Big data analytics: reducing unplanned admission in Nigeria

GBOLAHAN, Aramide

BIG DATA ANALYTICS: REDUCING UNPLANNED ADMISSION IN NIGERIA

Presented by

ARAMIDE GBOLAHAN

INTRODUCTION

- Big data analytics in healthcare provides insights for exploration of large datasets in order to improve health outcomes at reduced costs

(Wang, Kung and Byrd, 2016)

- Unplanned hospital admission are emergency admission that occurs at short notice of presentation at the A&E department. Patients often stay overnight in hospital

(Wallace et al 2014)

- Population size: 189,885,842 *(UN estimation 2016)*
- 20 teaching hospital across 36 states
- Larger proportion of hospital are predominantly run by private organisation
- Trends in mortality rate has progressively increased from 1999 - 2008 (Agan et al, 2010)

Unplanned hospital admission mostly result to death and healthcare cost

"Nigeria" as a developing country is faced with many limitations

- Increasing healthcare demand
- Inadequate healthcare fund
- Poor quality of care
- Inadequate health personnel
- Insufficient healthcare recourses
- Weak healthcare system
- Poverty
- Poor transportation network

AIM

To fit a model that helps to reduce unplanned hospital admission

OBJECTIVES

- Exploration of trends and pattern in the data such that data generating process (DGP) could be determined
- To identify predisposing factors to unplanned hospital admission using logistics regression model so as to condense its increasing rate in the population

SYSTEMATIC REVIEW OF LITERATURE

Author	Charles et al 1995 Ghana	Kolo et al 2012 Nigeria	Norman et al 2012 Ghana
Aim	Characterizing patients presenting to a rural hospital	Risk factor for hypertension related admission	Risk factor for hospital preparedness
Outcome	Agriculture , Transportation, Burn	Cholera, Hypertension related disease	Lack of preparedness, Anaesthesia, Surgery, Eye Problem
Method	OR and 95% CL	Descriptive Statistics	Logistic Regression

DATA ANALYSIS

Data Description : Patients hospital admission at the Intensive Care Unit (ICU), containing 200 observations and 9 variables

Source: Vincenter Elboundock (Open Source)

FORMAT

ID:	Patients ID
Survive :	1 = patient survived to discharge or 0 = patients died
Age :	Age in years
AgeGroup:	1= young (under 50), 2 = middle (50 – 69), 3 = old (70+)
Sex:	1= male or 2 = female
Infection:	1= infection suspected or 0= no infection
SysBP:	Systolic blood pressure (mm Hg)
Pulse:	Heart rate (beats / min)
Admission:	1= Unplanned or 0= Planned

Data Pre-processing: Data was checked for error s, missingness and outliers
Result shows that further adjustment is not required

Outcome measure: Identify the factors associated with unplanned admission so as to reduce the rate of such admission type in the population

PATIENTS' CLINICAL AND DEMOGRAPHIC CHARACTERISTICS

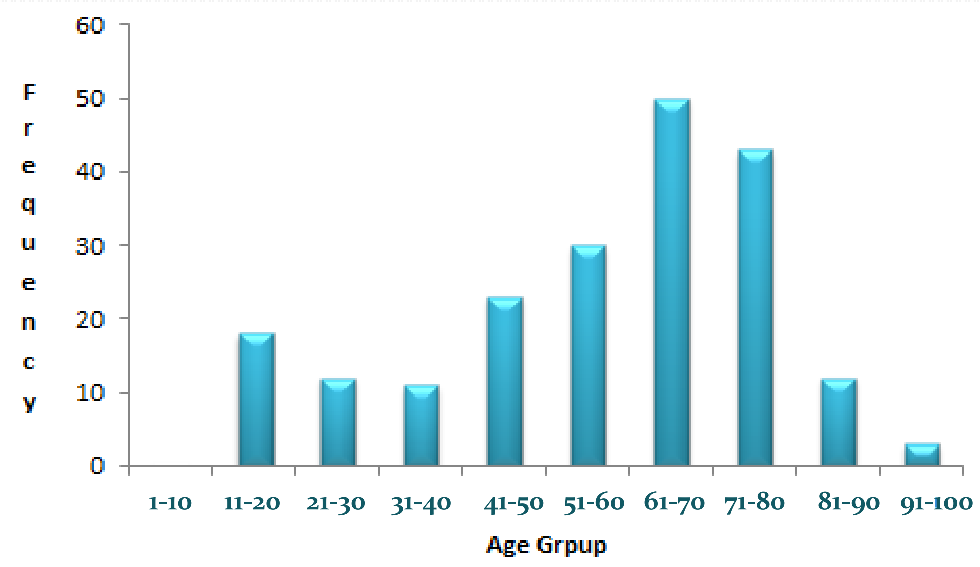
Parameter	Categories	Proportion (%)
Sex	**Female**	**62**
	Male	38
Survive	**Yes**	**80**
	No	20
Infection	Yes	42
	No	58
Admission	Planned	23
	Unplanned	**77**
AgeGroup	Young	27
	Middle	**40**
	Old	33

Frequency Estimate

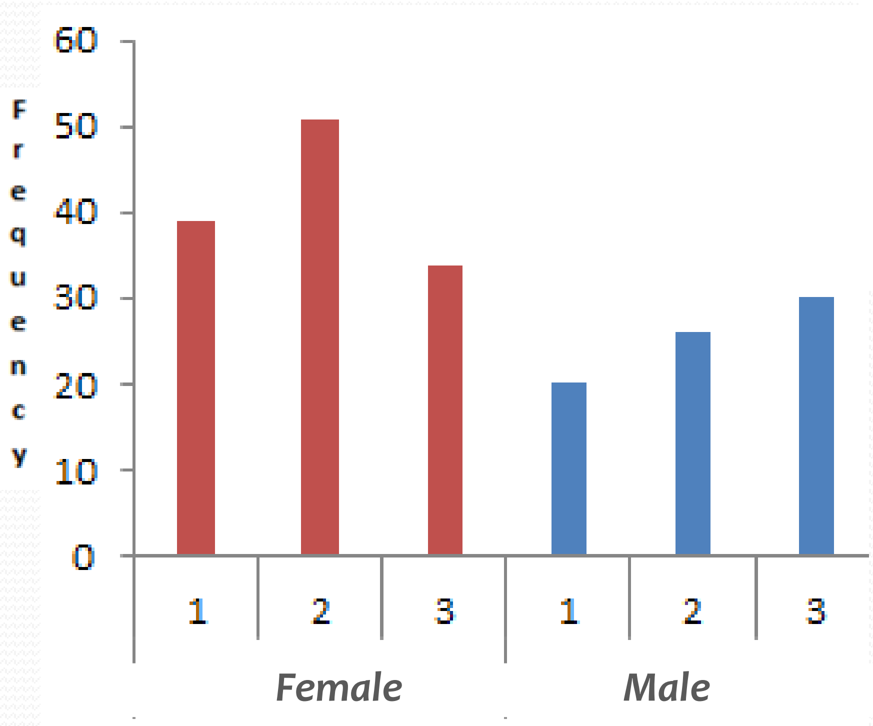
Parameter	Age	Pulse	SysBp
Mean	**58**	99	132
Median	63	98	130
STD	20	27	31
Min.Value	16	39	36
Max.Value	92	192	256

Summary Statistics

PATTERN AND TRENDS



Unplanned admission by AgeGroup



Gender and AgeGroup distribution of Unplanned Admission

LOGISTIC REGRESSION EQUATION

$$P(Y) = \frac{1}{1 + e^{-(\alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_n X_n + \varepsilon_i)}}$$

Where

Y: dependent variable
(Patient experience unplanned admission or not (YES/NO)

α: Intercept;

$\beta_{i's}$ $(\forall\, i = 1, 2, \ldots, n)$: represents the regression coefficients for the independent variables (X_i)

ε_i : Error term

$$P(Y) = \frac{1}{1 + e^{-(\alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_1 X_2 + \beta_5 X_1 X_3 + \beta_6 X_2 X_3 + \beta_7 X_1 X_2 X_3)}}$$

LOGISTIC REGRESSION MODEL: Backward Elimination Approach

The LOGISTIC Procedure

Analysis of Maximum Likelihood Estimates

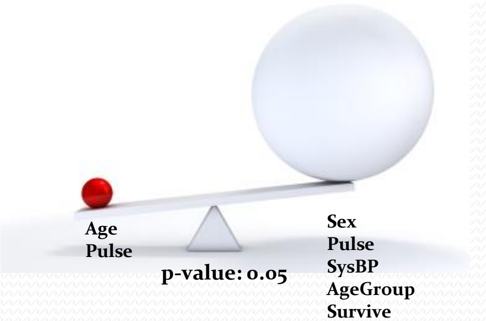
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	4.5046	1.3263	11.5351	0.0007
Sex	1	0.8884	0.3982	4.9771	0.0257
Pulse	1	0.0176	0.00716	6.0634	0.0138
SysBP	1	-0.0116	0.00585	3.9426	0.0471
AgeGroup	1	-0.8553	0.2472	11.9717	0.0005
Survive	1	-2.4145	0.7668	9.9164	0.0016

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
Sex	2.431	1.114	5.306
Pulse	1.018	1.004	1.032
SysBP	0.988	0.977	1.000
AgeGroup	0.425	0.262	0.690
Survive	0.089	0.020	0.402

Association of Predicted Probabilities and Observed Responses

Percent Concordant	78.9	Somers' D	0.580
Percent Discordant	20.8	Gamma	0.582
Percent Tied	0.3	Tau-a	0.227
Pairs	7791	c	0.790



ASSOCIATION CHECK

- Student T-test was used to compare continuous means
- Chi-square was used to compare means of proportion

LIMITATION

- Ungeneralised outcome
- Reliability of data (open source) cannot be ascertained
- Smaller sample size
- Inadequate variable

FURTHER CHECKS

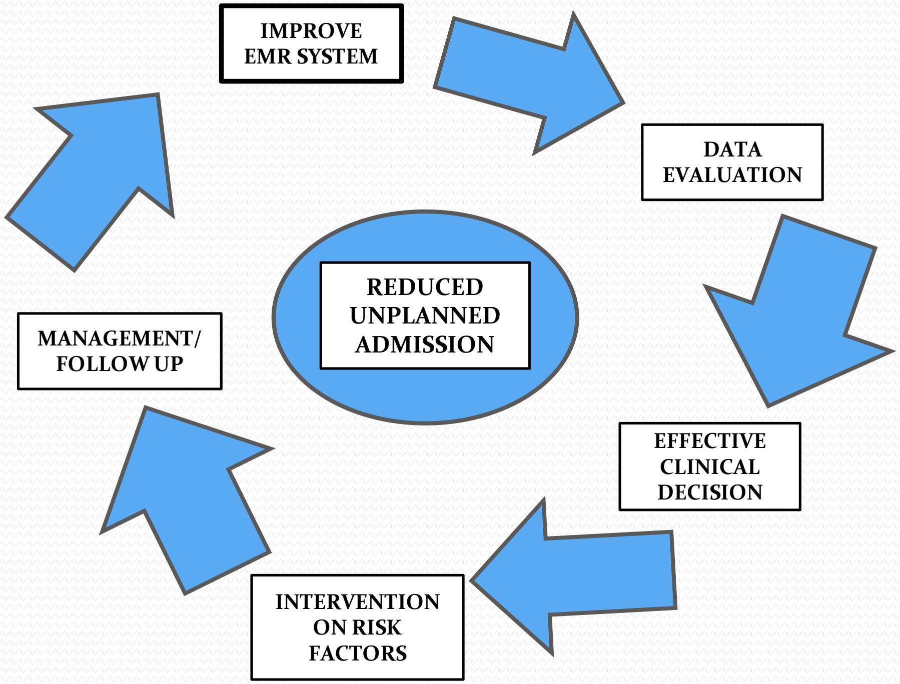
	Age	AgeGroup	Survive	Infection	Pulse	SysBp	Sex
Backward	-	Significant	Significant	-	Significant	Significant	Significant
Forward	-	Significant	Significant	-	Significant	Significant	Significant
Stepwise	-	Significant	Significant	-	Significant	Significant	Significant

	C Statistics	Concordant	Discordant
Backward	0.790	7.89	20.8
Forward	0.790	78.9	20.8
Stepwise	0.790	78.9	20.8

Comparing Different LR Approach

IMPACT OF BIG DATA ANALYTICS IN HEALTH CARE

- Analytical capability for patterns of care
- Better understanding of patients characteristics
- Analytical ability of data (structured and unstructured)
- Improve healthcare quality
- Reduce healthcare cost
- Reduction unexpected event (such as: death)
- Improve health outcome
- Decrease non-elective hospital admission
- Support clinical decision in real-time and offline
- Predictive capability of future event



CONCLUSION

An early intervention on known factors (such as: AgeGroup, Sex, Survive, SysBp and Pulse) could significantly reduce rate of unplanned hospital admission; which would serve as guide to effective clinical decisions and well-informed admission policy among stakeholders

ACKNOWLEDGEMENT

- Special appreciation to Sheffield Hallam University for hosting this seminar

Sheffield Hallam University

- Keynote Speaker / Guest Speaker / Co-Orgaisaiser
- CISDIDC Research Network
- Volunteers
- Attendees
- Presenters

REFERENCES

1. Nair, H., Simões, E.A., Rudan, I., Gessner, B.D., Azziz-Baumgartner, E., Zhang, J.S.F., Feikin, D.R., Mackenzie, G.A., Moiïsi, J.C., Roca, A. and Baggett, H.C., 2013. Global and regional burden of hospital admissions for severe acute lower respiratory infections in young children in 2010: a systematic analysis. *The Lancet*, *381*(9875), pp.1380-1390.
2. Wallace, E., Stuart, E., Vaughan, N., Bennett, K., Fahey, T. and Smith, S.M., 2014. Risk prediction models to predict emergency hospital admission in community-dwelling adults: a systematic review. *Medical care*, *52*(8), pp.751-765.
3. Wang, Y., Kung, L. and Byrd, T.A., 2016. Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations. *Technological Forecasting and Social Change*.
4. Hussein, J., Hirose, A., Owolabi, O., Imamura, M., Kanguru, L. and Okonofua, F., 2016. Maternal death and obstetric care audits in Nigeria: a systematic review of barriers and enabling factors in the provision of emergency care. *Reproductive health*, *13*(1), p.47.
5. Blatchford, O., Capewell, S., Murray, S. and Blatchford, M., 1999. Emergency medical admissions in Glasgow: general practices vary despite adjustment for age, sex, and deprivation. *Br J Gen Pract*, *49*(444), pp.551-554
6. Donnan, P.T., Dorward, D.W., Mutch, B. and Morris, A.D., 2008. Development and validation of a model for predicting emergency admissions over the next year (PEONY): a UK historical cohort study. *Archives of Internal Medicine*, *168*(13), pp.1416-1422.
7. Frost, S.A., Alexandrou, E., Bogdanovski, T., Salamonson, Y., Parr, M.J. and Hillman, K.M., 2009. Unplanned admission to intensive care after emergency hospitalisation: risk factors and development of a nomogram for individualising risk. *Resuscitation*, *80*(2), pp.224-230.

thanks for
listening!