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Poisson Log-linear Analysis of Postpartum Length of Stay

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Abstract:
The impact of postpartum length of stay (PLOS) has been widely reported. Different mothers often have different lengths of stay after child delivery. In order to determine the optimum PLOS, it becomes necessary to deliberate on the factors associated with it. An investigation was conducted on 150 women who delivered at War Memorial Hospital in Navrongo, Ghana. Analysis of the data using generalized Poisson log-linear model identified birth by cesarean section (P-value < 0.0001) and good newborns' condition (P-value < 0.0001) as significant factors that explain the variation in PLOS at the hospital.

Keywords: *Postpartum, Generalized, Poisson, Log-linear, Factors*

1. Introduction

Postpartum length of stay (PLOS) refers to the number of days that a mother spends in hospital after birth.

The length of postpartum hospital stay is of socio-economic as well as personal significance, and thus, has implications well beyond the simple physiological event, which marks it. The burden of extra postnatal care expenses and the trauma of parents staying longer at the hospital after delivery can be extremely stressful.

Despite its socio-medical importance, the optimal number of days to stay in the hospital after childbirth is contentious, and while the debate continues among the experts, new mothers and their babies continue to suffer early discharge or arbitrary detention at many health facilities.

Published literature on the subject has focused largely on the impact of early obstetrical discharge on maternal-neonatal health outcomes, and not the factors associated with, or predictive of who will be discharged early. Little effort has actually been made to provide evidence-based information on the factors associated with length of hospital stay after delivery, which may influence decisions about postpartum discharge timing.

The significance of this study is supported by the work of Madlon-kay et al (2005) who argue that childbirth constitutes the most frequent reason for hospital admission among women. The major goals of hospitalization are to identify maternal or newborn complications, provide assistance to the mother and newborn, and ensure that the mother is sufficiently recovered after delivery to look after herself and her newborn (Johnson et al, 2000; Madden et al, 2003). According to Johnson, the neonate who is discharged at less than 48 hours is at greater risk than the mother is, and is subjected to diseases like jaundice or dehydration and in some cases death. Conversely, studies to evaluate the premise that longer postpartum stays are beneficial in terms of infant morbidity and mortality, unfortunately, have not produced consistent findings.

The length of stay in hospital after childbirth has indeed decreased steadily over the last five decades (Brumfield et al, 1996). Between 1970 and 1992, the average postpartum length of stay for mothers who delivered vaginally declined by 46 percent, from 3.9 to 2.1 days. Over the same period, the length of stay for those delivering by cesarean section fell from 7.8 to 4.0 days, a drop of 49 percent (Thilo et al. 1998).

Because of these trends, health professionals and policy makers expressed concern that shorter hospital stays might jeopardize the health of both mothers and newborn. A number of tragic stories about mothers and newborns discharged early who later developed life threatening but preventable conditions fueled the desire of legislatures to address this issue (Madlon-kay et al, 2005). Therefore taking a critical look at the determinants of PLOS can greatly help in solving this problem.

Indeed, hospital stays became even shorter when insurers began limiting their postpartum coverage in an attempt to minimize costs. Concerns raised about the safety of early discharge led to recommendations from medical societies and ultimately to legislation (Madden et al, 2004) that require health insurance plans to provide coverage for minimum hospital stays of 48 hours for new mothers and their babies after normal vaginal deliveries and of 96 hours after cesarean births. A decision to discharge a patient before these time limits could be made by a physician only after consulting with the mother.

The system of health insurance in Ghana changed when the government of Ghana in 2003 introduced the National Health Insurance scheme (NHIS) (Act 650), which later became free for all pregnant women. An interaction with some mothers and hospital staff at the War Memorial Hospital in Navrongo indicated that almost every expectant mother that came to deliver at the hospital was covered by the NHIS. Is the NHIS playing any implicit role in determining PLOS in Ghana? This and many more are the answers the researcher is seeking to establish

PLOS depends on several other factors including birth-weight, gestational age, feeding problems, whether the delivery was by cesarean section or normal vaginal delivery, among others.

To be in a good position to draw valid conclusions on the optimal postpartum length of stay, we must employ a proven statistical model that succinctly describes PLOS and its confluence of causes.

To achieve this, the Poisson log-linear model, under the broader heading of generalized linear models (GLMs), was employed for data analysis using *SPSS*.

2. Generalized Linear Models (GLMs) for Modeling Counts

GLMs extend ordinary regression models to encompass non-normal response distributions and functions of the mean. The response variableY , of a GLM with independent observations $(y_1, \dots, y_N)$ from a distribution in the natural exponential family (Agresti, 2007) has probability density function or mass function of the form

$$f(y_i, \theta_i) = a(\theta_i) b(y_i) \exp[y_i Q(\theta_i)] , \quad (1)$$

The best-known GLMs for count data assume a Poisson distribution for the outcome response, (Cameron et al, 1998; Agresti, 2007). The Poisson distribution is used for counts of events that occur randomly over time or space when outcomes in disjoint periods or regions are independent. Its probability mass function (Poisson, 1837) is

$$f(y_i;\, \mu_i) = \frac{e^{-\mu_i} \mu_i^{y_i}}{y_i!}, i = 0,1,2, \quad (2)$$

The model has seen applications in many fields, including studies in road accidents, Medicine, Agriculture, and Demography (Cameron et al, 1998).

The Poisson probabilities depend on a single parameter, the mean μ. It satisfies the relationship

$E(Y) = var(Y) = \mu,$,allowing the variance to depend on the mean, but in practice, the observed variance of the data may differ, resulting in over-dispersion or under-dispersion. Under such circumstances, and in order to solve the problem of over-dispersion and under-dispersion, the generalized Poisson log-linear is the appropriate model to use (Breslow, 1996; Fahrmeir, 2001).

The Poisson distribution shown in equation (2), is a GLM with positive mean μ, and natural exponential form

$$f(y;\, \mu) = \exp(-\mu) \left(\frac{1}{y!}\right) \exp(y \log \mu), y = 0,1,2, \quad (3)$$

with $\theta = \mu,\ a(\mu) = \exp(-\mu), b(y) = \frac{1}{y!}, and\ Q(\mu) = \log \mu.$

When explanatory variables X_{ij} are included, then a vector $\eta_i = (\eta_1, \dots, \eta_N)$ is related to the explanatory variables via $\text{via}\, \eta_i = \sum_j \beta_j x_{ij}, i = 1, \dots, N.$ (4)

GLMs then specify a functional relationship between μ_i and via η_i $\text{via}\, \eta_i = g(\mu_i),$, where is a monotonic differentiable function, say, the logit (Nelder et al, 1972). This means that $g(\mu_i) = Q(\theta_i),$, (5) and $(\theta_i) = \sum_j \beta_i x_{ij}.$. (6)

Implying that $g(\mu_i) = \sum_j \beta_i x_{ij}, i = 1, \dots, N.$ (7)

Since the natural parameter is $\log \mu,$ then the canonical link function is the log link.

Implying that $\eta = \log \mu$ (8)

and $\log \mu_i = \sum_j \beta_j x_{ij}, i = 1, \dots, N$ (9)

where the link function, the logit, is monotonic and differentiable (Nelder et al, 1972).

From (9) $\mu = \exp(\alpha + \beta_j x_{ij}) = e^{\alpha}(e^{\beta_j})^{x_{ij}}$ (10)

This implies that a 1-unit increase in has a multiplicative impact of e^{β} on μ. .

The Poisson log-linear model commonly uses maximum likelihood (Ml) methods for parameter estimation. The ML process follows from equation (2). That is,

$$L(\beta) = \prod_i \frac{e^{-\mu_i} \mu_i^{y_i}}{y_i!} \quad (11)$$

The log-likelihood $\ell(\beta) = \sum_i log f(y_i; u_i) = \sum_i (y_i log\mu_i - \mu_i - log y!)$ (12)

We estimate the model parameters by differentiating (12) with respect to and equating the results to zero: $\partial\, \ell(\beta)/\partial\beta_j = \sum_i \partial\, \ell(\beta)/\partial\beta_j = 0$, for all j. for all (13)

Here, we use the chain rule: $\frac{\partial \ell(\beta)}{\partial \beta_j} = \frac{\partial \beta}{\partial \theta_i} \frac{\partial \theta_i}{\partial \mu_i} \frac{\partial \mu_i}{\partial \eta_i} \frac{\partial \eta_i}{\partial \beta_j}$. (14)

From (5), (6) and (7) $\theta_i = log\mu_i$, giving us $\mu_i = e^{\theta_i}$. (15)

Equation (12) now becomes $\ell(\beta) = y_i\theta_i - e^{\theta_i} - log y_i!$ (16)

Hence, $\frac{\partial \ell(\beta)}{\partial \theta_i} = y_i - \mu_i$ (17)

From (15), $\frac{\partial \mu_i}{\partial \theta_i} = e^{\theta_i} = \mu_i$, implying that $\frac{\partial \theta_i}{\partial \mu_i} = \frac{1}{\mu_i}$ (18)

Also, for the log link, $\eta_i = log\, \mu_i$ (8), we have $\mu_i = e^{\eta_i}$, and $\partial \mu_i / \partial \eta_i = e^{\eta_i} = \mu_i$. (19)

Furthermore, since $\eta_i = \sum_j \beta_i x_{ij}$, it means $\frac{\partial \eta_i}{\partial \beta_j} = x_{ij}$. (20)

Substituting (17), (18), (19), and (20) into (14) gives

$\frac{\partial \ell(\beta)}{\partial \beta_j} = (y_i - \mu_i) \times \frac{1}{\mu_i} \times \mu_{i\times} x_{ij}$. Hence, the maximum likelihood equations simplify to

$\sum_i (y_i - \mu_i) x_{ij} = 0$ (21)

The deviance $D(y; \hat{\mu}) = -2[L(\hat{\mu}; y) - L(y; y)]$, where $L(\hat{\mu}_i; y)$ and $L(y; y)$ 'denote maximized log likelihood for the model, and maximized log likelihood for the saturated model respectively describes lack of fit. It is the likelihood-ratio statistic for testing the null hypothesis that the model holds against the alternative that a more general model holds.

For a Poisson model, the likelihood ratio statistic comparing the two models is simply the difference between the deviances. That is $D(y; \hat{\mu}_0) - D(y; \hat{\mu}_1)$.This statistic is large when M_0 fits poorly compared to M_1.

3. Description of the Data

Data included all births over a period of three months (January to March 2014) at the War Memorial Hospital, Navrongo.

After obtaining the consent of new mothers to partake in the study, a structured questionnaire was used to elicit data pertaining to mother's socio-demographic characteristics, and newborn's information.

In order to meet the data requirement for this study, all singleton births to mothers who had medical history recorded at the medical facility during the course of their pregnancy were sampled.

Variables	**Meaning**
Age (A)	The age of mother
Gestational age (G)	Duration of pregnancy in weeks
Parity (P)	Number of previous children
Birth type (BT)	cesarean section or normal vaginal delivery
Postpartum hemorrhage (PH)	Whether mother bled during labor
Maternal condition after birth (MC)	Whether mother's condition is good, fair or bad
Newborn condition (NC)	Whether newborn's condition is good, fair or bad
Feeding problem (FP)	Whether newborn is able to feed well or not
Newborn sex (NS)	Sex of newborn baby
Birth weight (BW)	Weight of newborn soon after delivery

Postpartum length of stay (PLOS)	Length of stay after delivery until discharge in hours

Table 1: Study Variables and Data Description

4. Results

The average PLOS was 46.59 with a minimum of 10 hours and a maximum 216. The variability is quite large, that is a standard deviation of 37.99. The median lies more towards the lower quartile (Figure 1).

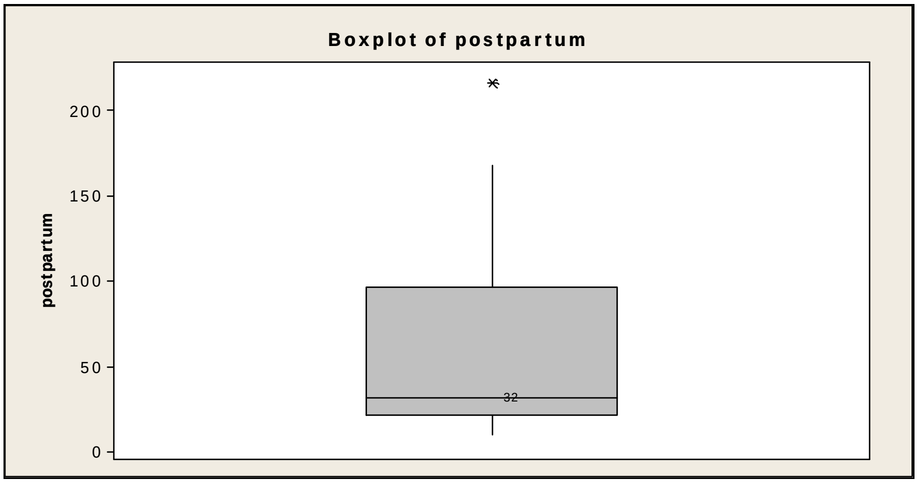

Figure 1 Box plot of PLOS

The distribution shows obvious asymmetry; being positively skewed (Figure 2). The variance (1443.88) is way more than the mean (46.59), clearly showing prove of over-dispersion. Hence, the appropriate model for this analysis is the generalized Poisson log-linear regression model.

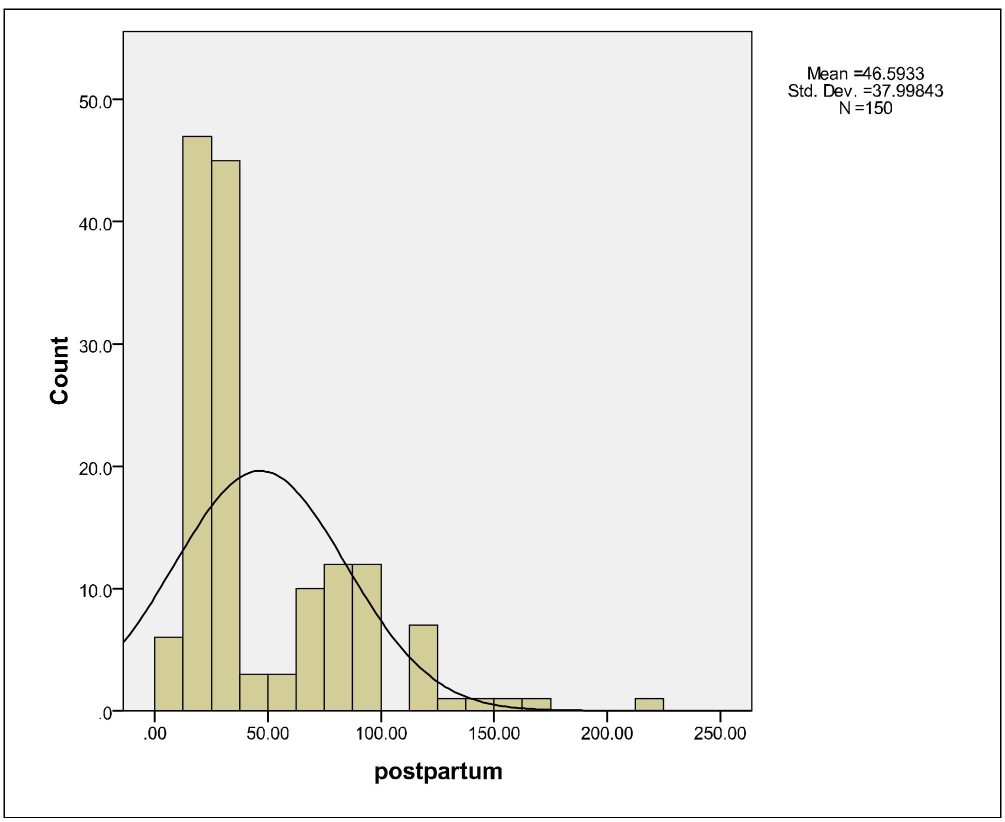

Figure 2: Distribution of PLOS for Kasina Nankana District

Table 2 shows the results of fitting a variety of Poisson log-linear models to the data.

Model	Deviance	d.f
Null	3909.36	149
A	3900.95	148
BT	2561.06	147
PH	3742.73	148
G	3892.06	148
MC	3634.24	148
NC	3148.84	147
FP	3848.22	148
BW	3878.60	148
P	3785.17	148
BT + NC	1742.69	145
BT + A	2530.09	146
BT + PH	2526.30	146
BT + MC	2494.94	145
BT + FP	2542.04	146
BT + NC + A	1740.57	144
BT + NC + A + MC.	1737.80	143
{ BT }{ NC }	1742.68	145
{ NC }{ A}	3147.31	146
All	1589.77	134

Table 2: Deviances for Models on PLOS at the War Memorial Hospital

The null model has a deviance of 3909.36 on 149 degrees of freedom. Each variable was then introduced one at a time, and their respective deviances noted (Table 2). The variable that reduced the value of deviance the most was 'Birth Type' (cesarean section or normal vaginal delivery). The substantial reduction of 1348.3 at the expense of only two degrees of freedom reflects the fact that the postpartum length of hospital stay largely depends on whether a woman delivered normally or otherwise. Clearly, it would not make sense to consider any subsequent model that does not include this variable as a necessary control. So, it was included in the model together with each of the remaining variables separately resulting in several models (Table 2).

The full model, containing all the variables (Table 2), has a deviance of 1589.77 on 134 degrees of freedom, hence, provides the best description of the data. The associated p-value < 0.0001 under the assumption of a generalized Poisson log-linear distribution passes the goodness-of-fit test (Table 3).

Likelihood Ratio Chi-Square	df	P-value
157.751	15	.000

Table 3 Omnibus Test to Compare the Fitted Model against the Intercept-only Model

Armed with this outcome, we included all the variables in our predictive generalized Poisson log-linear model. Model parsimony was not achieved though.

Table 4 presents parameter estimates and standard errors for the Poisson log-linear model showing significant association of PLOS with some maternal and newborn variables.

Parameter	B	Std. Error	P-value
Newborn's Condition			
➢ good	-0.108	0.7461	0.000
➢ fair	-0.831	0.647	0.021
➢ bad	0	.	.
Birth Type			
➢ cesarean section	2.061	0.0456	0.000

➢ normal delivery	0	.	.
Postpartum Hemorrhage ➢ yes	 0.942	 1.0306	 0.025
➢ no	0	.	.
Mother's Condition after birth ➢ good ➢ fair	 -0.023 -0.322	 0.0403 0.0378	 0.564 0.000
➢ bad	0	.	.
Feeding Problems ➢ no	 -0.137	 0.0415	 .815
➢ yes	0	.	.
Newborn's Sex ➢ male	 3.352	 0.0271	 0.3174
➢ female	0	.	.
Maternal Age Parity	-0.607 -1.112	0.445 1.0198	0.1749 0.6538
Gestational age	-0.159	0.7175	0.0252
Birth-weight	1.250	0.0247	0.0001
Intercept	3.625	0.2827	0.000

Table 4 SPSS Output: Parameter Estimates of the Model

5. Discussion

Findings of this study indicate that cesarean type of birth is the most powerful predictor of postpartum length of stay in the hospital. That is, birth by cesarean section more than doubled the length of stay compared to normal delivery. This might be due to the fact that mothers who delivered by the caesarean section generally had many complications. Bragg et al (1997) came to the same conclusion. In his findings, he stated that mothers who had cesarean deliveries or had complications during pregnancy or labour spent at least an extra day in the hospital.

Bragg et al (1997) reported in their study that, among the significant variables related to the postpartum length of stay is the mother's condition after birth. In this study, mother's "good" and "fair" conditions were significant, but the corresponding beta coefficients were negative, indicating an inverse relationship with PLOS. This means that a mother's good or fair condition would result in a shorter stay whiles a mother's bad condition (the sacrificed variable) would result in a longer PLOS.

Newborn's sex was however, not statistically significant (P-value = 0.3174), but showed increased risk of longer stay after delivery. For instance, we observe that being born a male increased the risk of longer stay by about 3.352 times compared to female babies. Parity was also not significant (P-value = 0.6538). However, we observe that a 1-unit increase in previous number of children led to a -1.112 decrease in PLOS.

Finally, we see that low birth-weight is associated with longer PLOS. For any type of birth, and irrespective of the newborns condition, a 1-unit increase in birth-weight would increase PLOS 1.250 times compared to those who delivered normal weight babies. According to Madden et al (2003), length of stay for preterm babies and babies with low birth weight are associated with postpartum length of stay possibly because these variables form part of the newborns' condition after birth.

6. Conclusion and Recommendations

The study brought to light that newborn's condition, type of birth, mother's condition and the weight of the baby after birth were the strongest predictors of postpartum length of stay since their p-values were each less than 0.0001.

Given the findings of this study, decisions about postpartum discharge timing should be influenced by maternal and neonate's welfare conditions. This will ensure that health personnel identify maternal or newborn complications and provide assistance to ensure that both mother and baby are sufficiently recovered after delivery before they are discharged. Future studies should be conducted with large sample size to be able to obtain findings that will be more reflective of the situation.

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