Methods

This research work was conducted at the Borno State Specialist Hospital Maiduguri, the biggest tertiary health care institution owned by the state government. Besides its primary function of providing health care services to patients, it also serves as training and research center for the state schools of nursing and midwifery, and school of health technology. Patronage of the hospital is very high because of affordability and availability of all medical sub-specialties with adequate qualified personnel who are well experienced in their various fields of specializations. Hospital records for five (5) years consisting of 44,871 in-patients who were diagnosed, admitted, treated and officially discharged from 2011-2015 was used for the study. A sample of size 1418 was randomly selected using systematic sampling and data on; hospital discharge counts, length of stay on admission, age, sex, occupation and educational level of each patient were collected for the study. Descriptive analysis of the admissions by the factors is presented to enable us understand the rate of dependencies of each sub-group on the health care facilities. The distribution of monthly admissions data was presented in Figure 1 to enable us visualize the trends of admissions at the state specialist hospital, Maiduguri.

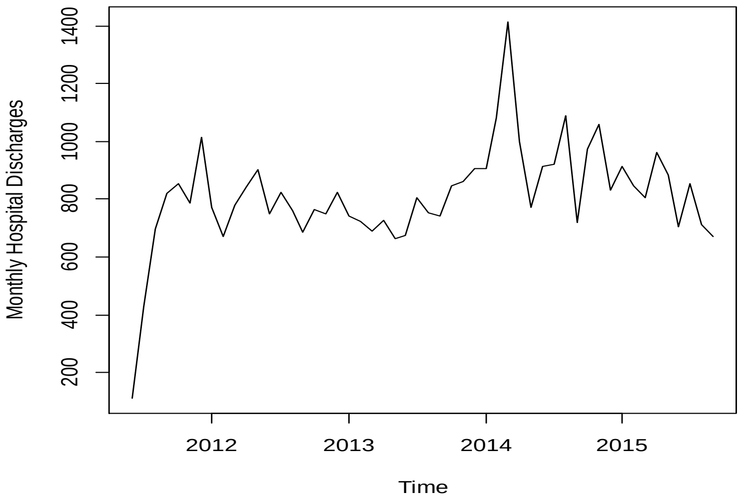

Figure 1: Monthly plot admissions from 2011 to 2015

IV. Results

We first present the descriptive analysis of the admissions data for each of the variables considered in tables 4.1-4.3 to see the dependency of each category on the available facilities and services.

Table 4.1: Distribution of Admissions by Gender

	Counts	Percent	Cumulative Percent
Male	590	41.60	41.60
Female	828	58.40	100

Table 4.1 shows the distribution of admissions by gender, the data shows that more women than men were admitted in the hospital for the duration of study. This suggest that special attention in terms of facilities and personnel be paid to issues and specific needs of women.

Table 4.2: Distribution of Admissions by Occupational Status

	Counts	Percent	Cumulative Percent
Civil Servants	111	07.83	07.83
House Wife	406	28.63	36.46
Self Employed	173	12.20	48.66
Children	728	51.34	100

The distribution of admissions by occupational status of the patients' shows that the children group are the most admitted followed by housewives (full time housewives) as shown in Table 4.2. This clearly shows where efforts and resources should be channeled to.

Table 4.3: Distribution of Admissions by Age Group

Age Group	Counts	Percent	Cumulative Percent
01-10	595	42.00	42.00
11-20	197	13.90	55.90
21-30	198	14.00	69.80
31-95	428	30.20	100

The distribution by age groups shows that patients with ages below 10 years and adults ranging from 30 years and older are the most active groups on the admission list as shown in table 4.3.

Table 4.4: Parameter estimates using Generalized Poisson regression model

Parameter	B	Std. Error	95% Wald C. I		Hypothesis Test			Exp(B)	95% Wald C.I for Exp(B)	
			Lower	Upper	Wald χ^2	df	Sig.		lower	upper
Intercept	1.926	0.0483	1.831	2.020	1590.875	1	0.000	6.861	6.241	7.542
Age	0.008	0.0006	0.006	0.009	149.023	1	0.000	1.008	1.006	1.009
Sex	-0.086	0.0231	-0.131	-0.041	13.830	1	0.000	0.918	0.877	0.960
Occupation	-0.042	0.0056	-0.053	-0.031	55.730	1	0.000	0.959	0.949	0.970

The discharge rate of the admitted patients shows that the data is over-dispersed where; $mean \neq variance$ $(\lambda < \lambda^2)$, hence, this justifies the use of generalized Poisson regression in modeling the data. We look at the socio-demographic factors of the patients to estimate how long each patient may stay on admission so that an effective mechanism for the utilization of the limited bed spaces can be developed. Table 4.4 shows estimates of the parameters where age is found to be significant at 1% level with *p = 0.0000* and the incidence rate ratio (IRR = 1.008) revealing that a unit change in age increases the period of stay in the hospital by 0.8% meaning that older persons tends to stay longer on admission than younger ones. Sex is also significant at 1% level with *p = 0.0000* where the IRR shows that there is a drop in the period of stay in the hospital by 0.082 for female patients against male patients. For occupation, civil servants tends to stay longer on admission in the hospital with IRR of 4.1%, this could be attributed to the age factor since majority of civil servants in the state are older persons. Our results concur with the findings of Kolo and Chijioke (2009) on hospital admissions in Nigeria in relation to gender where they found that female tend to use hospital more frequently with shorter length of stay than male counterparts who comes with more complications leading to longer period of stay on admission. Testing the model parameters, age, sex and occupation were statistically significant $(p = 0.000)$ showing that the model adequately fitted the data.

Table 4.5: Correlations Between the Variables

	Intercept	Age	Sex	Occupation
Intercept	1	-0.83	-0.6	-0.904
Age	-0.83	1	0.304	0.716
Sex	-0.6	0.304	1	0.402
Occupation	-0.904	0.716	0.402	1

The correlations between the variables shown in Table 4.6, indicates that the correlation between age and sex is 0.304, age and occupation is highly correlated with a coefficient of 0.716, and that of sex and occupation is 0.402.

Table 4.6: Anova of Monthly Discharges on Time

Source	SS	df	MS	F	p-Value
Model	229954	1	229954	8.52	0.005
Residual	1413215	53	26664.39		
Total	1643168	54	30429.03		

The result in Table 4.6 reveals that monthly discharge is significant and dependent on time with p-value of 0.005.

V. Conclusion and Recommendation

Our study shows that the admission rate for the different categories of the socio-demographic variables varies. By sex it shows females are the most admitted with 58.4% of the total admissions, however they spend less time on admission than males. Children up to 10 years and elderly persons over 30 years accounted for over 70% of the admissions but the elderly patients tends to stay longer on admission than younger ones. These interacting factors indicates how the hospital resources and services are demanded by the patients. The information obtained from the analysis provides a sound basis for health care providers and administrators to plan effectively on how to best utilize the limited resources in terms of bed spaces and other requirements for the care of the patients at the state specialist hospital Maiduguri. This study was limited to only the available information in the medical records; however, we believe that other socio-economic factors, such as place of residence, income, awareness on general hygienic practices, household size and educational level of both spouses or the individual will greatly help in modeling the admissions and discharge rates of patients to effectively manage the available resources. Effective linkages between hospitals could help in tapping unused resources to decongest or avoid wastages of resources in terms of facilities, services, time and personnel.

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