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Modeling Patient's Length of Stay Using Poisson Regression in Hospital Emergency Department

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Abstract: ***In this article, the congestion in Emergency Department(ED) of Federal Medical Centre, Yola Nigeria was investigated. Patient Length of Stay (LoS) were modeled using Poisson regression and queuing model respectively. Data were collected by observing the patients for a period of sixty (60) days. A total of 693 patients were observed. The peak period recorded twenty six (26) admitted patients in one day. Emergency cases were classified into six; Road Traffic Accident (RTA), disaster, medical, gynecology, gun shot, and snake bite. The data were analyzed using EasyFit, SPSS and TORA packages. Poisson regression revealed that the female patients are at higher risk of LoS (2.737) compared to the male patients. The results further showed that, RTA, gynecology and medical patients are also at risk of LoS compared to others. Queuing analysis indicates that the average number of dischargeand not discharge patients is approximately 7 and 8 patients per day respectively, and the capacity of the queue per day is 17 patients while theaverage time of discharged patients in the system is approximately 2 days. The traffic intensity of ED patients on discharge rates is 2 patients per day, implying that 2 patients are being turned away every day.***

Keywords: Length of Stay, Poisson regression, TORA, Traffic intensity, Emergency Department, Risk

1. Introduction

Operations of Emergency Department (ED) have been studied during the past few decades in many different ways and with many different methods. Solutions for the problems have been sought with the help of statistical methods, process analysis, mathematical modeling, etc. However, problems such as too long waiting times, too long Length of Stay (LoS) of patients, ineffective resource allocation and too low resource utilization remain the major concern of management. Musa (2015) recently model the Length of Stay of Psychiatric Patients in Adamawa State Specialist Hospital, Yola.

There has been a growing body of research that tackles operational problems of hospital management with Operations Research (OR) techniques. Green (2008) surveys the potential of OR in helping to reduce hospital delays, with an emphasis on queuing models. Jennings and de Véricourt (2007, 2008) and Green and Yankovic (2011) apply queuing models to determine the number of nurses needed in a medical ward. Green (2004) and de Bruin *et al*., (2009) rely on queuing models such as Erlang-C and loss systems, to recommend bed allocation strategies for hospital wards. Green *et al*., (2007) and Yom-Tov and Mandelbaum (2011) developed (time-varying) queuing networks to help determine the number of physicians and nurses required in an emergency unit.

There is also a growing acknowledgement of the significant role that data can play in patient flow research. For example, Kc and Terwiesch (2009) used econometric methods to investigate the influence of workload on service time and readmission probability, in Intensive Care Units (ICUs). This inspired Chan *et al*., (2011) to model an ICU as a state-dependent queuing network, in order to gain insight on how speedup and readmission effects influence the ICU. However, researchers in Canada used queuing theory on an organizational level to analyze the relationship between patient flow to Emergency Department (ED) and patient flow to the inpatient unit. They then used the queuing model to estimate the average waiting time for patients and the resources needed in unscheduled and inpatient care. The model was used to analyze the potential impacts on waiting time and resources of an alternative way of accessing unscheduled care and this helped managers in hospital to plan the resources needed to enhance patient flow (Lin *et al.*, 2013).

Several other researchers and research groups have conducted similar kinds of research. Kirkland *et al.* (1995) showed that the throughput time of patients in the emergency department can be reduced by over 38 minutes by allocating the resources in the most effective way. Evans *et al.* (1996), on their part, concentrated on the throughput time problem by examining work shifts. The best scenario decreased the throughput time by a little over five minutes. McGuire (1997) found the answer from resource allocation as well. By reorganizing shifts he managed to reduce the throughput time by 50 minutes.

In the studies described above, all the resources in the emergency department were under examination. However, in several studies in the literature the focus has been only on certain resources at a time. Kumar and Kapur (1989) for example focused only on nurses and their efficient allocation. The same kind of work was undertaken by Draeger (1992) who examined the utilization of nurses. The intention in both of these studies was to decrease the throughput time of patients in emergency departments.

Doctors were studied by Chin and Fleisher (1998). Their main objective was to examine patients' waiting times and doctors' idle time. They showed that by making the doctors more effective (i.e. increasing utilization) in the ED, it was possible to decrease both the patients' average throughput time as well as their long throughput times. Rossetti *et al.* (1999) focused in their study on doctor resources as well. Their results showed that by adding an extra doctor on the shift, from 10.00 am to 18.00 pm decreases the throughput time by 14.5 minutes per patient. In addition, the number of patients staying long in the ED is reduced.

All the above researches focused on finding solutions to resource allocation. The other way to approach the problem is through processes. From the processes point of view there are many studies in the literature as well.

A queuing model of a system is an abstract representation whose purpose is to those factors that relate to the system's ability to meet service demands whose occurrences and durations are random (Janos, 2010). Hillier *et al.* (2012) mentioned that, Queuing theory is the study of waiting, it uses queuing models to represent the various types of queuing systems (that involve queues of some kind) that arise in practice.

Wiler*et al.*, (2013), noted that, a queuing model used in a call center can be modified for use in healthcare. It was possible to use data about patient arrivals (admission), treatment time, and non-availability of beds to predict the proportion of patients who left without being seen. Also, queuing models can be analyzed with the help of mathematical models. A discrete-event simulation can also be used to analyze such systems and obtain performance metrics. Nafees (2007), asserts that, queuing models are used to represent the various types of queuing systems that arise in practice; the models enable the user to find an appropriate balance between the cost of service and the amount of waiting. It provides the analyst with a powerful tool for designing and evaluating the performance of queuing systems (Bank *et al.*, 2001). Hillier and Lieberman, (2002) clarified that, queuing model is commonly labeled as M/M/c/K, where first M represents Markovian (stochastic process) exponential distribution of inter-arrival times, second M represents Markovian exponential distribution of service times, c (a positive integer) represents the number of servers, and K is the specified number of customers in a queuing system. This general model contains only limited number of K customers in the system. However, if unlimited number of customers exist, which means $K = \infty$, then the model will be labeled as M/M/c.Kapodistria (2011) studied a single server Markovian queue with impatient customers and considers the situations where customers abandon the system simultaneously. He considers two abandonment scenarios. In the first one, all present customers become impatient and perform synchronized abandonments; while in the second scenario, the customer in service is excluded from the abandonment procedure. He extends this analysis to the M/M/c queue under the second abandonment scenario also; Kumar (2012), investigates a correlated queuing problem with catastrophic and restorative effects with impatient customers which have special applications in agile broadband communication networks. However, Kumar and Sharma (2012), apply M/M/1/N queuing model for modeling supply chain situations facing customer impatience.

Lane *et al.*, (2003) examined patients waiting times in the ED and noticed that there were two things which had a major effect on the selected target variables. These things were the accessibility of doctors and teaching. If the doctors were always available, without having to spend so much time on teaching younger doctors, the waiting time of patients would decrease. Centeno *et al.* (2001) focused only on the fast-track solution and showed that this solution would decrease the total average throughput time for patients by 25 **%.** Static and dynamic combination study was conducted by Martinez-Garcia and Mendez-Olague (2005). The results of their study showed that a combination of static and dynamic modeling can be used effectively in improving the operations of ED.

Gonzales *et al.* (1997) used a so-called mixed-technique using the concept of Total Quality Management (TQM) and showed that the quality of an emergency department can be improved.Ramis*et al.* (2001) studied the operation of a new ambulatory surgery center where patients would arrive and be discharged during the same day. The results show that the maximum number of surgeries (10) can be achieved by allocating beds as effectively as possible and handling the most difficult surgery first.

2. Materials and Method

Data for this work were collected for sixty days by observing patients in the ED at the Federal Medical Centre Yola, Adamawa State Nigeria. A total number of six hundred and ninety three (693) patients with diverse emergency cases were observed and processed with SPSS, MS-Excel, EasyFit, and TORA packages.

2.1 Data Requirement

The following data were collected for this research: The number of doctors and their shifting roaster at the ED, the number of nurses and their shifting roaster at the ED, the number of beds; stretchers, and conches in the ED, the mode of patient's arrival either walk-in or ambulatory, the patient's arrival time so as to deduce the inter-arrival rate, the type of Patient's emergency case whether accident; disaster; medical or gynecology, the Patient's waiting duration at each waiting point in the process and the Patient's activity duration of each event in the process, the Patient's gender, age group and education level.

2.2 Codes Adopted

The following codes were adopted in the data analysis:
1) Gender: Female = 0, Male = 1.
2) Marital Status: Single = 1, Married = 2, Divorce = 3, Widow = 4.
3) Age group: 0-15years = 1, 16-30years = 2, 31- 45years = 3, above 45years = 4.
4) Nature of illness: RTA = 1, Disaster = 2, Medical = 3, Gynecology = 4, Gunshot = 5, Snake bite = 6.

2.3 Modeling the admission and discharge rates

The M/M/1/N queuing model was considered for both admissions (arrivals) and discharge (service). Since the doctor on duty is the one to admit patients and to discharge patients, a single server is considered, and system capacity (bed space) is finite in the ED. Thus, the M/M/1/N queuing model is adopted;

$$P_n = \begin{cases} \dfrac{(1-\rho)\rho^n}{1-\rho^{N+1}}, \rho \neq 1 \\ \\ \dfrac{1}{N+1}, \rho = 1 \end{cases}, \quad n = 0, 1, \ldots, N \tag{1}$$

Where,
P_n- Steady-state probability of npatients in the ED.
N - System capacity (maximum number of beds, the system can take)
ρ - Utilization factor (traffic intensity)
n - Number of patients in the EDof F.M.C, Yola (in-queue plus in service).

2.3.1 Assumptions of the model

In every model abstraction, certain assumptions are used to simplify the modelling processes. Here we list the assumptions of the model employed as:

1) Input population is finite
2) Mean inter-arrival rate (admission rate) has a Poisson distribution
3) Service time (discharge rate) is exponentially distributed with mean $1/\mu$ [$\lambda<\mu$ or $\lambda>\mu$]
4) Patients admitted on the FCFS and Priority bases.
5) System capacity is finite (number of beds in ED = 18 beds and bed spaces are finite).
6) A patient is on admission before this analysis is conducted.

2.4 Poisson Regression

Poisson regression is similar to regular multiple regressions except that the dependent (*Y*) variable (LoS) is an observed count that is assumed to follow the Poisson distribution. Thus, the possible values of *Y* are the nonnegative integers 0, 1, 2, 3, and so on. It is assumed that large counts are rare. Hence, Poisson regression is similar to logistic regression, which also has a discrete response variable. However, the response is not limited to specific values as it is in logistic regression.

2.5 Negative Binomial

In a sequence of independent Bernoulli (*p*) trials, let the random variable *X* denote the trial at which the *rth* success occurs, where *r* is a fixed integer. Then

$$P(\boldsymbol{X} = \boldsymbol{x}|\boldsymbol{r}, \boldsymbol{p}) = \binom{x-1}{r-1}\boldsymbol{p}^{r}(\boldsymbol{1}-\boldsymbol{p})^{x-r}, x = r, r+1, \ldots \tag{2}$$

And we say that *X* has a negative binomial(*r*, *p*) distribution. In terms of our study, X = number of admission at which the r^{th} discharge occurs.

3. Results and Discussion

3.1 Analysis of Admission Rate for Emergency Patients

The admission rate of emergency patients with parameter λ is obtained from the data in Table 1.The mean admission rate λ and its variance is obtained as follows:

$$\text{Mean } (\lambda) = \frac{\sum_{i=1}^{n}(x_i p_i)}{\sum_{i=1}^{n}(p_i)} = 13.24 \tag{3}$$

$$\text{Variance} = \sum_{i=1}^{n}(x_i - \lambda)^2 p_i = 25.12 \tag{4}$$

Where, $x_i = \text{number of patients admitted on the ith day}, p_i = \text{the proportion of patient admitted on the ith day}, i = 1, 2, \ldots, 60.$

Based on the above computations it was observed that, the data is over dispersed with respect to a Poisson distribution, for which the mean is not equal to the variance. The goodness of fit obtained using the EasyFit analysis shows that the next appropriate distribution fit for the data is negative binomial with n= 16 and p= 0.59188. Thus we obtain mean admission rateλand its variance based on the negative binomial distribution model. From equation (2) in section 3.6.4 it follows that:

$$\text{Mean } (\lambda) = E(X) = n\frac{1-p}{p} = 11.0325 \tag{5}$$

$$\text{Variance} = Var(X) = n\frac{1-p}{p^2} = 18.6398 \tag{6}$$

3.2 Analysis of Discharge Rate

The discharge rate for emergency patients was obtained using the data in Table 2.The mean discharge rate μ_D for emergency patients and its variance is obtained as follows

$$\text{Mean } (\mu_D) = \frac{\sum_{i=1}^{n}(y_i p_i)}{\sum_{i=1}^{n}(p_i)} = 7.214 \tag{7}$$

$$\text{Variance} = \sum_{i=1}^{n}(y_i - \mu D)^2 p_i = 15.18 \tag{8}$$

Where, $y_i = \text{number of patients discharged on the ith day}$
$p_i = \text{the proportion of patient discharged on the ith day},$
$i = 1, 2, \ldots, 60.$

3.3 Analysis of Not Discharge Rate

The not discharge rate μ_{ND} for emergency patients was obtained using the data in Table 3, the mean of not discharge rate μ_{ND} for emergency patients and its variance is obtained as follows

$$\text{Mean } (\mu_{ND}) = \frac{\sum_{i=1}^{n}(z_i p_i)}{\sum_{i=1}^{n}(p_i)} = 8.44 \tag{9}$$

$$\text{Variance} = \sum_{i=1}^{n}(z_i - \mu ND)^2 p_i = 12.73 \tag{10}$$

Where, $z_i = \text{number of patients not discharged on the ith day}$
$p_i = \text{proportion of patient not discharged on ith day}$
$i = 1, 2, \ldots, 60.$

3.4 Computation for Expected Frequencies

Data analysis using EasyFitsoftware package for negative exponential values for emergency patients on discharge and not discharge rates gaveμ^{-1}_D = 0.21352 and μ^{-1}_{ND} = 0.14888 respectively (see Appendix IV and V). Thus, the Cumulative Density Function (CDF) is given by the relation;

$$F_x(x) = 1 - e^{-\lambda x_i} \tag{11}$$

The Cumulative Probability Density Function (CPDF) was computed using the cumulative integrals;

$$P(X=1) = \int_0^1 e^{-\lambda x_i}\, i = 0, 1 \dots 60 \quad (12)$$

$$P(X=2) = \int_1^2 e^{-\lambda x_i} - \int_0^1 e^{-\lambda x_i}\, i = 0, 1 \dots 60 \quad (13)$$

This will continue in this format until we obtain P (X = 60).

3.4.1 Goodness-of-fit test (for discharge patients)

H_o: exponential distribution is not an appropriate model for the discharge rate of emergency patients

H_1: exponential distribution is an appropriate model for the discharge rate of emergency patient Significance level, α = 0.05. Degree of freedom, (k-1-ρ) = 60-1-1 = 58

Test Statistic: $\chi^2 = \sum_{i=1}^{n} \frac{(Oi-Ei)^2}{Ei}$ (14)

Critical region: $\chi^2_{(k-1-\rho)\alpha} = \chi^2_{(60-1-1)0.05} = \chi^2_{58,0.05} = 79.08$ and $\chi^2 = 15{,}129$

Decision Rule: If $\chi^2 > \chi^2_{(k-1-\rho)\alpha}$ we reject the null hypothesis(H_o), otherwise accept.

Since $\chi^2 = 15{,}129 > \chi^2_{(k-1-\rho)} = 79.08$, we reject the null hypothesis(H_o) and conclude that the exponential distribution for modeling the discharge rate of emergency patients is appropriate.

3.4.2Goodness-of-fit test (Not Discharge patients)

H_o: exponential distribution is not an appropriate model for the not discharge rate of emergency patients

H_1: exponential distribution is an appropriate model for the not discharge rate of emergency patients. Significance level, α = 0.05 and Degree of freedom, (k-1-ρ) = 60-1-1 = 58

Test Statistic: $\chi 2 = \sum_{i=1}^{n} \frac{(Oi-Ei)2}{Ei}$ (14)

Critical region: $\chi^2_{(k-1-\rho)\alpha} = \chi^2_{(60-1-1)0.05} = \chi^2_{58,0.05} = 79.08$ and $\chi^2 = 20{,}876$

Decision Rule: If $\chi^2 > \chi^2_{(k-1-\rho)\alpha}$ we reject the null hypothesis(H_o), otherwise accept.

Since $\chi^2 = 20{,}876 > \chi^2_{(k-1-\rho)} = 79.08$, we reject the null hypothesis(H_o) and conclude that the exponential distribution is appropriate for modeling the not discharged rate of emergency patients

4. Computation of Queuing Model Parameters

The M/M/1/N model using queuing applications, for the discharge rate and not discharge rate patients is computed as follows;

$$P_o = \sum_{n=0}^{\infty} \left(\frac{(1-\rho)}{1-\rho^{N+1}}\right), \text{where } \rho = \frac{\lambda}{\mu} \left(\frac{\lambda}{\mu} > 1 \text{ is allowed}\right) \quad (15)$$

Where,

N -System capacity (number of beds at the ED of FMC Yola)

ρ -Traffic intensity for both discharge and not discharge patients ($\rho = \lambda/\mu_D$ and λ/μ_{ND}) respectively.

4.1 Discharge Patients Scenario 1

The admission and discharge rates as earlier obtained (λ = 11.0325 and μ_D = 7.21) were used to analyze the queuing parameters using TORA software package and the result are as follows:

a. Average number of ED patients on dmission including those about to be discharged, L_s;
   L_s= 17.34633 ≈ 17 patients per day.
b. Average number of ED patients onadmissions, L_q; L_q= 16.34633≈ 16 patients per day
c. Average time ED patients spend in the system on admission including discharge time, W_s; W_s =2.40587 Days ≈ 2 Days
d. Average time patients spends on admission, W_q; W_q =2.26717 ≈ 2 Days
e. The utilization factor (traffic intensity) is given as $\rho = \lambda/\mu_D$;
   $\rho_D = \frac{11.0325}{7.21} = 1.5302$ or 153%

$\therefore \rho_D \approx 2$ in-patients per day

In this case, the traffic intensity of discharge patients at the ED of FMC Yola is approximated to be 2 discharged in-patients per day, Since ρ> 1, it implies that the queue will continue to grow permanently.

The above results revealed that, the expected number of discharged patients in the system is approximately 7 patients per day, while the expected length of stay on admission is approximately 2 days. The implication of these results is that, the ED is fully occupied daily. With the average daily admission rate of 11 patients and the average daily discharge rate of 7 patients, this shows that, the ward is always full of patients. The traffic intensity of discharge patients in the system is approximately 2 patients per day, implying that some patients are being turn away every day, due to the fact that, there is a limited number of beds available for in-patients (i.e. blocking).

Table 4: Input data for the Discharge Patients Scenario (M/M/1/18 Model)

Scenario	Lambda (λ)	Mu (μ_D)	No of servers	System limit
Discharge	11.03	7.21	1	18

Since $\lambda > \mu_D$, the geometric series P_o in section 4.5 will not converge, and the steady-state probabilities, P_n will not exist. These results make intuitive sense because the admission rate is larger than the discharge rate of ED patients, which makes queue length continue to increase and no steady state can be reached.

4.2 Not Discharge Patients Scenario 2

Input data is shown in Table 5. The ED admission and the not discharge rates as earlier obtained (λ = 11.03 and μ_{ND}= 8.44) were used to analyze the queuing parameters using TORA software packageand the results are as follows:

a) Average number of ED patients on admission including those about to be discharged, L_s; L_s= 17.23481≈ 17 patients per day
b) Average number of patients on admissions, L_q; L_q= 16.23481≈ 16 patients per day
c) Average time ED patients spend in the system on admission including discharge time, W_s); W_s=2.40587 Days ≈ 2 Days
d) Average time ED patients spends on admission, W_q; W_q=2.26717 Days ≈ 2 Days

e) Utilization factor (Traffic intensity), The utilization factor is given as $\rho = \lambda/\mu_{ND}$;

$\rho_{ND} = \frac{11.03}{8.44} = 1.30687 \approx 130.69\%$

$\therefore$ $\rho_{ND} \approx 1$ in-patients per day.

f) This revealed that, traffic intensity of Not Discharge patients at FMC Yola ED is approximately 1patients per day. The value of ρ_{ND} is slightly greater than one which indicate that the queue will continue to grow permanently.

g) Average time ED patients spend in the system on admission including discharge time, W_s);

W_s= 2.04204Days≈ 2 Days

h) Average time ED patients spends on admission, W_q; W_q = 1.92356 Days ≈ 2 Days

Table 5: Input Data for the Not Discharge Patients Scenario (M/M/1/18 Model)

Scenario	Lambda (λ)	Mu (μ_{ND})	No of servers	System limit
Not discharge	11.03	8.44	1	18

a) Average time ED patients spend in the system on admission including discharge time, W_s);

W_s =2.04204Days ≈ 2 Days

b) Average time ED patients spends on admission, W_q; W_q= 1.92356 Days ≈ 2 Days

c) Utilization factor (Traffic intensity), The utilization factor is given as $\rho = \lambda/\mu_{ND}$;$\rho_{ND}=\frac{11.0325}{8.44}= 1.30717 \approx$ 130.72% ≈1 in-patients per day.

This revealed that, traffic intensity of Not Discharge patients at FMC Yola ED is approximately 2 patients per day. The value of $\rho_{ND}$is slightly greater than one which shows that the queue will continue to grow permanently.

The above results show that, the expected number of the not discharge patients in the system is approximately 8 patients per day, while the expected length of stay spent on admission is approximately 1 day. The implication of these results is that, the ED Unit is fully occupied daily. The average daily admission rate of 11 patients and the average daily not discharge rate of 8 patients indicates that, the ED unit is always full of patients. The traffic intensity (utilization factor) of not discharge patients in the system is approximately 1 patient per day, implying that some ED patients are being turned away every day, due to the fact that, there is a limited number of beds available for in-patients (i.e. blocking).Since $\lambda>\mu_{ND}$, the geometric series P_o in section 4.5 will not converge, and the steady-state probabilities, p_n will not exist. These results make intuitive sense because the daily admission rate of ED patients is larger than their not discharge rate, which makes queue length continue to grow permanently and no steady state can be reached.

Table 6 shows the comparative analysis of queuing characteristics for both scenarios, discharge and not discharge patients emergency cases using TORA software package.

4.3 Modelling the Length of Stay (LoS)

According to Chan (2003), Log-linear models are used to determine whether there are any significant relationships in multi-way contingency tables that have three or more categorical variables they can also be used to determine if the distribution of the counts among the cells of a table can be explained by a simpler, underlying structure (restricted model).

Table 6: Comparative Analysis for Scenario 1 & 2

Scenario	C	Lambda (λ)	Mu (μ)	L'da effective	P_o	L_s	L_q	W_s	W_q
Discharge	1	11.0325	7.21	7.21	0	17.34633	16.34633	2.40587	2.26717
Not discharge	1	11.0325	8.44	8.44	0	17.23481	16.23481	2.04204	1.92356

The saturated model contains all the variables being analyzed and all possible interactions between the variables.

4.4 Poisson regression

Poisson regression is used here to model the LoS and provide Relative Risk (RR) on having a longer LoS between genders and nature of illness. The LoS is considered as the dependent variable, while Nature of illness, Agegroup, Maritalstatus and Gender of Patients are the independent variables. We first consider the main effects of the restricted model given by the generating class;

Design; Constant +Gender +NatureIllness

Table 7 shows the goodness-of-fit for the restricted model (Gender +NatureIllness) and compares whether or not the model is an adequate fit to the data. Since the p-value is less than the assumed level of significance (0.05), the result is significant, which means that this restricted model is not adequate to fit the data. Hence the interaction terms are required. Table 8 shows the interaction terms and the corresponding parameter estimates given by the generating class;

Design: Constant + Gender + NatureIllness + interaction terms.

Table 8 reveals that, the female patients (Gender = 0) are at a higher risk of exp(0.847) = 2.333 of LoS compared to the male patients(Gender = 1). The results further show that, medical emergency patients (NatureIllness = 3) are also at risk of LoS compared to others. We can then add the variable Agegroup to the main effect model (Appendix IX) with the generating class;

Design: Constant + Gender + Agegroup + NatureIllness

As shown in Table 9 which also indicate inadequacy of the model to fit the data, but their corresponding interaction in Appendix X shows that the female patients (Gender = 0) are at higher risk of exp. (3.196) = 24.43 of LoS compared to their male counterpart, also the RTA and Gynecology Patients (NatureIllness 1 and 3) are at higher risk of LoS than others. We further add the last variable Maritalstatus to the modelwith generating class of;

Design: Constant + Gender + Agegroup + Maritalstatus + NatureIllness

This is shown in Table 10 which reveals similar result to Table 7 and 9 respectively. Since $p< 0.05$. we can then look at their interaction and corresponding parameter estimates revealed that the female patients (Gender =0) are at a higher risk of exp. (0.864) = 2.737 of LoS compared to the male patients (Gender = 1).

Table 7: Goodness-of-fit Tests for +Gender + NatureIllness

Test Statistic	Value	Df	p-value
Likelihood ratio	1.287E3	89	.000
Pearson chi-square	1.323E3	89	.000

Table 8: Parameter Estimates for Gender + NatureIllness +Interaction terms

Parameter	Estimate	Std. error	Z	p-value	95% Confidence interval	
					Lower bound	Upper bound
Constant	1.504	.471	3.191	.001	.580	2.428
[Gender = 0]	.847	.563	1.504	.133	-.257	1.952
[Gender = 1]	0^a	.	.	.	.	.
[NatureIllness = 1]	3.517	.478	7.351	.000	2.579	4.454
[NatureIllness = 2]	3.045	.482	6.310	.000	2.099	3.990
[NatureIllness = 3]	3.987	.476	8.380	.000	3.054	4.919
[NatureIllness = 4]	3.145	.481	6.533	.000	2.202	4.089
[NatureIllness = 5]	3.001	.483	6.214	.000	2.055	3.948
[NatureIllness = 6]	0^a	.	.	.	.	.
[Gender = 0] * [NatureIllness = 1]	-119	.578	-2.110	.035	-2.351	-.087
[Gender = 0] * [NatureIllness = 2]	-.796	.581	-1.369	.171	-1.935	.344
[Gender = 0] * [NatureIllness = 3]	-1.003	.571	-1.756	.079	-2.123	.117
[Gender = 0] * [NatureIllness = 4]	-1.108	.583	-1.902	.057	-2.250	.034
[Gender = 0] * [NatureIllness = 5]	-1.336	.589	-2.270	.023	-2.490	-.183
[Gender = 0] * [NatureIllness = 6]	0^a	.	.	.	.	.
[Gender = 1] * [NatureIllness = 1]	0^a	.	.	.	.	.
[Gender = 1] * [NatureIllness = 2]	0^a	.	.	.	.	.
[Gender = 1] * [NatureIllness = 3]	0^a	.	.	.	.	.
[Gender = 1] * [NatureIllness = 4]	0^a	.	.	.	.	.
[Gender = 1] * [NatureIllness = 5]	0^a	.	.	.	.	.
[Gender = 1] * [NatureIllness = 6]	0^a	.	.	.	.	.

a. is a redundant parameter.

Table 9: Goodness-of-fit Tests for Gender + Agegroup + NatureIllness

Test statistic	Value	Df	p-value
Likelihood ratio	344.013	38	.000
Pearson chi-square	354.133	38	.000

Table 10: Parameter Estimates for Gender + Agegroup + NatureIllness

Parameter	Estimate	Std. Error	Z	p-value	95% Confidence Interval	
					Lower Bound	Upper Bound
Constant	0.01	0.273	0.038	0.97	-0.524	0.545
[Gender = 0]	-0.21	0.057	-3.685	0	-0.322	-0.099
[Gender = 1]	0^a	.	.	.	.	.
[Agegroup = 1]	-1.281	0.119	-10.75	0	-1.514	-1.047
[Agegroup = 2]	0.43	0.071	6.022	0	0.29	0.57
[Agegroup = 3]	0.012	0.078	0.157	0.876	-0.141	0.166
[Agegroup = 4]	0^a	.	.	.	.	.
[NatureIllness=1]	2.902	0.274	10.573	0	2.364	3.44
[NatureIllness=2]	2.624	0.277	9.479	0	2.081	3.166
[NatureIllness=3]	3.468	0.271	12.778	0	2.936	4
[NatureIllness=4]	2.576	0.277	9.291	0	2.032	3.119
[NatureIllness=5]	2.338	0.28	8.353	0	1.789	2.886
[NatureIllness=6]	0^a	.	.	.	.	.

a: is redundant

Table 11: Goodness-of-fit Tests for Gender + Agegroup + Martalstaus + NatureIllness

Test statistic	Value	Df	p-value
Likelihood ratio	931.321	85	.000
Pearson chi-square	958.692	85	.000

The results further show that, RTA and medical patients (Natureillness 1 and 3) are also at risk of LoS compared to others.

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