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Logistic Regression Analysis on Child Mortality

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ABSTRACT

This paper is mainly focused on the application of logistic regression analysis on child mortality. A cross sectional study design is adopted with 836 sample observations and 31 prognostic variables are considered as determinants of child mortality. Out of those prognostic variables, 8 variables namely TTF (type of toilet facility), NHM (number of family members), TCB (total children ever born), CMT (use contraceptive), ING (ideal number of girls), DBF (duration of breastfeeding), DPT and PAR (parity) are found significant. And their amounts of impact on child mortality are explicitly expressed.

1. Introduction

The first five years of life are the most crucial to the physical and intellectual development of children and can determine their potential to learn and thrive for a life time. That is why it is specifically stated as one of the goals of the millennium development goals (MDGs) to reduce child mortality by two-thirds by 2015. Although there has been a substantial reduction in infant and child mortality rates in most developing countries in the recent past, it still remains a major public health issue in South Asian countries particularly in India.

Mortality and its converse indicator, longevity or life expectancy are among the most important measures of well-being and development in developing countries. Since child mortality has an overwhelming influence on life expectancy, it is important to analyze the determinants of child mortality in India and particularly in the state of Manipur. Moreover, child mortality indicates the health status of not only child but also the health status of mothers as well as society as a whole. The child mortality has received a new momentum of the study since there is a

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strong associationship between mortality and fertility as high mortality corresponds high fertility and vice-versa.

Thus, the study of especially on child has as immense contribution towards the regulation of population growth and enhancing the health status of the society.

The general medical definition distinguishes mortality of a child with respect to the child age: death within the first week of life is included with prenatal mortality (which also includes late foetal mortality) and death within the first month is referred to as neonatal mortality, and death within one year is referred to as infant mortality. The death under five is referred to as child mortality [Harper et al. (2011)]. The peri and neonatal mortality is heavily influenced by prematurity, fatal genetic conditions of the foetus, and problems associated with delivery. The mortality after first month is mostly related to socio-economic and health conditions of the household. It is possible to analysis the determinants of child mortality at various levels of causality [Mosley and Chen (1984)]. The biomedical and epidemiological literature typically focuses on the immediate determinants of child mortality, in particular the impact of various diseases and weakened resistance. In contrast, socio-economic, environment & sanitation, medical and health care, demographic, exposure to mass media, etc., are underlying determinants of child mortality that make children more vulnerable to the attack of various diseases. Moreover, the child mortality rates vary from countries to countries and even within the country also it is varied in region to region and state to state. In developed countries, the main factor influencing on child mortality is demographic factors whereas socio-economic, health care, etc., are main factors influencing on child mortality in developing countries. Thus, the study of child mortality is different from country to country and region to region.

2. Data

A cross sectional study with study period from 1st May, 2008 to 30th April, 2009 in four districts of Manipur is taken to determine the factors influencing on child mortality by using logistic regression analysis. In this study, every household in four districts of Manipur is considered as population unit and a random sample of 836 households have been selected by two stage sampling under proportional allocation. In the first stage, 23 villages and 7 towns altogether 30 inhabitants have been selected. In the second stage, 836 households of which 654 households from rural and 182 households from urban have been selected.

3. Logistic regression analysis on child mortality

Logistic regression analysis (LRA) extends the techniques of multiple regression analysis to research situations in which the outcome variable is categorical. In practice, situations involving categorical outcomes are quite common. In the setting of evaluating an educational program, for example, predictions may be made for the dichotomous outcome of success/failure or improved/not-improved. Similarly, in a medical setting, an outcome might be presence/absence of disease. In such situation involving such a binary response (dichotomous) variable, multiple regression analysis model is seldom used.

The selection of variables in the model is done with a careful analysis of each variable and 31 variables are selected for fitting the logistic model to explain the effect of them on child mortality. Out of these 31 prognostic variables, 6 variables are quantitative in nature viz., number of family members, present age of mother, total children ever born, age of mother at first birth, parity, age at delivery, and remaining 32 variables are qualitative in nature. These categorical variables are difficult to fit the model and thus dummy variables are used to represent categorical variables such as sex of child (1 if male, 0 otherwise), multiple birth (1 if yes, 0 otherwise), antenatal care (1 if yes, 0 otherwise) etc. Thus the variables included in the logistic regression model are as follows:

(I) Response variable

Child is alive(CAL):	1 if yes 0, otherwise

(II) Prognostic variables

1. Religion (Relm):	1 if Muslim, 0 otherwise
2. Educational level of mother (ELM):	1 if literate, 0 otherwise (illiterate)
3. Number of family members (NHM):	number
4. Antenatal visits (ANV):	number of visits
5. Source of drinking water (SDW):	1 if hygiene, 0 otherwise (non-hygiene)
6. Type of cooking fuel (TCF):	1 if smoke produce, 0 otherwise
7. Windows in the house (HHW):	1 if yes, 0 otherwise
8. Type of toilet facility (TTF):	1 if sanitation, 0 otherwise
9. Availability of radio (AVR):	1 if yes, 0 otherwise

10. Reading newspaper (FRN):	1 if not reading at all, 0 otherwise
11. Present age of mother (PAM):	year
12. Total children ever born (TCB):	number
13. Age of mother at first birth (AM1B):	year
14. History of abortion/ miscarriage etc. (ABM):	1 if yes, 0 otherwise
15. Multiple birth (MTB):	1 if yes, 0 otherwise
16. Parity (PAR):	number
17. Age at delivery (AAD):	year
18. Menstruation cycle (MC)	1 if regular, 0 otherwise
19. Duration of breastfeeding (DBF):	1 if less than 6 months, 0 otherwise
20. Plain water (GPW):	1 if yes, 0 otherwise
21. Use contraceptive (CMT):	1 if yes, 0 otherwise
22. Prenatal check up by doctor (PRD):	1 if yes, 0 otherwise
23. Place of delivery (POD)	1, if not at home, 0 otherwise
24. Antenatal care (ANC)	1 if yes, 0 otherwise
25. BCG (BCG):	1 if given, 0 otherwise
26. DPT (DPT):	1 if given, 0 otherwise
27. Polio (POL):	1 if given, 0 otherwise
28. Measles (MES):	1 if given, 0 otherwise
29. Iron tablets/syrup during pregnancy (ITS):	1 if given, 0 otherwise
30. Ideal number of boy (INB):	number
31. Ideal number of girl (ING):	number

4. Model formulation

The general form of multivariate logistic regression model for k prognostic variables is

$$\begin{aligned} logit\, P &= \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k \\ &= \beta_0 + \sum_{i=1}^{k} \beta_i X_i \end{aligned} \qquad (4.1)$$

Where, P = estimated probability of the variable of the interest (in the present study, it is estimated probability of surviving child), β_0= logit P-intercept and β_i= regression coefficient of the i^{th} prognostic variable X_i.

Using the present notation of the variables, the above multivariate logistic regression model can be written as

$$\text{logit}\,(\text{CAL}) = \beta_0 + \beta_1(\text{PAM}) + \beta_2(\text{Relm}) + \beta_3(\text{ELM}) + \beta_4(\text{SDW}) + \beta_5(\text{TTF}) + \beta_6(\text{AVR}) + \beta_7(\text{NHM}) + \beta_8(\text{FRN}) + \beta_9(\text{TCF}) + \beta_{10}(\text{AM1B}) + \beta_{11}(\text{ABM}) + \beta_{12}(\text{CMT}) + \beta_{13}(\text{GPW}) + \beta_{14}(\text{INB}) + \beta_{15}(\text{ING}) + \beta_{16}(\text{MTB}) + \beta_{17}(\text{TIB}) + \beta_{18}(\text{PRD}) + \beta_{19}(\text{DBF}) + \beta_{20}(\text{ANV}) + \beta_{21}(\text{POD}) + \beta_{22}(\text{ITS}) + \beta_{23}(\text{ANC}) + \beta_{24}(\text{BCG}) + \beta_{25}(\text{DPT}) + \beta_{26}(\text{POL}) + \beta_{27}(\text{MES}) + \beta_{28}(\text{HHW}) + \beta_{29}(\text{PAR}) + \beta_{30}(\text{AAD}) + \beta_{31}(\text{MC}) \quad (4.2)$$

The model in terms of odds ratio $\Omega = \frac{\text{CAL}}{1-\text{CAL}}$ can be expressed as

$$\Omega = e^{\beta_0+\beta_1(PAM)+\beta_2(Relm)+\cdots+\beta_{29}(AAD)+\beta_{30}(MC)} \quad \cdots (4.3)$$

For one unit change in any one of the prognostic variable holding other prognostic variables constant, the equation (4.3) becomes

$\Omega^* = \Omega.$ exp (β-coefficient corresponding to the concerned prognostic variable)

where Ω^* is new value of Ω which becomes the concerned prognostic variable when changes one unit.

Then,

$\frac{\Omega^*}{\Omega}$ = exp (β-coefficient corresponding to the concerned prognostic variable)

Here, the quantity exp (β-coefficient corresponding to the concerned prognostic variable) is known as an odds ratio for the reason that it is the ratio of the two odds that is Ω and Ω^*.

If the prognostic variable under consideration is PAM, then

$$\frac{\Omega^*}{\Omega} = \exp\ (\beta_1)$$

or, $\frac{\Omega^*}{\Omega} = e^{\beta_1}$ (4.4)

Thus, the odds ratio (e^{β_1}) represents the multiplicative effect of one unit change in the PAM prognostic variable on the odds of the response variable (CAL).

5. Results and Discussion

In logistic regression analysis, the odds ratio denoted by e^{β} is a measure of the effect of a prognostic variable under study on the response variable. The impacts of these prognostic variables are quantified by β-coefficients, P-values for test of significance for β-coefficients and e^{β} with 95% confidence interval (C.I.). This

confidence interval gives an idea of how precise the estimate of the odds ratio (OR) is, and can also indicate statistical significance of OR. An interval that includes the value of 1.0 is not statistically significant. For example, CI given here (5.7-10.8), 1.0 is not included, so we know that not only our estimate of the OR fairly precise, it also indicates statistically significant.

Logistic regression analysis of child mortality with unadjusted prognostic variables

The table 3.1 shows the β-coefficients, P-values for test of significance for β-coefficients and e^{β} with 95% confidence interval (C.I.) for prognostic variables for unadjusted logistic regression analysis. Here, unadjusted means the effect of one of the prognostic variables on the response variable is examined without considering the effects of all the remaining prognostic variables.

Table 1: Logistic regression analysis of child mortality with unadjusted prognostic variables

Variable	β	P-value	e^{β}	95% C.I. for e^{β}	
				Lower	Upper
PAM	0.013	0.654	1.013	0.958	1.072
Relm	-0.853*	0.025	0.426	0.202	0.898
ELM	0.748*	0.027	2.114	1.091	4.096
SDW	1.072*	0.045	2.920	1.026	8.308
TTF	2.481**	<0.001	11.956	6.073	23.538
AVR	0.828*	0.011	2.289	1.210	4.333
NHM	0.193*	0.022	1.213	1.028	1.431
FRN	-0.830*	0.039	0.436	0.198	0.959
TCF	-0.872*	0.039	0.418	0.182	0.957
TCB	-0.221*	0.003	0.802	0.693	0.927
AM1B	0.079*	0.050	1.082	1.000	1.172
ABM	-0.743*	0.024	0.475	0.249	0.908
CMT	1.839**	<0.001	6.290	2.750	14.391
GPW	0.901*	0.006	2.463	1.299	4.672
INB	-0.033	0.881	0.967	0.624	1.499
ING	0.385	0.147	1.470	0.874	2.472
MTB	-1.420	0.073	0.242	0.051	1.142
TIB	0.604**	<0.001	1.829	1.354	2.472

PRD	1.140**	0.001	3.128	1.633	5.990
DBF	-3.611**	<0.001	0.027	0.013	0.058
ANV	0.149	0.091	1.161	0.976	1.381
POD	1.131*	0.002	3.097	1.526	6.287
ITS	1.290**	0.001	3.633	1.752	7.533
ANC	0.756*	0.022	2.129	1.114	4.071
BCG	2.250**	<0.001	9.484	4.776	18.832
DPT	2.540**	<0.001	12.684	5.924	27.155
POL	1.935**	<0.001	6.923	3.587	13.362
MES	1.177*	0.002	3.245	1.565	6.729
HHW	0.867*	0.013	2.379	1.196	4.729
PAR	-0.128	0.118	0.880	0.749	1.033
AAD	0.085*	0.037	1.088	1.005	1.179
MC	1.023*	0.002	2.781	1.465	5.280

*Significant at 5% level of significance, **Significant at 1% level of significance

In the present study, the effects of 31 classified prognostic variables on survival status of child are being considered separately. Out of these 31 prognostic variables, the coefficients of 25 prognostic variables are found to be statistically significant, in the sense that these 25 prognostic variables have some significant impact on survival status of child. They are Relm (religion of mother is Muslim), ELM (educational level of mother), SDW (source of drinking water), TTF (type of toilet facility), AVR (availability of radio), NHW (number of family members), FRN (frequency of reading newspaper), TCF (type of cooking fuel), AM1B (age of mother at first birth), ABM (any abortion/miscarriage), CMT (use contraceptive), GPW (gave plain water), TIB (tetanus injections before birth), PRD (prenatal check up by doctor), DBF (duration of breastfeeding), POD (place of delivery), ITS (iron tablets/syrup during pregnancy), ANC (antenatal care), BCG (bacillus calmette-guerin), DPT (diphtheria, pertussis, tetanus), POL (polio), MES (measles), HHW (availability of window), PAR (parity), AAD (age at delivery) and MC (menstruation cycle).

Logistic regression analysis (adjusted)

Table 2 Omnibus tests of model coefficients for adjusted logistic regression

Omnibus tests of model coefficients				
		Chi-square	df	P-value
Step 1	Step	198.294	31	<0.001
	Block	198.294	31	<0.001
	Model	198.294	31	<0.001

Table 3 Model summary for adjusted logistic regression

Model summary			
Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	122.251[a]	0.513	0.963

a. Estimation terminated at iteration number 9 because parameter estimates changed by less than .001.

Table 4: Hosmer -Lemeshow test for adjusted logistic regression

Hosmer- Lemeshow test			
Step	Chi-square	df	p-value
1	1.554	8	0.992

The overall evaluation of the model in logistic regression analysis is tested by likelihood ratio test statistic (generally known as chi-square test) or sometimes called Omnibus tests for model coefficients. In the present logistic regression model, chi-square has a value of 198.294 for 31 degrees of freedom and $p<0.001$(as shown in table 2). This indicates that the predictors do have a significant effect and create essentially a different model. In the model summary table 3.3, Cox and snell R^2 is found to be 0.513 and it is indicating that 51.3 % of the variation in the dependent variable is explained by predictors, considered through the logistic model. And, the Nagelkerke's R^2 is 0.963 which also indicates a strong relationship of 96.3% between the predictors (prognostic variables) and the prediction.

Here, Hosmer-Lemeshow test for goodness of fit is used to test the null hypothesis that there is no difference between observed and model-predicted values, implying that the model's estimate fit the data well at an acceptable level. In the present

study, Hosmer- Lemeshow test statistic is 1.554 with p-value 0.992. Hence, we fail to reject the null hypothesis that there is no difference between observed and model predicted values, i.e., the model is found to be best fit.

Table 5: Logistic regression analysis of child mortality with adjusted prognostic variables

Variables	β	**P-value**	e^{β}	**95% C.I. for e^{β}**	
				Lower	Upper
PAM	0.013	0.892	1.013	0.842	1.219
Relm	-0.345	0.606	0.708	0.191	2.624
ELM	0.213	0.762	1.238	0.310	4.937
SDW	0.366	0.643	1.442	0.307	6.771
TTF	2.955**	<0.001	1.197	1.054	2.386
AVR	0.747	0.255	2.110	0.584	7.629
NHM	0.487*	0.002	1.627	1.200	2.204
FRN	1.118	0.160	3.059	0.642	14.573
TCF	0.016	0.984	1.016	0.216	4.782
TCB	-2.608**	<0.001	0.074	0.017	0.313
AM1B	-1.744	0.090	0.175	0.023	1.312
ABM	-0.871	0.159	0.418	0.124	1.407
CMT	0.986	0.196	2.681	0.601	11.967
GPW	0.272	0.637	1.312	0.425	4.055
INB	-0.519	0.251	0.595	0.245	1.444
ING	1.824*	0.002	6.195	1.980	19.389
MTB	0.522	0.787	1.685	0.038	74.627
TIB	-0.210	0.607	0.811	0.364	1.804
PRD	1.161	0.593	3.195	0.045	226.451
DBF	-3.359**	<0.001	0.019	0.004	0.084
POD	0.378	0.583	1.460	0.378	5.632
ITS	0.688	0.418	1.990	0.376	10.523
ANC	-1.985	0.369	0.137	0.002	10.430
BCG	0.902	0.317	2.464	0.422	14.390
DPT	1.432	0.168	4.186	0.548	31.963
POL	0.520	0.437	1.681	0.454	6.230
MES	-1.259	0.093	0.284	0.065	1.232
HHW	-0.665	0.348	0.514	0.128	2.064

PAR	2.088*	0.002	8.069	2.147	30.325
AAD	1.749	0.093	5.750	0.747	44.234
MC	0.529	0.433	1.697	0.452	6.368
Constant	-3.415	0.178	0.033		

*Significant at 5% level of significance, **Significant at 1% level of significance

Here, let us consider the logistic regression analysis of child mortality by adjusted method (enter method in SPSS program). The logistic regression analysis by adjusted method means an analysis of logistic regression for a particular prognostic variable after controlling the effects of remaining prognostic variables.

For instance, Out of 31 prognostic variables, five adjusted prognostic variables are found to have significant impact on the survival status of child. They are type of toilet facility (TTF), number of family members (NHM), total children ever born (TCB), ideal number of boys (ING), duration of breastfeeding (DBF) and parity (PAR). The type of toilet facility has significant effect on child mortality (β-coefficient=2.955, $p<0.001$). And the odds ratio for type of toilet facility on child survival is 1.054 with 95% C.I. (1.054−2.386) and it is indicating that survival chance of child living at home with sanitary latrine is 5.4% higher than the child living without sanitary latrine. The number of family members (NHM) has its β-coefficient = 0.487 with p-value for Wald's test statistic 0.002. And, the odds ratio for NHM on child survival is 1.627 with 95 % C.I. (1.200−2.204). This odds ratio is also found to be statistically significant since the value 1.0 is fall in the confidence interval. Thus, it suggests that number of family members is increased by one there is 62.7.0% higher chance of child survival after controlling the effects of other 30 prognostic variables on them. The prognostic variable, total children ever born (TCB) has significantly negative impact of child survival as evident by β-coefficient= −2.608 with p-value<0.001. The odds ratio for the variable i.e., total children ever born (TCB) is 0.074 with 95% C. I. (0.017−0.313) and it indicates that an increase of one child there is 92.6% less chances of child survival or there is 92.6% more chances of child death when the effects other remaining variables are kept constant.

The parents' desire ideal number of girls (ING) has significantly adjusted impact on child survival (β coefficient =1.824, p=0.002). And, the odds ratio for ING on child survival is 6.195 with 95% C.I. (1.980−19.389) after controlling the effects of other variables. It shows that one unit change in ideal number of girls desired

by parents there is 6.195 times higher chances of their child survival. This finding is contradicts to the above finding that there was negative impact of total children ever born on child survival. It needs to examine deeply in future analysis of stepwise logistic regression.

The duration of breastfeeding (DBF) is found to have statistically high significant impact on child mortality. The odds ratio for DBF is 0.019 with 95% confidence interval (0.004 – 0.084). Thus, an increase of one month of duration of breastfeeding there is 98.1% less chances of child mortality after controlling the effects of other prognostic variables.

Step-wise logistic regression analysis (forward Wald) of child mortality

Further, stepwise logistic regression analysis (Wald's forward method) is adopted to select the most important variables to be considered in the model and to find out the best set of prognostic variables which can explain the causes of child mortality. In present study, all 31 prognostic variables are included in the model and try to find out a most important set of variables to be explained for causes of child mortality. Omnibus tests for model coefficients, both likelihood ratio tests and Hosmer-Lemeshow tests for goodness of fit are conducted to assess the fit of the model in every step of the analysis.

Table 6: Omnibus tests of model coefficients for step-wise logistic regression

Omnibus tests of model coefficients				
		Chi-square	**df**	**P-value**
Step 1	Step	74.020	1	<0.001
	Block	74.020	1	<0.001
	Model	74.020	1	<0.001
Step 2	Step	43.470	1	<0.001
	Block	117.491	2	<0.001
	Model	117.491	2	<0.001
Step 3	Step	12.758	1	<0.001
	Block	130.248	3	<0.001
	Model	130.248	3	<0.001
Step 4	Step	8.550	1	0.003
	Block	138.798	4	<0.001
	Model	138.798	4	<0.001
Step 5	Step	8.328	1	0.004

	Block	147.126	5	<0.001
	Model	147.126	5	<0.001
Step 6	Step	6.461	1	0.011
	Block	153.587	6	<0.001
	Model	153.587	6	<0.001
Step 7	Step	13.878	1	<0.001
	Block	167.465	7	<0.001
	Model	167.465	7	<0.001
Step 8	Step	9.209	1	0.002
	Block	176.674	8	<0.001
	Model	176.674	8	<0.001

Table 7: Model summary for stepwise logistic regression

Model summary			
Step	-2 Log likelihood	Cox & Snell R square	Nagelkerke R square
1	246.525[a]	0.085	0.266
2	203.055[b]	0.132	0.412
3	190.297[b]	0.145	0.453
4	181.747[b]	0.154	0.481
5	173.419[c]	0.163	0.507
6	166.959[c]	0.169	0.527
7	153.080[c]	0.183	0.570
8	143.871[c]	0.192	0.599

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

b. Estimation terminated at iteration number 7 because parameter estimates changed by less than .001.

c. Estimation terminated at iteration number 8 because parameter estimates changed by less than .001.

Table 8: Hosmer- Lemeshow test for stepwise logistic regression

Hosmer-Lemeshow test			
Step	Chi-square	df	P-value
1	0.000	0	.
2	0.053	1	0.818

3	0.425	2	0.809
4	6.622	7	0.469
5	3.903	8	0.866
6	13.809	8	0.087
7	2.901	8	0.940
8	3.450	8	0.903

For all steps of the analysis, model coefficients are found to be statistically significant (as shown in table 6). This indicates that the predictors (prognostic variables) do have a significant effect and create essentially a different model. Table 7 shows the model summary for stepwise logistic regression analysis including chi-square test (-2 log-likelihood), Cox and Snell R^2 and Nagelkerke R^2. At the first step Nagelkerke R^2 is 0.266 and it indicates that 26.6 % of the variation in the response variable is explained by the logistic model. Further, it is continuously increased up to step 9 and found as 0.599. Thus, at the step 9, 59.9% of the variation in the response variable is explained by the model with 8 prognostic variables.

Table 8 shows the Hosmer-Lemeshow test for goodness of fit. At first step, there is only one prognostic variable as such the test statistic is invalid. In the second and consequent steps, Hosmer-Lemeshow test statistic is found to be statistically insignificant. Hence, there are no differences between observed and model predicted values, i.e., the models are good fit and the logistic model obtained at step 8 is the best model among the fitted ones.

Table 9: Step-wise logistic regression analysis (forward Wald) of child mortality

Step	Variable	β	P-value	e^{β}	95% C.I. for e^{β}	
					Lower	Upper
1	DBF	-3.602	<0.001	0.027	0.013	0.059
	Constant	3.602	<0.001	36.667		
2	DBF	-3.701	<0.001	0.025	0.01	0.063
	DPT	2.609	<0.001	13.591	5.648	32.704
	Constant	2.307	<0.001	10.04		
3	TTF	1.675	<0.001	5.339	2.226	12.804
	DBF	-3.482	<0.001	0.031	0.011	0.083
	DPT	2.307	<0.001	10.048	4.108	24.577
	Constant	1.067	0.006	2.906		
4	TTF	1.908	<0.001	6.738	2.693	16.857
	NHM	0.272	0.006	1.313	1.079	1.597

	DBF	-3.419	<0.001	0.033	0.012	0.09
	DPT	2.353	<0.001	10.517	4.206	26.295
	Constant	-0.677	0.358	0.508		
5	TTF	2.098	<0.001	8.152	3.165	20.999
	NHM	0.290	0.005	1.336	1.092	1.635
	CMT	1.418	0.008	4.130	1.451	11.752
	DBF	-3.252	<0.001	0.039	0.014	0.109
	DPT	2.010	<0.001	7.461	2.932	18.986
	Constant	-1.258	0.108	0.284		
6	TTF	2.323	<0.001	10.208	3.797	27.448
	NHM	0.398	0.001	1.489	1.181	1.877
	TCB	-0.319	0.011	0.727	0.568	0.931
	CMT	1.610	0.003	5.001	1.700	14.710
	DBF	-3.402	<0.001	0.033	0.011	0.097
	DPT	1.768	<0.001	5.857	2.217	15.473
	Constant	-0.903	0.266	0.405		
7	TTF	2.483	<0.001	11.973	4.224	33.935
	NHM	0.426	0.001	1.531	1.198	1.956
	TCB	-1.597	<0.001	0.203	0.097	0.422
	CMT	1.726	0.002	5.621	1.853	17.047
	DBF	-3.512	<0.001	0.030	0.01	0.092
	DPT	1.568	0.002	4.799	1.772	13.000
	PAR	1.306	<0.001	3.691	1.848	7.370
	Constant	-0.538	0.53	0.584		
8	TTF	2.565	<0.001	12.999	4.465	37.845
	NHM	0.462	<0.001	1.587	1.227	2.054
	TCB	-1.952	<0.001	0.142	0.063	0.321
	CMT	1.402	0.015	4.062	1.311	12.578
	ING	1.019	0.004	2.769	1.372	5.590
	DBF	-3.549	<0.001	0.029	0.009	0.091
	DPT	1.753	0.001	5.774	2.046	16.296
	PAR	1.558	<0.001	4.749	2.246	10.039
	Constant	-1.558	0.101	0.210		

As shown in table 9, the stepwise logistic regression is run up to 8th step. At the first step, the prognostic variable DBF is selected as most important variable out of 31 variables. In the second step, in addition to the variable selected at first step, the method searches second variable among the remaining 30 prognostic variables which will give the most significant contribution to along with the first

selected variable to the model and variable thus selected is DPT. This process is continued up to 8th step and finally 8 prognostic variables are entered to the model. The prognostic variables thus selected as the best set of variables by the stepwise method are TTF (type of toilet facility), NHM (number of family members), TCB (total children ever born), CMT (use contraceptive), ING (ideal number of girls), DBF (duration of breastfeeding), DPT and PAR (parity). The two viz., CMT and DPT are newly entered to the model by stepwise method over the six prognostic variables which were found significant in enter method.

According to the model, the log of the odds of child survival is positively related to type of toilet ($p<0.001$), number of family members ($p<0.001$), use contraceptive ($p=0.015$), ideal number of girls ($p=0.004$), DPT ($p<0.001$) and parity ($p<0.001$); and negatively related with total children ever born ($p<0.001$) and duration of breastfeeding ($p<0.001$).

The odds ratio for type of toilet on child survival is 1.197 with 95% C.I. (1.054−2.386) and it is indicating that the survival chance of child living at home with sanitary latrine is 19.7% higher than the child living without sanitary latrine. Moreover, type of toilet is found to have significant effect on child mortality for all cases of analyses i.e., univariate, unadjusted, adjusted and stepwise logistic regression analyses.

In favour of this finding, Roth and Kurup (1989) suggest that good public sanitation systems may constitute a more important preventive aspect of child mortality. In the latter study of Kabir and Amin (1993) in Bangladesh also highlights that the households with sanitary latrines have low risks of child mortality. The similar finding is reported by Pandey et al. (1998) on their study of infant and child mortality in India, a subject report of NFHS-2 and they have mentioned that access to a flush or pit toilet households have substantial and often statistically significant adjusted effects on infant and child mortality. The adjusted effect on mortality of household access to a flush or pit toilet is strongest for the neonatal period and becomes weaker at later ages. The adjusted effect tends to be statistically significant in states with relatively high levels of neonatal mortality: Uttar Pradesh, Orissa, West Bengal and Assam. This pattern suggests that the lack of access to a flush or pit toilet is associated with increased risk of neonatal tetanus. As highlighted by Klaauw and Wang (2004), access to sanitary facilities i.e., access to toilet facility can reduce under-five mortality rate significantly in rural areas of India as a whole. In urban Kenya, access to modern sanitation facilities (flush toilets) reduces diarrhoea prevalence in urban areas and ultimately reduces the child mortality. In a study of Balk et al. (2005), the principal component analysis is used to combine the correlated variables which

influence on mortality. From this analysis, it is confirmed that the mortality is correlated positively with the complete lack of toilet facilities and negatively with access to flush toilets. It is also suggested by Vos et al. (2005) that the availability of better sanitation will decrease the probability of infant death since better sanitation and drinking water access of the household should positively improve hygienic and health conditions for all members.

On the other hand, Baker (1999) and Rutstein (2000), in contrary to above findings, and observe that access of pit latrine does not have a significant effect on child mortality.

The odds ratio for number of family members on child survival is 1.587 with 95% C.I. (1.227 – 2.054). This odds ratio is also found to be statistically significant since the value 1.0 is not fall in the confidence interval. Thus, it suggests that number of family members is increased by one there is 58.7% higher chance of child survival. This variable is also one of the most important factor influencing on child mortality because, this variable is found significant for all cases, whether the effect of other variables have been eliminated or controlling the effects of other variables. Many researchers like Gulland (2014) and Xi et al. (2014), also suggested the same finding and concluded that the effect of family size on child mortality is statistically and substantially strong .

The total children ever born (fertility) has negative impact on child survival ($\beta = -0.952$, $p<0.001$) and the odds ratio of total children ever born on child survival is 0.142 with 95% C.I. (0.063–0.321). Thus, when the total child ever born is increased by one there is 85.8% less chances of child survival. It is observed from the above finding that total children ever born is found to have significant effect on child mortality whatever the effects of other variables are eliminated or kept control on them. Hence, the total children ever born have really significant effect on child mortality and an increase total child ever born corresponds to reduce child mortality.

The present finding is same as the findings of Jacob et al. (2015), Garma and Mexico (1983), Knodel and Hermalin (1984), Hobcraft JN et al. (1985), Basu and Basu (1991), Pandey et al. (1998), Bhuyan (2000), Rutstein (2000), Klaauw and Wang (2004), Adair (2004), Bahlotra and Soest (2005), Maitra and Pal (2007) and IIPS (2007). Gaecia suggests that the reduction of fertility and increase of pregnancy can have a collateral effect which will continue to the decline of excessive infant mortality. Knodel & Hermalin (1984) also suggest in their study that mothers with a large number of births will tend to have shorter intervals and a number of other characteristics, such as shorter breast feeding and

more pressure on limited resources that contribute to higher infant and child mortality.

In a report of infant and child mortality in India by Pandey et al. (1998) mentions that decline in fertility by reducing the proportion of higher order births, will tend to lower the overall level of child mortality. Bhuyan (2000) in his word, the upward trend in child mortality is significantly and positively associated with fertility, thus higher fertility levels are associated with higher probabilities of child deaths.

Use of contraceptive methods (CMT) and survival status of child are positively associated and the odds ratio for use of contraceptive method is 4.062 with 95% C.I. (1.311−12.578). The mother using contraceptive method has 4.062 times higher chance of her child survival than the mother not using any contraceptive methods. Although, it is one of the important variables among the 31 prognostic variables, it was found to have no significant effect on child mortality after controlling effect of other variables as observed in previous analysis of adjusted logistic regression.

The present finding is in line of the findings of Victora (2013) and Musenge et al. (2013). Saha & Soest (2013) also express that effective contraceptive use could reduce infant mortality of birth order two and higher by 7.9 percent. The net effect of effective contraceptive use on the total infant mortality rate is small, however, because the favorable effect on higher order births is partly offset by the rise in the proportion of high-risk first births.

The effect of parent's desired ideal number of girls on child mortality is not significant when the effects of other variables have been eliminated whereas it is significant when the effects of other variables hold constant. Moreover, it is selected as one of the most important variables for child mortality by stepwise method. It may be due to interaction effect of the variable with the other variables. At the 8^{th} step, the odds ratio for ideal number of girls is 2.769 with 95% confidence interval (1.372−5.590) and it infers that the child survival is approximately 3 times as likely with an increase of parent's desired ideal number of girls by one.

The odds ratio of duration of breastfeeding on child mortality is 0.029 with 95% C.I. (0.009−0.091). This odds ratio expresses that the child mortality is 2.9% less when the duration of breastfeeding is more than 6 months. The present finding is reaffirmed with the previous findings of Chen et al. (2015), Fauvcau et al. (1990) and Sandiford et al. (1991) , Hiil and Pande (1997), Pandey et al. (1998) and Claeson et al. (1999), they suggest that breastfeeding promotion might be expected to have its largest effect on infant mortality. And it is also

reported by Bhuyan (2000) that duration of breastfeeding and ages of mother at marriage have some influence in reducing mortality level of children. In a study of Rutstein (2000), suggests that an increase in the duration of breastfeeding is associated with a fall in post-neonatal mortality. A rise in the percentage of children aged 7-9 months who were both breastfed and getting solid foods is associated with decrease in both post natal and infant mortality rates. Biswas et al. (2000) also reported in their study on impact of some biosocial variables on infant and child mortality that breastfeeding appeared to be prime factor influencing infant, second year (12-23) months and early child (24-59) months. Further they suggest breastfeeding more than one year appears to have greatest potential for reducing infant and childhood mortality.

In case of DPT (diphtheria, pertussis, tetanus) vaccine, its odds ratio is 5.774 with 95% confidence interval (2.046−16.296) and it thus suggests that the child who received DPT vaccine has approximately 6 times higher chance of survival than the child who did not received DPT vaccine. So, DPT vaccine has significantly and substantially strong impact on child mortality.

The present finding supports the findings of Kabir and Amin (1993) and Aaby et al. (1993). They suggest that the health interventions such as immunization programmes might have had an effect on lowering infant and child mortality.Pandey et al. (1998) also suggest that mother's tetanus immunization has a substantial effect on unadjusted and adjusted neonatal mortality. It is also in agreement with the finding of [(Claeson et al. (1999); Claeson et al. (2000))] and they feel that the coverage of key child health care interventions such as immunizations rate (include BCG, DPT, polio, etc.) and reduction in child mortality rates are positively correlated. Thus child health program interventions have contributed to a reduction in child mortality rates in India. Again, the present finding supports the past findings of Griffiths et al. (2001), Houweling et al. (2005) and Vos et al. (2005).

The parity or birth order is observed to have a significant effect on child mortality and its odds ratio is 4.749 with 95% confidence interval (2.246−10.039). Thus, the survival chance of child is 4.749 times high when order of birth is increased by one. In univariate analysis in chapter-II, it was also already observed that the parity on child mortality is found to be significant and the most favourite order of birth for reducing child mortality was 6-8 orders while the child mortality rates were high when parity is below 6 and above 8.

The present finding is in agreement with the past findings of Pandey et al. (1998), Berger et al. (2002), Syamala (2004), Bahlotra and Soest (2005). Pandey et al. (1998) and their findings suggest that birth order and mother's age at childbirth

have highly and substantially influenced on under5 mortality. Syamala (2004) also points out that the risk of dying during the first year of life is higher among children of lower and higher order births. Bahlotra & Soest have established the relationship between child mortality and parity as it exhibits U-shaped curve. Hobcraft JN et al. (1985) and Majumder et al. (1997) are against the present finding and they highlight that during infancy, birth order is highly significant effect on mortality but it seems to be invisible during children of age between 1 to 5 years. A report of NFHS-3 of India (2008)(IIPS (2007)) also highlights the first birth are more likely to be delivered in an institution than births at higher birth orders and hence first birth children are likely less chance of death than higher birth order due to unavailability of health care facility.

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