LOG-LINEAR MODEL FOR OUTCOME ON ADMISSION IN A HOSPITAL

A CASE STUDY IN CENTRAL REGIONAL HOSPITAL-CAPE COAST (2006-2010)

BY

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DECLARATION

I hereby declare that this submission is my own work towards the Master of Science and that, to the best of my knowledge, it contains no material previously published by another person nor material, which has been accepted for the award of any other degree of the University, except where due acknowledgment has been made in the text.

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ABSTRACT

Recent studies show that that there are over 17,000 hospitals in the world including public and private hospitals.

The hospital is a health facility that provides medical and surgical care to sick or injured people. They also provide treatment and therapies to patients with intent to improve symptoms and cure the patient's medical problem. It provides institution of measures to protect a person from the occurrence of disease to which a person has been or may be exposed.

Hospitals have been subjected to systematic efforts to change organizational behavior by offering a good environment in which to practice medicine.

There are many health care facilities in the central region, where patients visit for medical care. These include hospitals and clinics.

The broad goal of health services delivery is to improve the health of all people living in the municipality regardless of age, ethnicity, religious conviction, political affiliation or socio-economic standing. This broad goal encompasses many specific objectives, among them, an increase in life expectancy, reduction in morbidity and fertility rates, and improvement in quality of life.

The purpose of this study is to determine the outcome of patients' admission in the medical ward (male, female and paediatrics) in the Central Regional Hospital

The specific objectives of the study are as follows: to determine association between Outcome of admission(alive and death) Year of admission conditioning on the type of Medical Ward, to determine association between Medical Ward and Outcome of admission(alive and death)

conditioning Year of admission, to determine association between Year of admission, Medical Ward and Outcome of admission(alive and death) and determine associations among variables by means of log-linear model Statistics and likelihood ratios

The statistical tools used in analyzing the data were Microsoft excel and SAS. The Outcome of admission variable was categories into two levels; the medical ward had three levels and year variable had five levels and is ordinal. The model approach based on log-linear models was used. In this case, the homogeneous association was tested by comparing the saturated model (SM) and a model assuming homogeneity (HAM). The conditional independence was checked by comparing the HAM model with different models assuming conditional independence. The best model was chosen to conduct further analysis on the effect of medical ward on the outcome of admission while controlling by year.

It realized that total number of patients admitted in the hospital was twelve thousand four hundred and twenty six (12426) for the 5 year period. Ten thousand seven hundred and sixty one (10761) were discharged (alive); representing 86.6%. Also one thousand six hundred and sixty five died; representing 13.4% for the same five year period.

We observed that the female medical ward recorded highest patients' death in the hospital from 2006 to 2010.

In this model, the conditional likelihood ratio between any two variable are identical. We therefore concluded that the best model is the saturated log-linear model.

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I have depended on the help of several people in preparation of this work. I owe first a dept of gratitude to the Almighty God who by His Grace has seen me through my work successfully

I wish to register my deep appreciation to my supervisor Mr. Nana Kena Ferempong, I would also like express appreciation to Dr. S.K Ampomsah former head of department and Mr.F.K. Darkwah for their healthy criticisms and guidance. Sir, you have transformed the way I think and motivated me with your academic guidance.

I would like to acknowledge Mr. E. M Larbi and Mr. S.K Nandam who willingly provided me with some assistance. I also owe a debt of gratitude to my sibling for their invaluable support and encouragement.

DEDICATION

This work is dedicated to my mum Miss Theresa Essuman, my wife Mrs. Cynthia Amoakoh and children Dorothy, Mayfair and Patricia Amoakoh for their love and support through my University education.

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CHAPTER ONE

INTRODUCTION

1.1 Background to the study

Today, you might describe a hospital as "an institution for health care providing patient treatment by specialized staff and equipment… providing for longer-term patient stays" its historical meaning until relatively recent times was "a place of hospitality" (John, 1985). The Chelsea Royal Hospital was established in 1681as a facility to house veteran soldiers. Today hospitals are funded in a variety of ways, including support from the public sector, health organizations (for profit or non-profit), health insurance companies, charities and direct charitable donations. Historically speaking, hospitals were often founded and funded by religious orders or charitable individuals and leaders. Conversely professional physicians, surgeons and nurses, largely staff modern-day hospitals whereas in history this work was usually performed by the founding religious orders or by volunteers. Today, there are various Catholic religious orders, such as the Alexia's and the Bon Secours Sisters which still focus on hospital ministry.

Recent studies show ~~that that~~ there are over 17,000 hospitals in the world including public and private hospitals (Eden, 2011).The first recorded hospitals arose in the Byzantine Empire in the fifth and sixth centuries AD. Hospitals in Western Europe emerged later, beginning in the monasteries, a legacy reflected in the religious designations of many present-day European hospitals. Most health care relied on extended families and local communities since formal health services had little to offer. The industrial revolution brought enormous social changes that impacted on health and health care. The rapid growth of cities provided opportunities for transmission of infections, unsafe factories increased injuries, death rates rose rapidly, and social supports crumbled with increasing population mobility

By the twentieth century the hospital was beginning to take on its present-day role. Advances in chemical engineering laid the basis for a pharmaceutical industry, for instance research on chemical dyes led to the invention of sulfonamides. Hospitals began to offer cure rather than care, and as the scope for clinical intervention increased technology became more complex and expensive.

The greatest changes occurred from the 1970s onwards, however, with advances in laboratory diagnosis and the recognition of new and often treatable diseases. By the beginning of the twenty-first century, the work of a major hospital in an industrialized country has been transformed from that of a century earlier.

1.1.1 The role of the hospital

The hospital is a health facility that provides medical and surgical care to sick or injured people (Johnson Avery, 2010). They also provide treatment and therapies to patients with intent to improve symptoms and cure the patient's medical problem. It provides institution of measures to protect a person from the occurrence of disease to which a person has been or may be exposed.

Hospitals have been subjected to systematic efforts to change organizational behaviour by offering a good environment in which to practice medicine.

Differences in hospital staffing may influence outcomes for patients with acute conditions, depending on which day of the week the patients are admitted. Most acute-care hospitals provide routine care with full staff on the weekdays and work on a more limited or reduced staff complement on weekends (Fonarow GC et al, 2008). Furthermore, there are differences in physician coverage of patients on weekdays compared with weekends. Recent studies suggest admission on the weekends is associated with a higher death rate than weekday admissions for acute myocardial infections and other serious medical conditions (Kostis et al, 2007). Admission and discharge day of the week may also influence hospital length of stay (LOS). These studies underscore potential adverse consequences of reduced hospital and physician staffing on weekends which is practiced by most hospitals in Cape Coast Municipality.

1.1.2 Ghana Health Service (GHS)

The GHS is a Public Service body established under Act 525 of 1996 as required by the 1992 constitution. It is an autonomous Executive Agency responsible for implementation of national policies under the control of the Minister for Health through its governing Council - the Ghana Health Service Council. GHS includes all the public hospitals in Ghana, thus it does not include Teaching Hospitals, Private and Mission Hospitals.

1.1.3 Mandate

To provide and prudently manage comprehensive and accessible health service with special emphasis on primary health care at regional, district and sub-district levels in accordance with approved national policies. The service has the following objectives:

- Implement approved national policies for health delivery in the country.
- Increase access to good quality health services, and
- Manage prudently resources available for the provision of the health services.

1.1.4 Central Regional Hospital

The Cape Coast Central Regional hospital (Interberton) was established as part of a mandate. It is the leading, newest, most modern hospital in Ghana. It is made up of small pods for each department with ultra-modern 240 bed capacities. It is located at Pedu-Abura, a sub of Cape Coast. Interberton is among the 193 health facilities comprising of 77 public, 100 private and 16 mission/quasi in the region. Most of these private institutions are located in the district capitals and other big towns.

Central Regional Hospital, in collaboration with the Cape Coast Metropolitan Hospital and University of Cape Coast Hospital provide support to sub-districts in disease prevention and control, health promotion and general education of the public on health issues (Antwi, 2008).

In 2010 the President John Evans Atta Mills made a vow to upgrade Central Regional Hospital into a teaching hospital, thereby enabling students at the University of Cape Coast Medical School (UCCSMS) to carry out their clinical studies in Cape Coast. The President was moved when the Dean of UCCSMS Professor Harold Amonoo-Kwofie approached him. The dean explained that if the Regional Hospital was not developed into a teaching hospital, his students would be compelled to carry out their clinical work at the teaching hospitals in Accra and Kumasi (GNA, 2010).

1.1.5 Mission statement

The activities and functions of Central Regional Hospital are guided by an appropriate Mission Statement as follows: The Central Regional Hospital will be the centre of excellence for the delivery of health services, research and training.

The broad goal of health services delivery is to improve the health of all people living in the municipality regardless of age, ethnicity, religious conviction, political affiliation or socio-economic standing. This broad goal encompasses many specific objectives, among them, an increase in life expectancy, reduction in morbidity and fertility rates, and improvement in quality of life. The specific objective of the health care delivery in line with the Government's Poverty Reduction Strategy for 2002-2004 is to:

- Improve the health status of the poor in the country by ensuring a balance between direct health care delivery on one hand and the preventive aspects such as the provision of potable drinking water and good sanitation on the other;

- Promoting equity in health service provision with special emphasis on reducing spatial disparities in the country;
- Enhancing efficiency in health services delivery;
- Ensuring sustainable financial arrangements that protect the poor and the vulnerable; and
- Strengthening links with health-related sectors of society.

1.1.6 Profile of service

Central Regional Hospital is primarily a referral centre for the region. The full ranges of services are as follows:

1.1.7 Curative care

Curative care refers to treatments and therapies provided to a patient with intent to improve symptoms and cure the patient's medical problem. It includes Medical cases such as malaria cases, hypertension, diabetes, cerebra-vascular accident, and diarrhea. It also encompasses surgical cases such as hernia, appendectomy- appendicitis, and internal obstruction. It also includes obstetrics and gynecology department, an outpatient department, and emergency services just to mention a few.

1.1.8 Prevention and Prophylactic treatment

Prevention and prophylactic treatment is classified as a procedure, measure, substance or program designed to prevent a disease from occurring or a mild disorder from becoming more severe. Various diseases are prevented by immunization with vaccines, antiseptic measures, the avoidance of smoking, regular exercise, prudent diet, adequate rest, correction of congenital anomalies and screening programs for the detection of pre-clinical signs of disorders. It includes post-natal care, health education, immunization, mother and child nutrition, home visits and school health lectures.

1.2 Statement of the Problem

If critically ill patients are admitted and do not receive proper care, death may occur at any time. Statistical research on hospital admissions and outcome are usually ignored because of lack of qualified personnel. This study explored the situation as it exists at Central Regional Hospital using statistical methods.

1.3 Objective of the Study

The broad goal of health services delivery is to improve the health of all people living in the municipality regardless of age, ethnicity, religious conviction, political affiliation or socio-economic standing. This broad goal encompasses many specific objectives, among them, an increase in life expectancy, reduction in morbidity and fertility rates, and improvement in quality of life. The specific objectives of the study are as follows:

- To determine association between Outcome of admission and Year of admission conditioning on the type of Medical Ward.
- To determine association between Medical Ward and Outcome of admission conditioning on Year of admission
- To determine association between Year of admission, Medical Ward and Outcome of admission.

1.4 Methodology

Table records of all patients' admissions from 2006 to 2010 were collected and retrospectively analyzed using a model based on log-linear model. The statistical software's employed in this study are SAS and Microsoft Excel 2007. Information regarding sex, admission, and the discharge or death outcome was recorded.

1.5 Significance of the study

The result of the study would among other things help the government and the outside world to have an idea of the association between medical ward and outcome of admission, association between outcome of admission and year of admission and association between medical ward and outcome. It will also help the government to seek ways to identify and eliminate inappropriate admission outcome. The results of the study will be made available for discussion at conferences of medical practitioners to see how findings could be addressed. Finally, this report will serve as a source of reference for further studies.

1.6 Organization of the study

The purpose of the research is to model the length of stay in the Central Regional Hospital wards using log-lineal model. The chapter one dealt with the background to the study, statement of the problem, objectives of the study, methodology of the study, significance of the study and organization of the study.

Chapter two deals with literature review which work is done on the topic. In three, the researcher discusses the methodology to used, mathematical tools to be used and programming language to be used, for chapter four, log- linear model will be used to analyze the data. The results will be interpreted and discussed. The final chapter, which is chapter five deals with the conclusion, recommendation and summary of the findings.

CHAPTER TWO

REVIEW OF RELATED LITERATURE

2.1 Introduction

In this chapter attention will be focused on review literature related to the study, as any good educational research is built on sufficient relevant related literature. Studies that showed substantial agreement as well as those that seemed to present conflicting conclusions were reviewed. The process of examining related literature will help to establish a theoretical framework for this study, and will serve as a guide in the research process. The works that provided support for this aspect of the study have been reviewed under the following subheadings:

i. Log-linear models
ii. Admission to Hospital medical Wards
iii. Outcome of Admission in Medical Wards
iv. Trends in Mortality and Admissions in Hospitals
v. Management of Patient in Hospitals

2.2 Log-linear Model

According to Angela Jeansonne (2002) categorical variables were typically analyzed by calculating chi-square values testing the hypothesis of independence. When tables consisted of more than two variables, researchers would compute the chi-squares for two-way tables and then again for multiple sub-tables formed from them in order to determine if associations and/or interactions were taking place among the variables. In the 1970's the analysis of cross classified data changed quite dramatically with the publication of a series of papers on log-linear models by L.A. Goodman. Many other books appeared around that time building on Goodman's work (Bishop, Finberg & Holland 1975; Haberman 1975). The introduction of the log-linear model provided them with a formal and rigorous method for selecting a model or models for describing associations between variables.

The log-linear model is one of the specialized cases of generalized linear models for Poisson-distributed data. Log-linear analysis is an extension of the two-way contingency table where the conditional relationship between two or more discrete, categorical variables is analyzed by taking the natural logarithm of the cell frequencies within contingency table. Although log linear models can be used to analyze the relationship between two categorical variables (two-way contingency tables), they are more commonly used to evaluate multiday contingency tables that involve three or more variables. The variables investigated by log linear models are all treated as "response variables". In other words, no distinction is made between independent and dependent variables. Therefore, log-linear models only demonstrate association between variables.

If one or more variables are treated as explicitly dependent and others as independent then logit or logistic regression should be used instead. Also, if the variables being investigated are continuous and cannot be broken down into discrete categories, logit or logistic regression would again be the appropriate analysis.

The basic strategy in log-linear modeling involves fitting models to the observed frequencies in the cross-tabulation of categorical variables (Jeansonne, 2002).

The models can then be represented by a set of expected frequencies that may or may not resemble the observed frequencies. Models will vary in terms of the marginal's they fit, and can be described in terms of the constraints they place on the associations or interactions that are present in the data. The pattern of association among variables can be described by a set of odds and by one or more odds ratios derived from them. Once expected frequencies are obtained, we then compare models that are hierarchical to one another and choose a preferred model, which is the most parsimonious model that fits the data. It's important to note that a model is not chosen if it bears no resemblance to the observed data. The choice of a preferred model is typically based on a formal comparison of goodness-of-fit statistics associated with models that are related hierarchically (models containing higher order terms also implicitly include all lower order terms). Ultimately, the preferred model should distinguish between the pattern of the variables in the data and sampling variability, thus providing a defensible interpretation.

According to Alan Agresti (1996) log-linear models are used to analyze categorical data. They model the means of cell counts in contingency tables by describing the association patterns among a set of categorical variables without specifying any variable as a response (dependent) variable. Log-linear models are most natural when at least two variables are response variables. When only one variable is a response, it is more sensible to use logit models directly." Logit models correspond to log-linear models when there is one respon se variable and it is easier to analyze and interpret results of a logit model, particularly when the response variable is binary.

The term log-linear comes from the form of the model; the natural logarithm of cell counts is modeled as a linear function of the effects of categorical variables and their interactions. For example, suppose that we want to investigate relationships between three categorical variables X, Y and Z, where X has I categories, Y has J categories and Z has K categories. Then the full (saturated) log-linear model is:

$$\log(m_{ijk}) = \lambda + \lambda_i^X + \lambda_j^Y + \lambda_k^Z + \lambda_{ij}^{XY} + \lambda_{ik}^{XZ} + \lambda_{jk}^{YZ} + \lambda_{ijk}^{XYZ},$$

In clinical investigations of Howell (2007) we often have response and explanatory variables that are both categorical. The categories here are nominal. There is no ordering between them. Sometimes the categories could be ordered, and we say that the variable is ordinal. For example survived; survived with deficits; died.

In the case of categorical data one is commonly looking for association between two variables. The χ^2 test is one example. Usually the χ^2 test is performed for a 2 × 2 contingency table. Even though the test is still valid for larger tables, one can run into difficulties with interpretation. All that a significant χ^2 test tells us is that the pattern of data as depicted in the table could not arise by chance. In a 2 x 2 contingency table the presence or absence of association between the two variables is often clear from inspection alone. The formal statistical test merely confirms (or refutes) it. In the case of complicated contingency tables involving several variables a more robust form of analysis is the log-linear analysis.

It is noted that the χ^2 test involves entering the frequency counts for the two categorical variables in rows and columns together with the marginal totals (i.e. totals for each row and each column), as well as the full overall total. From these totals the expected frequency for each cell is calculated. Then $\chi^2 = \Sigma$ (Observed frequency − Expected)^2 ÷

Expected. Also observed, that the probability of the joint occurrence of two independent events is the product of their separate probabilities). A log-linear model is best thought of as a model for the expected frequencies in a contingency table. But it is more than just an alternative form of the χ^2 test. Its strength lies in that it can be extended to quite complicated contingency tables involving several variables.

In a 2 × 2 contingency table the probability of an individual occupying a given cell is the product of the marginal totals, since they represent the respective main effects probabilities. Log-linear analysis is based on the fact that the logarithm of a product is the sum of the individual logarithms of the individual terms in the product. In other words $\log(p \times q) = \log p + \log q$. To put it in the statistical jargon, the logarithm of the cell frequencies is a linear function of the logarithms of the components.

In log-linear analysis tables are formed that contain one-way, two-way, and higher order associations. The logarithm of the cell frequency is estimated by means of a linear equation (function in mathematical terminology). The log-linear model so developed starts with all the one-way, two-way, and higher order associations. The aim is to construct a model such that the cell frequencies in a contingency table are accounted for by the minimum number of terms. This is done by a process of backward elimination. What this means is that one begins with the maximum number of terms, and then drops a term in each round. Statisticians refer to it as the backward hierarchical method.

In practice, one commences the analysis by including all the variables. This is referred to as the saturated model. It can usually be expected to predict the cell frequencies perfectly. Then the highest order interaction is removed, and its effect on how closely the model can now predict the cell frequencies is noted. This process of progressive elimination is continued. Each time a variable is removed a statistical test is performed to determine whether the accuracy of prediction falls to an extent such that the component most recently eliminated should be one of the components of the final model. At each stage the assessment of goodness-of-fit is made by means of a statistic known as the likelihood ratio. The final model includes only the associations necessary to reproduce the observed frequencies.

A comparison of the observed and expected frequencies for each cell using the likelihood ratio makes the evaluation of the final model. In the same way as in the case of χ^2 test, small expected frequencies can lead to loss of power. It is recommended that all expected frequencies should be greater than1, and not more than 20% should be less than 5.

2.3 Admission to Hospital Medical Wards

"The decision to admit patients to the medical wards is determined by age, co-existing illness (co morbidity), physical and laboratory findings, the ability of the patient to comply reliably with an oral medication, and the resources available to the patient outside the hospital" (Ali, Woldie and Mirkuzie, 2010). In studies done in developed countries, medical admissions accounted for 22.2%, 33.0%, and 13.0% of total hospital admissions in U.S.A, Western Australia and Hong Kong, respectively (Oregon Health &Science University Pharmacy).

In a South African study, admissions to the medical wards constituted 40% of the total hospital admissions. In developed countries non-communicable diseases namely cardiovascular diseases are the main reasons for medical admissions. (Elias Ali, 2010)

For instance the Australian study, the most common reason for admissions to the medical wards (29% of patients) was cardiovascular disease. In another study, admissions to medical wards at a hospital in Hong Kong were most frequently associated with the cardiovascular system, which made up 30.3% of all medical cases. However, in cities and towns of developing countries, the increasing urbanization and westernization of the population is changing the morbidity pattern of diseases. It is becoming widely accepted that non-communicable or chronic diseases are also now the major causes of death and disability in low and middle-income countries, (Elias Ali, 2010).

Particular, smoking is increased in underdeveloped countries. The annual cigarette consumption per adult (in cigarettes) has increased from 860 in the early 1970s 1410 in 1995. The reason was aggressive marketing of tobacco companies, delay in implementing antismoking regulations, and because of the public perception of the risk of smoking is still low. This has been supported by studies from South Africa, (Elias Ali, 2010).

Referral hospitals are often a highly specific focal point for disease-specific health promotion and education. Even though review of records of referral hospital admissions may not indicate the actual prevalence of diseases in the community, it will provide clues about the changing pattern of diseases. Unfortunately data on the specific diseases that indicate reasons for admission to referral hospitals and their outcomes is scarce. In addition, the study did not determine the relationship between the reasons for admission and socio-demographic variables such as sex, and place of residence. It also lacked the assessment of outcomes in relation to hospital stay. Therefore, the objective of the study was to describe the reasons and outcomes of admissions to the medical wards of JUSH.

A retrospective cross-sectional study was conducted from May 16 to May 26, 2009 on patients who were admitted to the medical wards of Jimma University Specialized Hospital from January 1, 2008 to December 31, 2008, (Elias Ali, 2010).

The hospital serves about 11 million people living within a very wide catchment area of about 250 km radius. It is a training center for about 700 health sciences students each year. The hospital has four major (Medical, Surgery, Gynecology/ obstetrics, and pediatrics) and five other departments. The hospital provides postgraduate training in Internal Medicine, Surgery, Gynecology/ obstetrics, Pediatrics, and Ophthalmology. It has 450 beds and a total of more than 550 employees. Internal medicine department has 67 beds. The main diagnostic modalities in the hospital are routine laboratory investigations, radiology and histo-pathologic techniques. All patients who were admitted to the medical wards of JUSH during the study period (January.1, 2008 to December. 31, 2008) and whose case notes were available in the hospital registration room archive was included. A case note was classified according to year of admission. The recent case notes of patients admitted to the medical wards in the year 2008 was retrieved. Hence, all cases found during the study period was included in the study and no sampling technique was used. The dependent variables in the study were reasons for admission and outcome of admission, while the explanatory variables included socio-demographic characteristics of the patients in the case notes reviewed, co-morbidities, complications, duration of hospital stay and month of admission (Ali *et al* 2008).

The following operational definitions were used in the study:

- *Reason for admission*: is the primary diagnosis given to the illness of the patient by the physician when the patient was admitted.

- *Co-morbidity*: is an illness which had occurred with the primary diagnosis during the time of admission
- *Complications*: Severe symptoms of the disease which could lead to death unless treated.
- *Season of admission*: the particular time (month) of the year during which the patient was admitted.
- *Outcome of admission*: is diagnosis at discharge.

2.4 Outcome of Admission in Medical wards

Leng et al. (1999) stated that in recent years have seen rises in readmission both in the UK and the US. In Oxfordshire, readmission rates almost doubled between1968 and 1985, with 75% increase in emergency readmissions. A similar rise was also seen in Scotland, where the overall readmission rate rose from 7.1% in 1982 to11.4% in 1994.7 8 Unfortunately, the definition of readmission has varied considerably between many studies, including the time since discharge before readmission, and the type of readmission (elective or emergency). This focuses on unplanned, or emergency, readmissions. The rising trend in emergency readmissions is worrying partly because of implications about quality of care but also because of the burden placed on provision of hospital services. Reasons for the increase are less clear and are likely to be complex. Possible explanations include changes in the social and demographic structure of the population, falling lengths of stay, and the medical condition itself. The increasing number of elderly people in the population may be particularly important in generating the rise because admission rates increase dramatically with age, especially in those living alone. It has also been suggested that readmissions are related to recurring medical problems, indicated by a higher than expected number of admissions in the period before the readmission.

Huffman (1990) stated that the medical record "must contain sufficient data to identify the patient, support the diagnosis or reason for attendance at the health care facility, justify the treatment and accurately document the results of that treatment"

The main purpose of the medical record is: To record the facts about a patient's health with emphasis on events affecting the patient during the current admission or attendance at the health care facility, and for the continuing care of the patient when they require health care in the future.

A patient's medical record should provide accurate information on: who the patient is and who provided health care; what, when, why and how services were provided; and the outcome of care and treatment.

The medical record has four major sections: Administrative, which includes demographic and socioeconomic data such as the name of the patient (identification), sex, date of birth, place of birth, patient's permanent address, and medical record number; legal data including a signed consent for treatment by appointed doctors and authorization for the release of information; financial data relating to the payment of fees for medical services and hospital accommodation; and clinical data on the patient whether admitted to the hospital or treated as an outpatient or an emergency patient.

Amit G. et al. (2003) reveal that acute myocardial infarction is a leading cause of morbidity and mortality in Israel and the western world. It is believed that part of the decline in coronary artery disease mortality over the last10±15 years is attributable to new treatments and their availability. The customary management of a patient presenting with AMI includes admission to a coronary intensive care unit, which is accepted as the optimal site for patient monitoring and delivery of care. However, CCU beds are a limited and expensive resource. The decision of whether to admit to the CCU or to an alternative department (usually an internal medicine ward) is based on the patient's clinical characteristics as well as on logistic considerations such as availability of a CCU bed. Indeed, clinical criteria for referral of low risk patients to alternative and less costly admission units are constantly being suggested. Nevertheless, there is an imbalance regarding the admission to CCU for some demographic groups such as women and the elderly that might affect prognosis. Although the total number of CCU beds in Israel has increased, data based on discharge diagnoses of 80% of Israeli hospital admissions (1994), showed that almost half the AMI patients were initially was to compare the demographic and clinical characteristics, treatment patterns and mortality of AMI patients treated in a CCU with those treated in an internal medicine ward.

Denise Colmer (2009) explained that it is important to remember that first impressions are often those that the patient or relative/career remembers most. Being admitted to hospital is a very stressful event for the patient and the family. It is essential that the staff be friendly, confident and professional, offering reassurance, explanation and information.

Research shows that giving too much information at the time of admission can be confusing to the patient and only a small percentage is retained. Initial information should be enough to guide the patient/relative through the first 24 hours. The extent of the patient's assessment and the development of the care plan will be dependent upon the patient's condition and circumstances of admission. It is suggested that all discharge and aftercare arrangements must be made in a manner which ensures a safe and smooth transition from a stay in hospital or residential setting to returning home or to community based treatment care. Arrangements should also ensure that patient's receive a service that meets their individual needs.

Again, there must be effective channels of communication to inform care coordinators and General Practitioners of any unplanned attendance, admission and discharge of a child who has a Child Protection Plan, including Trust safeguarding children staff

The procedure for discharge will be facilitated by the named nurse, in collaboration with the care coordinator and the MDT. The procedure for discharge will include processes as detailed in the respective services processes and in line with Care Programme Approach.

Geoffrey Yeo (1999), reveal that Hospitals deal with the life and health of their patients. Good medical care relies on well-trained doctors and nurses and on high-quality facilities and equipment. Good medical care also relies on good record keeping. Without accurate, comprehensive up-to-date and accessible patient case notes, medical personnel may not offer the best treatment or may in fact misdiagnose a condition, which can have serious consequences. Associated records, such as X-rays, specimens, drug records and patient registers, must also be well cared for if the patient is to be protected. Good records care also ensures the hospital's administration runs smoothly: unneeded records are transferred or destroyed regularly; keeping storage areas clear and accessible; and key records can be found quickly, saving time and resources. Records also provide evidence of the hospital's accountability for its actions and they form a key source of data for medical research, statistical reports and health information systems.

It is still common in many hospitals to give each department total autonomy in the management of its records. Unfortunately, this decentralization of records care often leads to poorly designed filing systems, loss of information, premature destruction or unnecessary retention of records and ultimately to inefficiency and wasted resources.

It is noted that, patient care will be adversely affected if correct records are not maintained or if records are inadequately managed or if there is no means of coordinating the care the same patient receives in different departments. A structured and effective records management program me, covering all departments and all records irrespective of media, should be the aim of every hospital.

Yusuf (1998) looked at the association between rates of invasive and revascularization cardiac procedures and the risk of re-admission for unstable angina in a six-month follow-up study among 7,987 consecutive patients presenting with unstable angina or suspected myocardial infarction without ST-segment elevation recruited prospectively from 95 hospitals in six countries.

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Herlitz (1988) studied the relationship between size of myocardial infarct and risk of re-hospitalisation in a five-year follow-up study of 809 patients with recent myocardial infarction.

In the Philbin (1999) study it was concluded that, while patient characteristics, hospital features and processes of care may be used to estimate the re-admission risk, some of the variation may be the result of clinical decision making. The 21% of patients re-admitted having had congestive heart failure were characterized by: greater proportion of black people, more co-morbidities, higher prevalence of health insurance, and use of telemetry monitoring in initial admission.

Patients less likely to be re-admitted were: treated at community hospitals, those having echocardiograms and cardiac catheterization and discharged to skilled nursing facilities.

Glasgow (1991) compared the characteristics of children with diabetes re-admitted to a children's hospital between 1984 and 1989 with those of new-onset patients admitted for stabilization and education and with those of out-patients in the diabetes program.

Minkovitz (1999), examined the effects of medical history, ambulatory care prior to hospitalization, and ambulatory care after discharge on the risk of re-hospitalization within one year among 119 low-income urban children (aged 0-14 years) hospitalized for asthma between July 1993 and June 1995.

In the study by Hayward (1993), it was observed that, the quality of care for a stratified random sample of admissions was evaluated using structured implicit review. The key findings were that patients who died in-hospital were substantially more likely than those who were discharged alive to be rated as having had substandard care (30% vs. 10%; $p < 0.001$), whereas cases who had subsequent early re-admissions did not have poorer quality ratings.

Patients who die in hospital may be more likely to have had substandard care than those discharged alive (Hayward, 1993), while death shortly after leaving hospital may be the result of premature discharge (Brook, 1992). For particular diagnoses, an inverse relationship may exist between a hospital's in-patient death rate and the early re-admission rate.

Ashton (1996) suggests that for certain conditions, death or re-admission within a specified time period may be an appropriate composite indicator of quality of care.

Wray (1995) found that for certain conditions, poor quality in-patient care would be more likely to lead to death than to early re-admission. For such conditions, outcome indicators based on case-fatality rates will be more appropriate than those based on re-admission rates.

Taylor (1995) stated that patients admitted to a 30 bedded acute geriatric medical ward in 1993 were followed up to discharge. The admission rate on weekend days was half that for weekdays. Six percent of ward discharges occurred at weekends, over half being due to death. Respiratory, cardiovascular and central nervous systems disorders were the commonest reasons for admission (56%) and death (73%). Greater emphasis should be placed on discharging patients at weekends

2.5 Trends in Mortality and Admissions in Hospitals

Congestive heart failure (CHF) is a common disease requiring admission to hospital among elderly people and is associated with a high mortality rate (Feldman, 2001). The objective of the study was to examine trends in CHF mortality and admissions to hospital in Montreal between 1990 and 1997 for individuals aged 65 years or more. They obtained information about deaths from the Quebec Death Certificate Registry database and information about admissions to hospitals from the Quebec Med-Echo database.

Although age-adjusted rates of mortality from CHF did not change significantly between 1990 and 1997, the annual rate of admission to hospital for CHF increased from 92 per 10 000 population in 1990/91 to 124 per 10 000 population in 1997/98 ($p < 0.01$). Deaths due to CHF, expressed as a proportion of all cardiovascular deaths, increased among women from 5.6% in 1990 to 6.2% in 1997 ($p = 0.01$). The rate of readmission for all causes following a first admission for CHF during that year rose over the study period from 16.6% to 22.0% within one month ($p < 0.001$) and from 46.7% to 49.4% within 6 months ($p = 0.03$). Conversely, mean annual length of stay per admission decreased from 16.4 days in 1990/91 to 12.2 days in 1997/98.

The increase in rates of admission to hospital for CHF and the stable rates of CHF mortality suggest that the management of CHF and its antecedents has improved in recent years. The mortality rate for individuals with congestive heart failure (CHF) remains high; however, rates of survival are improving in some countries. The increasing use of effective treatments to reduce death and complications due to ischemic heart disease, which is a major cause of CHF, may have resulted in an increasing number of people alive with CHF. These treatments include pharmacological therapy, such as thrombolytic therapy, angioplasty and coronary artery bypass surgery. The aging of the population and its effects on the incidence and prevalence of heart failure suggest that this problem will become more pronounced in the future. Advances in heart failure management may reduce morbidity and improve survival; however, CHF remains a frequent cause for admission to hospital among elderly people. The objective of this study was to describe trends in the mortality rate and in admissions to hospital for individuals aged 65 years or more with CHF, living in Montreal.

This investigation was limited to residents of Montreal between 1990 and 1997 who were aged 65 years or more. Mortality data were obtained from the Quebec Death Certificate Registry database, whereas information about admissions to hospital was obtained from the Québec Med-Écho database (Brown, David, LambertandBogaty, 2010).

The former reports deaths per calendar year (January 1 to December 31), and the latter provides information about hospital discharges per hospital financial year (April 1 to March 31). CHF mortality rates, by sex and age group (65 – 74, 75 – 84, ≥ 85 years), were calculated by dividing the number of patients who died from CHF by the population alive during that year. Furthermore, an age-standardized mortality rate was calculated for all those aged 65 years and more. The standard population used for the age standardization was the population of Montreal in 1996. The observed annual rates of CHF for the groups aged 65 – 74 years, 75 – 84 years, and 85 years and more was applied to this standard population in order to calculate the yearly age-standardized rates. The proportion of CHF deaths among total cardiovascular disease deaths was calculated. The mean annual number of CHF admissions per patient was calculated as the number of

CHF admissions divided by the number of individuals admitted for CHF in that year. An annual rate of admission to hospital was calculated by dividing the number of admissions to hospital by the annual population aged 65 years and over. A rate of admission to hospital was also age-standardized. A readmission rate was calculated as the number of patients admitted within one or 6 months after the date of discharge following their first admission for CHF during that year. The Montreal population for each year of the study period was obtained from the Quebec Ministry of Health and Social Services. The test for log linear trend in proportions was used to evaluate the statistical significance of trends observed through time.

The number of people aged 65 years and more living in Montreal during the study period ranged between 249 899 and 269 354, whereas the number of deaths from CHF ranged between 239 and 300 per year(Feldman, 2001). Men had higher mortality rates than women for all years except 1993 and 1996. The crude rate of death from CHF for women increased from 9.9 per 10 000 population in 1990 to 10.3 per 10 000 population in 1997 ($p = 0.02$). When standardized for age, the observed increase in mortality among women no longer reached statistical significance. Between 1990 and 1997, all cardiovascular disease deaths increased by 1.7% in men and by 3.6% in women. The proportions of CHF deaths among all cardiovascular disease deaths in women were higher compared with those in men, and increased in women from 5.6% in 1990 to 6.2% in 1997. Death rates from CHF ranged between 2.0 per 10 000 population in 1990 and 3.1 per 10 000 population in 1997 among the 65–74-year age group, between 10.0 per 10 000 population in 1990 and 13.1 per 10 000 population in 1997 in the 75–84-year age group, and between 41.2 per 10 000 population in 1990 and 62.4 per 10 000 population in 1997 for those aged 85 years and more. Men consistently had higher mortality rates than women among individuals aged less than 85 years, however women aged 85 years and more had higher rates in 1991 and 1996.

2.6 Admissions to Hospital

Annual rate and age-adjusted rates of admission to hospital increased significantly ($p < 0.001$) for both men and women. Rates for men remained higher than those for women. Rates of admission to hospital increased in all age groups, but most rapidly in those aged 85 years or more. There was an increase in both the number of admissions and patients admitted (Feldman, 2001). During the study period, mean length of stay decreased from 16.4 days in 1990/91 to 12.2 days in 1997/98, and length of stay was consistently higher in women than in men. The rate of readmission for all causes following a first admission for CHF during that year increased significantly from 16.6% to 22.0% within one month of discharge ($p < 0.001$) and from 46.7% to 49.4% ($p = 0.03$) within 6 months. Readmissions within one month due to cardiovascular problems rose from 10.3% to 13.5% ($p < 0.001$) and from 29.9% to 32.9% ($p = 0.003$) within 6 months.

Although mortality rates did not change significantly, an increase was observed in the number of women dying from CHF as opposed to other cardiovascular disease death-related mortality. Rates of admission to hospital increased significantly for both men and women, whereas respective inpatient days per episode decreased for both sexes. Concurrently, readmission rates increased among both men and women.

The information obtained from these administrative databases has its limitations. First, these databases do not store information on clinical severity. Second, diagnostic coding may be problematic; because only primary diagnoses of CHF were considered for this study, we may well have underestimated the number of people with CHF. Although these factors may affect the absolute number of admissions to hospital and deaths, this probably does not affect the overall conclusions regarding the trends observed through time.

Declining length of stay may be due to improvements in the management of CHF or increased pressure on beds because of an increasing number of patients. During the study period, the number of hospital beds available in Montreal decreased as part of the health care reforms that was introduced in Quebec, which involved a shift toward more ambulatory care and the closure of several hospitals. Differences between women and men in admissions and mortality may reflect differing clinical profiles associated with different mortality risks for men and women. In men, coronary artery disease is the more frequent underlying cause of CHF, whereas in women it is associated with diabetes, hypertension or a trial fibrillation, and left ventricular systolic function is often preserved. Gender differences in the use of services may reflect different requirements, demographic differences or differences in access to services by men and women, as has been observed for coronary heart disease.

Specific CHF programs and specialized clinics were being introduced in Montreal, subsequent to our study. Some studies suggest that these measures reduce hospital admissions and improve quality of life. In order to evaluate continuously the use, cost and outcome of CHF service provision in Montreal, a multicentre prospective monitoring system is currently being established.

Kolo P. M and Chijioke Adindu (2010) revealed that the risk of dying is known to differ for men and women in terms of age at and cause of death. The gender disparities depend on the environment, level of economic development and some biological factors. Available statistics showed that the life expectancy of females at birth exceeds that of males by three years (66 versus 63) in developing countries and by 7 years (79 versus 72) in the developed nations of the world. Although, women generally have a higher life expectancy at birth, there is the concern that women in third world countries are disadvantaged in terms of mortality. The increase in mortality among women in developing countries has been attributed to poor access to health care services, economic depression and negative cultural practices. In the developed world, longevity is higher in females because of high quality of obstetric care and lower coronary disease risk profile compared with males.

However, in developing countries, the life expectancy gap is narrowed by unfavorable socio-cultural factors and high maternal deaths among women.

Recent population studies have shown that most developing regions of the world are undergoing gradual epidemiological transition resulting in high burden of both communicable and non-communicable diseases. The duration of hospital stay has also been observed to be inversely related to the mortality rate in the medical wards. Although, we have recently reviewed the causes of death in medical wards of our hospital, but the influence of gender on the current trends in mortality among medical admissions has not been well defined. They therefore studied sex-differences in causes of death in the medical wards of UITH, Ilorin, Nigeria between January, 1996 and December, 2005 (ten years). UITH, Ilorin is a tertiary health institution strategically located in the North-Central zone of Nigeria with bed capacity of 515. One hundred and ten of the bed spaces are dedicated to the medical admissions.

In the retrospective study, information was obtained from hospital death register and case records of all patients who died during the period under review. The age, sex, occupation, principal diagnosis, duration of hospital stay, primary cause of death, type of previous treatment and post-mortem examination results were noted. The total number of admissions during the period was recorded. Most of the patients were referred either from private and/or government hospitals while some had self-referral or were brought by relatives in emergency situations. The data was analyzed using the SPSS statistical software version 15 and mean ± SD was generated for continuous variables. Student t-test was used to compare means of continuous variables while chi-square test was used to test significance of difference between two proportions. P-value of <0.05 was taken as a measure of statistical significance.

Seventeen thousand six hundred and fifty patients, consisting of 10,040 (56.9%) males and 7,610 (43.1%) females were admitted during the period under review. Of these, 4220 died which was made up of 2624 (62.2%) males and 1596 (37.8%) females (37.8%) with overall percentage mortality of 23.9%. Mortality rate was significantly higher (Chi ^{2} = 62.5, p = 0.0001) in males (26.1%) than in females (20.97%) with sex ratio (number of male deaths per 100 female deaths) of 160:100. However, mean age of the deceased females (46.9±19.4 years) was similar to that of the males (46.7±17.9 years), p = 0.87.

The percentage of women aged 10-19 who died (5.3%) was higher (p = 0.03) than that of males (3.9%). The mortality rates were however similar in females and males aged 20-49 years. On the other hand, percentage of deceased males in the age group 50-59 years was higher ($p = 0.0001$) than that of females. The proportion of deceased females who were 80 years and above was higher ($p = 0.0001$) than that of males. Sex differences in duration of hospital stay before death was displayed. The mean duration of hospital stay before demise was significantly longer ($p = 0.0001$) in females (15.7 ±26.1 days) than in males (10.9 ±17.7 days). The percentages of males who died on the 1st day, 6-10th and 11-20th day of admission were higher ($p = 0.0001$) than females. However, more females died after 30th day of hospitalization.

The systemic distribution of causes of death by gender was discussed, although, infections and diseases of the central nervous system were leading causes of death in both sexes, the percentage of females (38.4%) who died from infections was significantly higher ($p = 0.006$) than that of males (34.2%). HIV/TB infections either alone or as co-infection accounted for majority of deaths due to infections in females. While deaths from gastrointestinal system and liver, and endocrine system were higher in males (p = 0.0001 and 0.02 respectively), deaths due to neoplasm and hematological disorders were higher in females (p = 0.0001 and 0.0001). However, deaths from nervous, cardiovascular, renal and respiratory systems were similar in both sexes. The top ten causes of mortality in both females and males are displayed. HIV/TB and septicemia were the first and second commonest causes of death in the two groups respectively. Chronic liver disease ranked third in males, followed by stroke, chronic heart failure, chronic renal failure, meningitis, respiratory failure, diabetic complications and primary liver cell carcinoma in that order. In the females, stroke was the third commonest cause followed by chronic heart failure, chronic renal failure, meningitis, anemia, leukemia/lymphoma and primary liver cell carcinoma in descending order.

The results of the present study indicated that the number of admissions and mortality rate in the adult female medical wards were less than that of male medical wards. This is in accord with earlier studies which showed that females have a lower mortality and longer life expectancy than males. Although, socio-cultural factors may account for lower hospital admissions among women studied, this does not explain the lower mortality rate among them. The precise explanations for the gender difference in life expectancy still elude scientists because of the apparent complex interplay of biological, social, and behavioural conditions. However, the observed lower risk of coronary artery disease and lower rate of cigarette smoking among females compared with males may contribute significantly to the difference.

Age is a recognized natural risk factor for death. In the study, the percentage of deceased females in the age group 10-19 was higher than that of males. The higher adolescent deaths among the females may be related to higher rates of HIV/TB infections among them than males. However, percentage mortality among males in age group 50 - 59 years was significantly higher than in females. This may be due to higher risk of cardiovascular deaths among males of this age group than females. In contrast, more deaths occurred in females aged 80 years and above in this study which may be a reflection of the fact that there are more females than males in this age group in most populations of the world.

Early mortality following hospitalization occurred more in males than females. This may be related to health seeking behaviors in the population studied. In our environment, many women are not gainfully employed and the family economic power rest with the men. Women who are very sick may likely die before decisions are made to take them to the health care facilities which may lead to under-representation of their mortality profile. It is also possible that the inverse relationship between hospital stay and mortality rate in males may be related to late presentation to hospital due to ignorance and poverty. In related study by Garko et al (2003) short duration of hospital stay was observed to be associated with increased mortality.

Although infections were the leading causes of death in this study, the percentage of females (38.4%) who died from infections was significantly higher ($p = 0.006$) than that of males (34.2%). The higher percentage (19.5%) of women who died from HIV/TB infections compared to males (14.4%) contributed significantly to the sex difference in mortality due to infections. Globally, heterosexual transmission is the most important mode of acquisition of HIV infection in women. Some of the factors identified in women for engaging in high risk sexual behaviors include; financial gains, low self esteem, need to feel loved by a male figure, alcohol and drugs. The on-going government programmes designed to empower women financially and discourage girl child abuse should be vigorously pursued in order to reduce the burden of HIV infection among women.

Deaths from gastrointestinal tract, liver and endocrine disorders occurred more in males than in females. Ethanol abuse among males and hepatitis B viral infection may account for this difference in mortality. On the other hand, more females died from hematological disorders and neoplasm than males.

In conclusion, gender differences have been observed in duration of hospital stay, mortality and causes of death in our medical wards with females having longer stay before death and lower death rate compared with males. Although, the overall mortality was higher among males, the risk of dying from infections, HIV/TB, hematological disorders and neoplasm was higher in females. While more males died from chronic liver disease and endocrine diseases. The percentages of deaths from cardiovascular, renal and nervous systems were similar between the two groups. They recommended gender specific community interventions for the control of HIV/AIDS, TB and liver diseases in the population studied.

2.6 Management of Patients in Hospitals

It is necessary to obtain empirical measures of performances rooted in the principles of production economics, in the management of critically ill patients and to evaluate the factors that are contributing to hospital performance in treating these patients. The method was applied to the individual clinical decisions relative to 993 critical patients in different intensive care units in Catalonia (Spain) in 1991and1992 (Puig-Junoy, 1998). They identify patients who have been treated in an intensive care unit (ICU) as critically ill. Critical care is being closely scrutinized given the important contribution of these health care services to growing health care expenditures. Intensive care units were deemed to account for 1% of the Gross Domestic Product (GDP) and 28% of hospitals costs in the US. Intensive care unit performance measurement is obviously relevant from the policy point of view. These are partial but theoretically rooted indicators of intensive care unit performance. An intensive care unit is technically inefficient in treating a patient if it does not minimize its inputs given its outputs. Technical efficiency has been advocated as an adequate measure to compare performance of firms having different ownership regimes or legal status, especially to evaluate and compare public sector and not-for-profit activities performance, which are predominant in the hospital sector. Data envelopment analysis (DEA) has proved especially valuable in hospitals and in many institutional settings where non-marketed multiple output are considered and the correct weighting of outputs cannot be defined. Empirical measurement of inefficiency ranges from two main alternative methodologies: stochastic parametric regression-based methods to non-stochastic non-parametric mathematical programming methods. Data envelopment analysis is the more commonly used family of linear programming models. Parametric methodology obtains efficiency measures computed in terms of the distance that lies between the observation and the estimated function. Thus, scores may differ according to the chosen functional specification. Data envelopment analysis, in contrast, assumes no measurement error or random fluctuations in input–output measures, being a completely deterministic method.

Simulation studies comparing data envelopment analysis with competing forms of statistical regressions indicate the relation between them depends on the choice of the functional form. Comparisons of both methods show that some observations misclassified as efficient by data envelopment analysis may be corner observations: those not appearing in the envelope of any inefficient observation. Recent research comparing the two approaches suggested that econometric and linear programming results do not differ dramatically, when based on the same data and conceptual framework. An increasing number of researchers have recently applied data envelopment analysis to institutional health care providers (hospitals, nursing homes, primary health care centers, and pharmacies) to measure efficiency. Institutions comprise many different decision levels, thus there are difficulties in attributing responsibilities for inefficiency in the organization. At both the institutional and physician levels some patients may not be treated efficiently, however, they cannot be identified. A unit may be efficient in treating some specific type of patients but not in others. Health care may be interpreted as a very heterogeneous production process given the presence of patients as an input which requires decisions about resource allocation to be specific for each of them. Most data envelopment analysis studies do not consider previous patient characteristics as an input or consider them in a very rough aggregate form (the number of admissions). In this case, obtained efficiency scores may be strongly influenced by missing or erroneous measurements in individual data. Hospitals produce a wide range of heterogeneous outputs in differing proportions. Output dimensions have proved to be very difficult to measure. A way to alleviate this measurement problem in efficiency analysis is to use more homogenous and less aggregated units by observing specific services in the hospital, such as the intensive care units.

Clinical performance was measured as the difference between the actual achieved survival rate of patients treated in an intensive care unit and the survival rate expected by the model. The resource use performance for each hospital was computed as the expected mean weighted hospital days minus actual observed mean weighted hospital days. The study conducted by Shortell et al. (1998) using data from 42 intensive care units with 200 or more beds was intended to shed light on 'more efficiently managing intensive care units and reducing the variation in patient outcomes'. Measures of performance in the study are: risk-adjusted mortality, risk-adjusted length of stay, evaluated technical quality of care, evaluated ability to meet family member needs and nurse turnover. Ordinary least square results showed that factors' explaining risk-adjusted mortality was technological availability and diagnostic diversity, the first with a negative effect and the second with a positive one; caregiver interaction appeared negatively related to risk-adjusted intensive care unit length of stay. Technological availability was measured by how many of 39 recommended items were available in the unit. Past literature presents two main limitations to measuring and explaining intensive care unit performance.

First, no homogenous and theoretically rooted concept of efficiency is used describing a clear relationship between inputs and outputs. Usually a broad set of non-related performance indicators is presented ranging from input (length of stay) to output (mortality) variables which have limited value in measuring productive efficiency. Thus, reviewed studies do not permit measurement and explanation of productive efficiency. Second, ratios between observed and expected values may only reflect average functions, but do not permit a best practice pattern of the input–output relationship to be estimated, a matter of considerable importance in an industry where incentives to cost minimization are scarce.

In the paper, they propose to explore the usefulness of data envelopment analysis to measure technical efficiency at the patient level. Decision-making units are defined as the intensive care units taking resource allocation decisions in an individual production process, that is, a patient.

Defining this level of analysis allows them to consider in detail patient characteristics, which constitute necessary dimensions of the input and output set. To assess the impact of health care providers on health outcomes it is necessary to use measures of inputs and outputs among individuals. The shortage of individual health data probably explains the exclusive use of aggregated data to assess the efficiency of providers. Production frontier and efficiency scores are computed through the comparison of homogenous patients treated in the same or different hospitals. In the econometric frontier approach Bosmans and Fecher provide an exception.

In the rest of the text they use the term intensive care unit performance as being equivalent to performance in clinical management of critically ill patients. As treated in the paper, and as it is in reality, management of critically ill patients is a broader subject than intensive care unit management, strictly speaking.

The paper makes a contribution to the existing literature on data envelopment analysis and performance of critically ill patient management in three areas. First, it applies an extended data envelopment analysis model (non-discretionary and categorical variables, and weight constraints under consideration) to the measurement of technical efficiency of intensive care units at the patient level. Second, it incorporates severity of illness and quality measures in the input–output set obtained from Mortality Probability Models. And, third, it presents results from a log linear regression model of environmental factors explaining differences in efficiency scores.

A major problem in efficiency analysis of health care providers is the difficulty of appropriately measuring the presence of the patient in the input (severity of illness) and the output set (improved health status). This problem represents that productive efficiency literature usually restricts performance measures to the production of intermediate outputs (activity). Measurement of efficiency in health services is biased by the way that the quality dimension of output is measured. To the extent that outputs are measured with some error, inefficiency could simply represent difficulties in measuring output and adjusting for quality. The present survey measures severity of illness by the probability of hospital mortality at admission to the intensive care unit. Variables considered by the researchers at admission are: cirrhosis, metastatic cancer, chronic renal insufficiency, heart rate, systolic blood pressure, presence of coma, acute renal failure, cardiac dysrhytmia, cerebrovascular incident, gastrointestinal bleeding, intracranial mass effect, age, type of admission, cardiopulmonary resuscitation prior to intensive care unit admission and mechanical ventilation. The relatively small number of variables minimizes the burden of data collection and the potential for error. Outcome of critical patients after hospital treatment is measured by survival status at discharge.

Severity measures have tended to focus exclusively upon the risk of one particular outcome, death. Existing scoring systems equate the severity of illness with the risk of mortality in intensive care unit patients. The most validated of these scoring systems for intensive care unit is patients are the Acute Physiology and Chronic Health Evaluation. The admission model is calibrated well in developmental and validation samples (goodness-of-fit tests: p 0.623 and p_0.327, respectively, where a high p-value represents goodness-of-fit between observed and expected values) and discriminated well (area under the receiver operating characteristic curve_0.837 and 0.824, respectively). All scoring systems are based on rigorous research and reported performance is good.

Different discretionary outputs are defined for every critically ill patient in the model: the number of days surviving in the hospital, and the surviving discharge status. Survival status is defined as a binary variable with two possibilities: death or surviving at hospital discharge. For a patient not surviving at discharge, the only output considered is the number of days the patient has survived in the hospital.

The number of days of surviving at the hospital may also be viewed as a measure of hospital activity (length of stay), an output measure being traditionally considered in DEA models measuring hospital efficiency. When the patient has survived hospital discharge, we additionally consider the surviving status as a second output, and probably the most important. Both output variables reflect differences in quality of life for in-hospital and after discharge days. Death or survival may be a reasonable proxy for quality of care when we are considering the management of severely ill patients.

Studies have illustrated the need to restrict weight flexibility in DEA models when introducing quality variables in the measurement of prenatal care efficiency (Thanassolulis et al, 1998). In this case, flexible weights may clearly result in unacceptable efficiency scores. First, given the input–output set definition, all cases may be deemed highly efficiently managed by assigning a high weight to the number of days of surviving at the hospital and a null weight to the surviving discharge status, i.e. considering activity only as an output (patient days or simply discharge) and omitting activity outcomes.

Second, social output values or preferences must be considered, before total weight flexibility, when assigning weights to the importance of a survival in contrast to merely surviving as an inpatient, or death discharge. Social values would express preferences over output variables when there are no observable prices for outputs. We assign greater preference or social value to survival at hospital discharge in relation to surviving inpatient days (as given in relation to dead status) by defining a relative output constraint: The problem of weight flexibility is even more important when data is restricted to death or survival at discharge given that the number of days a patient survives after discharge is unknown, as in this study. However, if the number of days a patient is expected to survive after discharge were known, there would also be need to restrict flexibility to weight pre- and post-discharge weights. The problem is the value to assign to d, in absence of reasonably rooted criteria. They arbitrarily define values between 1 and 100 to test for differences in the scores. As the value of d increases, the greater value assigned to a survival discharge relative to an inpatient day.

Assuming that efficiency in the management of critically ill patients is the ICU responsibility, intensive care unit efficiency can be obtained as an average of the efficiency with which the patients have been treated. An intensive care unit will be considered as efficient only if all patients treated in this hospital are considered efficiently managed when compared with patients in this or in other hospitals in the same mortality risk level. The DEA model defined in this paper makes it possible to obtain efficiency scores for patients grouped according to their mortality risk at admission for the overall sample and for every intensive care unit.

As efficiency scores are obtained from comparing patient management in the same risk group, these results may indicate that higher risks are treated less efficiently, i.e. increasing resources without obtaining a survival discharge. Differences in efficiency between risk groups widen as d value increases. The observation may indicate that higher risk patients may have been treated without taking into consideration the survival probability. Or in the context of our input–output data set, valuing more in-hospital surviving days than surviving at hospital discharge, this could be the case of units applying only palliative measures.

The paper technical efficiency in the management of critically ill patients has been analyzed by means of an extended version of data envelopment analysis (non-discretionary and cate gorical variables, and weight constraints under consideration). The paper has proposed a limited set of seven inputs and two outputs for use in measuring the relative efficiency, including mortality risk level at admission and survival status at discharge. Efficiency measured in this context may be interpreted as a short-term measure, given that only some inputs are considered as discretionary ones. Usefulness of data envelopment analysis in the measurement of technical efficiency of clinical decisions at the patient level has been illustrated. In this context, an intensive care unit is only considered efficient if all patient treatments are considered efficient. And patient management is considered efficient if it compares favorably with an established comparison group which includes all similar patients in the same and in other hospitals. According to their results, three main findings may be emphasized. First, the introduction of output weight structures reflecting social values or preferences over the outputs in the data envelopment analysis model results in an efficiency level being a function of the unknown relative weighting structure.

Data envelopment analysis scores should be interpreted more as a rank other than as an absolute value. In this study, efficiency scores are a decreasing function of the weight attached to the survival of patients in relation to activity measures such as number of patient days or discharges. Weight flexibility in the estimation of health production in data envelopment analysis models, as used in the majority of previous studies, may provide efficiency scores reflecting unacceptable or implausible relative shadow prices. The results illustrate the need to restrict output weights in data envelopment analysis models to obtain meaningful scores, and they also show that the results appear to vary markedly with the weighting structure. The latter fact emphasizes the interest to develop theoretical and empirical bases for the weighting structures and their implications.

Second, efficiency scores are not distributed homogenously in the three mortality risk levels. Higher risk patients are systematically managed less efficiently than lower risk ones. This evidence is in line with past literature observing that a large amount of resources was being devoted to more severe patients who died. Regression results confirm that inefficiency significantly increases when intensive care units treat patients with higher levels of risk. These results indicate that changes in clinical decisions may improve efficiency, given that the present resource allocation decisions do not seem to be closely related to the expected outcome.

CHAPTER THREE

METHODOLOGY

3.1 Introduction

This chapter deals with the procedure used in collecting and analyzing data. The researcher used log-linear models to determine the association among variables and pattern of admission outcome from 2006-2010 in Central Regional Hospital, Cape Coast.

3.2 When to use log-linear models:

The log-linear model is one of the specialized cases of generalized linear models for Poisson-distributed data. Log-linear analysis is an extension of the two-way contingency table where the conditional relationship between two or more discrete, categorical variables is analyzed by taking the natural logarithm of the cell frequencies within a contingency table. Although log-linear models can be used to analyze the relationship between two categorical variables (two-way contingency tables), they are more commonly used to evaluate multi-way contingency tables that involve three or more variables. The variables investigated by log-linear models are all treated as "response variables". In other words, no distinction is made between independent and dependent variables. Therefore, log-linear models only demonstrate association between variables if one or more variables are treated as explicitly dependent and others as independent, then logitor logistic regression should be used instead. Also, if the variables being investigated are continuous and cannot be broken down into discrete categories, logit or logistic regression would again be the appropriate analysis.

Suppose we are interested in determine the relationship/association among variables- medical wards (male, female and pediatrics), year of admissions and outcome of hospital admissions (death and alive). We could take a sample of hospital patients and determine the approximate hospital admissions, as male, female and pediatrics. The continuous variable, outcome of admissions, is broken down into two discrete categories: discharge and death.

3.3 Basic Strategy and Key Concepts:

The basic strategy in log-linear modeling involves fitting models to the observed frequencies in the cross-tabulation of categorical variables. There can then be models represented by a set of expected frequencies that may or may not resemble the observed frequencies. Models will vary in terms of the marginal's they fit, and can be described in terms of the constraints they place on the associations or interactions that are present in the data. The pattern of association among variables can be described by a set of odds and by one or more odds ratios derived from them. Once expected frequencies are obtained, we then compare models that are hierarchical to one another and choose a preferred model, which is the most parsimonious model that fits the data. It's important to note that a model is not chosen if it bears no resemblance to the observed data. The choice of a preferred model is typically based on a formal comparison of goodness-of-fit statistics associated with models that are related hierarchically (models containing higher also implicitly include all lower order terms). Ultimately, the preferred model should distinguish between the pattern of the variables in the data and sampling variability, thus providing a defensible interpretation.

3.4 The Log-linear Model

The following model refers to the traditional chi-square test where two variables, each with two levels (2 x 2 tables), are evaluated to see if an association exists between the variables:

$$\text{Log}\,(m_{ij}) = \mu + \lambda_i^{X} + \lambda_j^{Y} + \lambda_{ij}^{XY} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1.1)$$

$\text{Log}(m_{ij})$ = is the log of the expected cell frequency of the cases for cell ij in the Contingency table.

μ = is the overall mean of the natural log of the expected frequencies

λ = terms each represent "effects" which the variables have on the cell frequencies

X and Y = are treated as outcome variables

i and j refer to the categories or level within the variables X and Y

Therefore:

λ_i^{X}= the main effect for variable X

λ_j^{Y}= the main effect for variable Y

λ_{ij}^{XY}= the interaction effect for variables X and Y

The above model in equation *(1.1)* is considered a Saturated Model because it includes all possible one way and two-way effects. Given that the saturated model has the same amount of cells in the contingency table as it does effects, the expected cell frequencies will always exactly match the observed frequencies, with no degrees of freedom remaining .For example, in a 2 x 2 table there are four cells and in a saturated model involving two variables there are four effects, μ, λ_i^{X}, λ_j^{Y}, λ_{ij}^{XY}

XY, therefore the expected cell frequencies will exactly match the observed frequencies. Thus, in order to find a more parsimonious model that will isolate the effects best demonstrating the data.

Patterns, a non-saturated model must be sought. This can be achieved by setting some of the effect parameters to zero. For instance, if we set the effects parameter λij^{XY} to zero (i.e. we assume that variable *X* has no effect on variable *Y* or vice versa) we are left with the unsaturated model:

$$\text{Log}(m_{ij}) = \lambda_i^X + \lambda_y^Y + \quad \text{..(1.2)}$$

This particular unsaturated model is titled the Independence Model because it lacks an interaction effect parameter between *X* and *Y*. Implicitly, this model holds that the variables are unassociated. Note that the independence model is analogous to the chi square analysis, testing the hypothesis of independence.

Tables1and table 2 is the cell counts and cell probabilities in a 2 × 2 contingency table respectively.

Table1: Cell Counts in a 2 × 2 Contingency Table

Level of X	Level of Y		Total
	1	2	
1	n_{11}	n_{12}	n_{1+}
3	n_{21}	n_{22}	n_{2+}
Total	n_{+1}	n_{+2}	n

Table 2: Cell Probabilities in a 2× 2 Contingency Table

Level of X	Level of Y		Total
	1	2	
1	π_{11}	π_{12}	π_{1+}
3	π_{21}	π_{22}	π_{2+}
Total	π_{+1}	π_{+2}	1

The motivation for the use of log-linear models is that statistical independence can be express in terms of a linear combination of the logarithms of the cell probabilities. In particular if the variables X and Y in a 2×2 table are statistically independent, then the probability of individuals being in the first row (level 1 of X) among those in the first column (level 1 of Y) would be the same as the probability for the first row among those in the second column (level 2 of Y).

Therefore, $\frac{\pi 11}{\pi+1} = \pi_{1+}$ .... (1.3)

And $\pi_{11} = \pi_{1} * \pi_{+1}$. Similar arguments lead to the general result that if the row and column variables are independent, then $\pi_{ij} = \pi_{i+} * \pi_{+j}$, for $i, j = 1, 2$.

You can then express independence as a general relation involving all four cell probabilities. First, if X and Y are statistically independent.

$$\frac{\pi_{11}}{\pi_{+}} = \frac{\pi_{12}}{\pi_{+}} \quad \text{...} \quad (1.4)$$

Since $\pi_{+1} = \pi_{11} + \pi_{21}$ and $\pi_{+2} = \pi_{12} + \pi_{22}$, the relationship is

$$\frac{\pi_{11}}{\pi_{11} + \pi_{21}} = \frac{\pi_{12}}{\pi_{12} + \pi_{22}} \quad \text{..} \quad (1.5)$$

so that $\pi_{11}(\pi_{12}+\pi_{22}) = \pi_{12}(\pi_{11} + \pi_{21})$. This simplifies to $\pi_{11}\pi_{22} = \pi_{12}\pi_{21}$. Therefore, the row and column variables are independent if

$$\psi = \frac{\pi_{11}\,\pi_{22}}{\pi_{12}\,\pi_{21}} = 1 \quad \text{...} \quad (1.6)$$

Where ψ is called the cross-product ratio, or the odds ratio. Taking logarithms of both sides expresses statistical independence as a linear combination of the logarithms of the cell probabilities:

$\text{Log}\ \psi = \log \pi_{11} - \log \pi_{12} - \log \pi_{21} + \log \pi_{22} = 0$ .... (1.7)

Log-linear models for 2 x 2 contingency tables involve the logarithm of the cross-product ratio in a special way.

The saturated log-linear model for a 2x2 table is:

$\text{Log}\ (m_{ij}) = \mu + \lambda_i^X + \lambda_j^Y + \lambda_{ij}^{XY}$; $i,j = 1,2$ .... (1.8)

Where $m_{ij} = n\pi_{ij}$ is the expected frequency in the (i, j) cell. This model is similar to the two-way analysis of variance model for a continuous response y:

$E\ (y_{ij}) = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij}$ ....(1. 9)

With overall mean μ, main effects α_i and β_j and interaction effects $(\alpha\beta)_{ij}$. The use of the terms λ_i^X, λ_j^Y, and λ_{ij}^{XY} instead of αi, βj and $(\alpha\beta)ij$ is the common log-linear model notation and is especially convenient when considering tables of higher dimensions.

Since there is 1 + 2 + 2 + 4 = 9 parameters in the saturated log-linear model, but only four observations, the model is over parameterized. Imposing the usual sum-to-zero constraints:

$$\sum_{i=1}^{2} \lambda_i^X = 0 \qquad \sum_{j=1}^{2} \lambda_j^Y = 0 \qquad \sum_{i=1}^{2} \lambda_{ij}^{XY} = 0 \qquad \sum_{j=1}^{2} \lambda_{ij}^{XY} = 0$$ .... (2.1)

Yields three non redundant λ parameters $(\lambda_1^X, \lambda_1^Y, \lambda_{11}^{XY})$. The fourth parameter, μ, is fixed by the total sample size n. table (1) displays the expected cell frequencies mij in terms of the model parameters μ, λ_1^X, λ_1^Y, and λ_{11}^{XY}

The odds ratio can also be expressed as a function of the expected frequencies:

$$\Psi = \frac{m_{11}m_{22}}{m_{12}m_{21}}$$

Table 3: Log-linear Model Expected cell counts

Level of X	Level Y	
	1	2
1	$\exp(\mu + \lambda_1^X + \lambda_1^Y + \lambda_{11}^{XY})$	$\exp(\mu + \lambda_1^X - \lambda_1^Y - \lambda_{11}^{XY})$
2	$\exp(\mu - \lambda_1^X + \lambda_1^Y - \lambda_{11}^{XY})$	$\exp(\mu + \lambda_1^X - \lambda_1^Y) + \lambda_{11}^{XY})$

So that:

$\log\psi = \log m_{11} - \log m_{12} - \log m_{21} + \log m_{22} = 4\lambda_{11}^{XY}$ ......s.......... (2.2)

Therefore, the hypothesis of independence of X and Y is equivalent to:

$H_0: \lambda_{11}^{XY} = 0$. The corresponding independence log-linear model is given by

$\text{Log}(m_{ij}) = \mu + \lambda_i^X + \lambda_j^Y \quad i, j = 1, 2$ ....,, (2.3)

This model has one degree of freedom for testing lack of fit. The Pearson chi-square test of independence for a 2 x 2 contingency table. An alternative approach is the test H_0: $\lambda_{11}^{XY} = 0$ using the likelihood ratio test to compare the fit of the independence and saturated log-linear models.

The likelihood ratio test of independence can be derived directly from the multinomial likelihood.

$$f(n_{11}, n_{12}, n_{21}, n_{22}) = \frac{n!}{n_{11}!\, n_{12}!\, n_{21}!\, n_{22}!} \quad \pi_{11}^{\,n11}\, \pi_{12}^{\,n12}\, \pi_{21}^{\,n21}\, \pi_{2} \text{ ......(2.4)}$$

The unrestricted maximum likelihood estimates (MLEs) of the π_{ij} values are given by $P_{ij} = \frac{nij}{n}$. the maximized likelihood is then:

$$\max L = \frac{n\,!}{n_{11}!\, n_{12}!\, n_{21}!\, n_{22}!} \prod_{i=1}^{2} \prod_{j=1}^{2} (\underline{n_{ij}})^{nij} \text{ .... (2.5)}$$

Under the independence hypothesis $H_0{:}\pi_{ij} = \pi_i + \pi +_j$, the likelihood is:

$$L_0 = \frac{n!}{n_{11}!\, n_{12}!\, n_{21}!\, n_{22}!} \quad \pi_{1+}^{\,n_1+}\ \pi_{2+}^{\,n_2+}\ \pi_{+}^{\,n_{+1}}\ \pi_{+2}^{\,n_{+2}} \text{ ....(2.6)}$$

The MLEs for the π_{ij} under this model are $P_{ij} = n_{i+}\,n_{+j}\,/\,n$ and the maximized log-likelihood is

$$\max L_0 = \frac{n!}{n_{11}!\, n_{12}!\, n_{21}!\, n_{22}!} \prod_{i=1}^{2} \prod_{j=1}^{2} \left(\frac{n_{i+} n_{+j}}{n} \right)^{n_{ij}} \text{ .... (2.7)}$$

The likelihood ratio is:

$$\text{Max } L_o = \lambda \frac{\max L_o}{\max L} = \prod_{i=1}^{2} \prod_{j=1}^{2} \left(\frac{m_{ij}}{n_{ij}} \right)^{n_{ij}} \text{ ....(2.8)}$$

Where $m_{ij} = n_{i+}\, n_{+}n$ and the likelihood ratio statistics is

$$G^2 = -2 \log \lambda = 2 \sum_{i=1}^{2} \sum_{j=1}^{2} n_{ij} \log \left(\frac{n_{ij}}{m_{ij}} \right) \qquad \text{.....................(2.9)}$$

The statistic G^2 has an asymptotic chi-square distribution with 1 df if H_0 is true, and it is asymptotically equivalent to the Pearson chi-square statistic.

3.5 Log-linear Model for the s × r Table

When a sample of n observations is classified with respect to two categorical variables, one having s levels and the other having r levels, the resulting frequencies can be displayed in an s× r contingency table as shown in table 4 below. The corresponding cell probabilities are π_{ij}, with row and column marginal probabilities $\{\pi_{j+}\}$ and $\{\pi_{j+}\}$, respectively. The generalization of the log-linear models from the table to the s × r table straightforward. The saturated model is

$$\text{Log} (m_{ij}) = \mu + \lambda_i^X + \lambda_j^Y + \lambda_{ij}^{XY} \quad I = 1, \ldots\ldots s, \;\; j = 1 \ldots\ldots, r \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.0)$$

Where $m_{ij} = n\pi_{ij}$ is the expected frequency in the (I, j) cell. The parameters μ is fixed by the sample size n and the model has $s + r + s\,r$ parameters λ_j^X, λ_j^Y, and λ_{ij}^{XY}. The sum-to- zero constraints

$$\sum^{s} \lambda_i^X = 0 \quad \sum^{r} \lambda_i^Y = 0 \quad \sum^{s} \lambda_{ij}^{XY} = 0 \quad \sum^{r} \lambda_{ij}^{XY} = 0$$

Table 4: Cell Counts in an s × r Contingency Table

Level of X	Level of Y: 1	2	.	.	.	r	Total
1	n_{11}	n_{12}	.	.	.	n_{1r}	n_{1+}
2	n_{21}	n_{22}	.	.	.	n_{1r}	n_{2+}
.	.	.				.	.
.	.	.				.	.
.	.	.				.	.
s	n_{s1}	n_{s2}	.	.	.	n_{sr}	n_{s+}
Total	n_{+1}	n_{+2}	.	.	.	n_{+r}	n

Implies (s-1) + (r-1) + (s- 1) (r -1) = sr-1 parameters and zero df for testing lack of fit. Letting $m_{ij} = n_{i+} n_{+j} / n$, the likelihood ratio statistic:

$$G^2 = 2 \sum_{i=1}^{S} \sum_{j=1}^{r} n_{ij} \log (n_{ij} / m_{ij})$$

Test the null hypothesis H_0: $\lambda_{ij}^{XY} = 0$, for I = 1…S-1, j =1… R-1. Under the null hypothesis of independence. G^2 has an approximate chi- square distribution with (S-1)(r-1) df.

If H_0 is true, the reduced model $\log (m_{ij}) = \mu + \lambda^X + \lambda^Y$ is the model of independence of X and Y. This model has (s-1) + (r-1) linearly independent λ parameters and (s-1) (r-1) df for testing lack of fit.

3.6 Hierarchical Approach to Log-linear Modeling

The following equation represents a 2 x 2 x 2 multi-way contingency table with three variables, each with two levels. Here, this equation is being used to illustrate the hierarchical approach to Log-linear modeling:

$$\text{Log}(F_{ij}) = \mu + \lambda_i^X + \lambda_j^Y + \lambda_K^Z + \lambda_{ij}^{XY} + \lambda_{ik}^{XZ} + \lambda_{jk}^{YZ} + \lambda_{ijk}^{XYZ} \text{ ………………(3.2)}$$

Saturated model

The model has

$1+(I-1)+(J-1)+(K-1)+(I-1)(J-1)+(I-1)(K-1)+(J-1)(K-1)$

$+(I-1)(J-1)(K-1) = IJK$

Parameters and zero *df* for testing lack of fit. The saturated model allows for three- way interaction, that is, each pair of variables may be conditionally dependent, and an odds ratio for variables may vary across levels of the third variables. The reduced model

$$\mu + \lambda_i^X + \lambda_j^Y + \lambda_K^Z + \lambda_{ij}^{XY} + \lambda_{ik}^{XZ} + \lambda_{jk}^{YZ} \text{ ………………………………… (3.3)}$$

is called the log-linear model of no three- factor interaction. In this model, no pair of variables is conditionally independent. Thus, for each pair of variables, marginal odds ratios may differ from partial odds ratios. The "no three- factor interaction" model implies that the conditional odds ratios between any two variables are identical at each level of the third variable. Except in special cases, closed form expressions for the expected cell frequencies do not exist.

There are three hierarchical models in which only one pair of variables is conditionally independent. For example, if X and Y are conditionally independent, given Z, the corresponding log-linear model is

$$\mu + \lambda_i^X + \lambda_j^Y + \lambda_K^Z + \lambda_{ik}^{XZ} + \lambda_{jk}^{YZ} \text{ ………………………………………(3.4)}$$

The parameter (λ_{ik}^{XZ}) and (λ_{jk}^{YZ}) pertain to the *X, Z*, and *Y, Z* partial associations. There are also three models in which only one pair of variables is conditionally dependent. For example if *Y* is jointly independent of *X* and *Z*, the corresponding model is

$$\text{Log}\ (m_{ijk}) = \mu + \lambda_i^X + \lambda_j^Y + \lambda_K^Z + \lambda_{ik}^{XZ} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \ (3.5)$$

In this model, the parameter (λ_{ik}^{XZ}) pertain to the dependence between *X* and *Y*.
Finally, the log-linear model corresponding to mutual independence is

$$\text{Log}\ (m_{ijk}) = \mu + \lambda_i^X + \lambda_j^Y + \lambda_K^Z$$

In this model, each pair of variables is also conditionally and marginally independent

$$\text{Log}\ (m_{ijk})\ \mu + \lambda_{ij}^{XY} + \lambda_{ik}^{XZ} + \lambda_{jk}^{YZ} \quad \text{(Homogeneous model)} \ \ldots\ldots\ldots\ldots\ldots \ (3.6)$$

$$\text{Log}\ (m_{ijk}) = \mu + \lambda_i^X + \lambda_j^Y + \lambda_K^Z \quad \text{(Mutually independent model)} \ \ldots\ldots\ldots\ldots \ (3.7)$$

Furthermore, hierarchy of models exists whenever a complex multivariate relationship present in the data necessitates inclusion of less complex interrelationships. For instance, in the above equation if a three-way interaction is present (*XYZ*), the equation for the model must also include all two-way effects (*XY, XZ, YZ*) as well as the single variable effects (*X, Y, Z*) and the grand mean (μ). In other words, less complex models are nested within the higher-order model (*XYZ*). Note the shorter notation used here to describe models. Each set of letters within the braces indicates a highest order effect parameter included in the model and by virtue of the hierarchical requirement, the set of letters within braces also reveals all lower order relationships which are necessarily present. SAS uses this model to generate the most parsimonious model; however, some programs use a non-hierarchical approach to log-linear modeling. Reverting back to the previous notation, a non-hierarchical model would look like the following:

$\text{Log}\,(m_{ij}) = \mu + \lambda_i^{X} + \lambda_{ij}^{XY}$ .... (3.8)

Notice that the main effect term λ_i^{Y} is not included in the model therefore violating the hierarchical requirement. The use of non-hierarchical modeling is not recommended, because it provides no statistical procedure for choosing from among potential models.

3.7 Choosing a model to Investigate

Typically, either theory or previous empirical findings should guide this process.

However, if an a priori hypothesis does not exist, there are two approaches that one could take:

- We start with the saturated model and begin to delete higher order interaction terms until the fit of the model to the data becomes unacceptable based on the probability standards adopted.
- We start with the simplest model (independence model) and add more complex interaction terms until an acceptable fit is obtained which cannot be significantly improved by adding further terms.

3.8 Fitting Log-linear Models

Once a model has been chosen for investigation the expected frequencies need to be tabulated. For two variable models, the following formula can be used to compute the direct estimates for non-saturated models. (Column total) * (row total)/grand total for larger tables, an iterative proportional fitting algorithm (Deming-Stephan algorithm) is used to generate expected frequencies. This procedure uses marginal tables fitted by the model to insure that the expected frequencies sum across the other variables to equalsthe corresponding observed marginal tables

3.9 Testing for goodness of fit

Once the model has been fitted, it is necessary to decide which model provides the best fit. The overall goodness-of-fit of a model is assessed by comparing the expected frequencies to the observed cell frequencies for each model. The Pearson Chi-square statistic or the likelihood ratio (G^2) can be used to test a models fit. However, the (G^2) is more commonly used because it is the statistic that is minimized in maximum likelihood estimation and can be partitioned uniquely for more powerful test of conditional independence in multi way tables:

$G^2 = 2\Sigma\, n \log\, (n/m_{ij})$ ....(3.9),

where n and m denote the observed and fitted cell frequencies. The corresponding Pearson chi- square statistics is equal to;

$Qp = \Sigma(n - m)$ .... (4.0)

G^2 follows a chi-square distribution with the degrees of freedom (df) equal to the number of lambda terms set equal to zero. Therefore, the G^2 statistic tests the residual frequency that is not accounted for by the effects in the model (the λ parameters set equal to zero). The larger the G^2 relative to the available degrees of freedom, the more the expected frequencies depart from the actual cell entries. Therefore, the larger G^2 values indicate that the model does not fit the data well and thus, the model should be rejected. It is often found that more than one model provides an adequate fit to the data as indicated by the non-significance of the likelihood ratio. At this point, the likelihood ratio can be used to compare an overall model within a smaller, nested model (i.e. comparing a saturated model with one interaction or main effect dropped to assess the importance of that term).

The equation is as follows:

G^2 comparison = G^2 model1 – G^2model 2

Model 1 is the model nested within model 2. The degrees of freedom (*df*) are calculated by subtracting the df of model 2 from the df of model 1. If the L^2 comparison statistic is not significant, then the nested model (1) is not significantly worse than the saturated model (2). Therefore, choose the more parsimonious (nested) model.

3.10 Log-linear Residuals

In order to further investigate the quality of fit of a model, one could evaluate the Individual cell residuals. Residual frequencies can show why a model fits poorly or can point out the cells that display a lack of fit in a generally good-fitting model The process involves standardizing the residuals for each cell by dividing the difference between frequencies observed and frequencies expected by the square root of the frequencies expected ($F_{obs} - F_{exp} / \sqrt{F_{exp}}$). The cells with the largest residuals show where the model is least appropriate. Therefore, if the model is appropriate for the data, the residual frequencies should consist of both negative and positive values of approximately the same magnitude that are distributed evenly across the cells of the table.

3.11 Limitations to Log-linear Models

3.11.1 Interpretation

The inclusion of so many variables in log-linear models often makes interpretation very difficult.

1.12.2 Independence

Only a between subjects design may be analyzed. The frequency in each cell is independent of frequencies in all other cells.

1.12.4 Size of Expected Frequencies

For all two-way associations, the expected cell frequencies should be greater than one, and no more than 20% should be less than five. Upon failing to meet this requirement, the Type I error rate usually does not increase, but the power can be reduced to the point where analysis of the data is worthless. If low expected frequencies are encountered, the following could be done:

- Accept the reduced power for testing effects associated with low expected frequencies.
- Collapse categories for variables with more than two levels, meaning you could combine two categories to make one "new" variable. However, if you do this, associations between the variables can be lost, resulting in a complete reduction in power for testing those associations. Therefore, nothing has been gained.
- Delete variables to reduce the number of cells, but in doing so you must be careful not to delete variables that are associated with any other variables.
- Add a constant to each cell (.5 is typical). This is not recommended because power will drop, and Type I error rate only improves minimally.

It is important to note that some packages such as SPSS and SAS will add 0.5 continuity corrections under default.

CHAPTER FOUR

DATA ANALYSIS

4.1 Introduction

This chapter deals with results, finding and discussions. It is divided into two subsections, thus preliminary discussion and further discussion. This is to establish whether or not there is association existing between the variables, effects of variables on Outcome of admissions and also determine the pattern of admission in the Central Regional Hospital, Cape Coast.

4.2 Preliminary Analysis

Table 5: Cross Tabulation between Outcome of admission and medical ward

Medical Ward (X)	Outcome of Admission (Y)					
	Alive		Death		Total	
	Freq	%	Freq	%	Freq	
Male	3589	87.77	500	12.23	4089	33
Female	2279	75.59	736	24.71	3015	24
Paedics	4893	91.19	429	8.06	5322	43
Total	**10761**	**88.6**	**1665**	**13.4**	**12426**	**100**

Table 5 deals with Cross tabulation Outcome of Admission and Medical Ward.

It was observed that more patients were discharged / alive in the paediatric ward

Representing 4893 (91.19%) than those discharge in the male and female medical ward representing 3389 (87, 77%) and 2279 (75.58%) respectively.

On the other hand, it was also noted that female medical ward recorded highest number of death representing 736 (24,71%) than paediatrics and female medical wards representing 429 (8.06) and 500 (12.23) respectively.

Table 6: Cross Tabulation between Outcome of admission and year of admission

	Outcome of Admission (Y)				
YEAR	**Alive**		**Death**		
(Z)	**Freq**	**%**	**Freq**	**%**	**Total**
2006	1905	82.29	410	17.71	2315
2007	1843	85.52	312	14.48	2155
2008	2215	86.83	336	13.17	2551
2009	2337	88.96	290	11.03	2627
2010	2461	88.58	317	11.41	2778
Total	**10761**	**86.60**	**1665**	**13.39**	**12426**

In table 6, we realized that the year 2009 recorded highest number of patients discharged/ alive representing 2337 (88.96%). This is followed by year 2010 also representing 2461 (88.58). Also year 2006 recorded least number of patients discharge.

On the other hand, year 2006 recorded highest of death representing 401 (17.71%). Meanwhile, year 2009 recorded least number of patients death representing 290

(11.03%). It was noted that, values obtained for both patients alive and death are evenly distributed within the five year period.

Finally, patients admitted in the medical wards from 2006-2010 were 12426. Of this patients discharge was 10761(86.60%) and 10605 (13.39%) representing death rate during the same per

4.3 Further Analysis

4.3.1 Introduction

The Outcome admission data is a data from a Central regional Hospital for the patients admitted to the medical ward from 2006 - 2010. Male, female, and paediatirics were the three Medical wards used. The objectives of this analysis are to analyze association between the three variables (Medical ward (*X*), Outcome of admission (*Y*) and the Year of admission (*Z*) and to examine the effects of Medical ward and Year on the Outcome of admission.

4.3.2Methods

The Outcome of admission variables was categorical with two levels; the medical ward had three and year variable had five levels and is ordinal. Three approaches were used to analyze the data. The model approach based on log-linear models was used. In this case, the homogeneous association was tested by comparing the saturated model (SM) and a model assuming homogeneity (HAM). The conditional independence was checked by comparing the HAM model with different models assuming conditional independence. The best model was chosen to conduct further analysis on the effect of medical ward on the outcome of admission while controlling by year.

Model 1(a) $\log(m_{ij}) = \mu + \lambda_i^X + \lambda_j^Y + \lambda_{ij}^{XY}$ .... (4.1)

Table 7: Maximum Likelihood Analysis of Variance

Source	DF	Chi-Square	Pr > Chi-Sq
Medical (*X*)	2	11.81	0.0027
Outcome (*Y*)	1	4634.43	<.0001
medical*outcome(*XY*)	2	419.35	<.0001
Likelihood Ratio	0	.	.

Table7 displays the analysis of variance table. Since the three multinomial cell probabilities sum to one, there are three linearly independent expected frequencies m_{ij}. Since there are parameters, the model is saturated and the expected counts m_{ij} are equal to the observed counts m_{ij}. Thus the likelihood ratio statistics G^2 is zero. Although the model was fit using maximum likelihood, the test statistics in the analysis of variance table are Wald tests.

Model 1b:

$\log(m_{ij}) = \mu + \lambda_i^X + \lambda_j^Y$ .... (4.2)

Table 8: Model 1(b) Maximum Likelihood Analysis of Variance

Source	DF	Chi-Square	Pr > ChiSq
Medical (*X*)	2	630.73	<.0001
Outcome (*Y*)	1	5021.19	<.0001
Likelihood Ratio	2	417.40	<.0001

As shown in model 1b, the likelihood ratio statistic for testing the null hypothesis of independence of medical wad and outcome of admission is (G^2 = 417.40). Therefore, there is clear evidence that the two variables are not independent.

Outcome of admission is associated with medical ward. The main effect Medical ward tests the null hypothesis the subjects are evenly distributed over the levels of this variables. The strongly significant results of this tests (Qw = 630.73, 2 df

P = 0.0001) reflect the fact that 88.6% of the patients were alive and 13.4% were death.

Model 2(a)-Saturated model $\log(m_{jk}) = \mu + \lambda_j^Y + \lambda_k^Z + \lambda_{jk}^{YZ}$ .... (4 3)

In table 6, it is observed that there is an association between Outcomes of admission and the year of admission. The year 2009 recorded the highest number of patients d 88.scharged 96% and 2006 also recorded least number of patients discharged 82.25%. The subjects were relatively evenly distributed.

Table 9: Maximum Likelihood Analysis of Variance

Source	DF	Chi-Square	Pr > Chi Sq
Year(Z)	4	18.62	0.0009
Outcome(Y)	1	4957.15	<.0001
year*outcome(ZY)	4	60.70	<.0001
Likelihood Ratio	0		

As shown in model 1b, the likelihood ratio statistic for testing the null hypothesis of independence of Year of admission and outcome of admission is (Qw = 60.70 Therefore, there is clear evidence that the two variables are not independent.

Year of admission is associated with outcome of admission. The main effect Year of admission tests the null hypothesis the subjects are evenly distributed over the levels of this variables. The strongly significant results of this tests (Qw = 18.72, 4 df P < 0.0009) reflect the fact that 88.6% of the patients were alive and 13.4 were death.

Model 2c

$$\log(m_{jk}) = \mu + \lambda_j^Y + \lambda_k^Z \qquad \text{(4.4)}$$

Table 10: Maximum Likelihood Analysis of Variance

Source	DF	Chi-Square	Pr > ChiSq
Year(Y)	4	99.54	<.0001
Outcome(Y)	1	5021.19	<.0001
Likelihood Ratio	4	59.61	<.0001

The analysis of variance table provides strong evidence that Year of admission and Outcome of admission are not independent (G^2 = 59.61, 4 df, p < 0.0001). Year of admission is more associated with medical ward. Outcome is also associated with medical ward *(Qw* = 5021.19, 1df, p =0.0001)

Model 2d

Saturated model for *X, Y, Z* $\log(m_{ijk}) = \mu + \lambda_i^X + \lambda_j^Y + \lambda_k^Z + \lambda_{ij}^{XY} + \lambda_{ik}^{XZ} + \lambda_{jk}^{YZ} + \lambda_{ijk}^{XYZ}$ ..(3.2)

Table 11: Maximum Likelihood Analysis of Variance

Source	DF	Chi-Square	Pr > Chi- Square
Year (*Z*)	4	11.67	0.0199
Medical (*X*)	2	3.67	0.1599
year*medical (*ZX*)	8	56.29	<.0001
Outcome (*Y*)	1	3855.54	<.0001
year*outcome(*ZY*)	4	37.98	<.0001
medical*outcome (*XY*)	2	414.80	<.0001
year*medical*outcome(*ZXY*)	8	553.25	<.0001
Likelihood Ratio	0	.	.

The Likelihood ratio test in the analysis of variance table compares this model to the saturated model and thus tests the null hypothesis of no three- factor interaction. Since the model is saturated, the likelihood ratio test is equal to zero (table 14) The wald test of the three – factor interaction is $(QW = 553.25$, 8 df, p = 0.0001) is significant.

$$\log(m_{ijk}) = \mu + \lambda_i^X + \lambda_j^Y + \lambda_k^Z \quad \text{...} \quad (4.6)$$

Table 12: Maximum Likelihood Analysis of Variance

Source	DF	Chi-Square	Pr > Square
Year (*Z*)	4	99.54	<.0001
Medical (*X*)	2	630.73	<.0001
Outcome (*Y*)	1	5021.19	<.0001
Likelihood Ratio	22	1814.87	<.0001

We could evaluate the difference in the Chi-square statistics, based on the difference in the degrees of freedom; if the differential Chi-square statistic is significant, then we would conclude that the three-way interaction model provides a significantly better fit to the observed table than the model without this interaction. Therefore, the three-way interaction is statistically significant.

Year (*Z*), Medical ward (*X*), Outcome(*Y*) Variables

$\text{Log}(m_{ijk}) = \mu + \lambda_i^X + \lambda_j^Y + \lambda_K^Z + \lambda_{ij}^{XY} + \lambda_{ik}^{XZ} + \lambda_{jk}^{YZ} + \lambda_{ijk}^{XYZ}$ ………… (3.2) Saturated model

$\text{Log}(m_{ijk})\ \mu + \lambda_{ij}^{XY} + \lambda_{ik}^{XZ} + \lambda_{jk}^{YZ}$ ……………………………………………… (4.6) Homogeneous model

$\text{Log}(m_{ijk}) = \mu + \lambda_i^X + \lambda_j^Y + \lambda_K^Z$ ……………………..(4.5) Mutually independent model

The log-linear models were used to check for associations. In this approach, based on fitted models, it was checked whether the homogeneity assumption holds and thus, whether conditional independence models, joint independence models or the mutually independent model gave a good fit to the data. First of all, the goodness of fit was tested for each model. The table 13 summarizes the results. The likelihood ratio statistic (G^2)

was used when testing goodness of fit. The choice of G^2 was suggested mainly by the fact that it can be partitioned. This property allows the comparison of nested models and the saturated model. The values of G^2 in 14 are differences of likelihood ratio for a given model and the likelihood ratio for the saturated model. A large P-value indicates that there is no significant difference of the related model and the saturated model. It can be seen that the homogeneity assumption holds since the model ((*ZX*, *ZY*, *XY*) is significantly different of the saturated model (P-value < 0.0001), thus there is a homogeneous association between the three variables. The homogeneous association model can therefore be considered as baseline to check conditional independence among the variables. Table 14 gives results on comparison of nested models to the HAM. The model (*ZY, XY*) (*P*-value< 0.0001) is significantly different from the HAM. Thus, year and outcome are conditionally independent given the medical ward and outcome of admission. The model (ZX, XY), assuming conditional independence of Medical ward and the outcome of admission given year, showed a p-value=0.0001. This means that interaction *ZY* cannot be removed from the HAM. It is deduced that year and the outcome of admission are not independent. Thus, the three variables are not mutually independent. The last association checked is the joint independence of medical ward to year and outcome of admission. By taking the conditional independence model (*ZY, ZX*) as baseline, it is shown in table 15 that joint independence model (*X, ZX*) is not significantly different from the model (*ZY,ZX*) (P-value=0.0001) which means that medical ward is jointly independent to therapy and response-to-chemotherapy.

Table 13: Goodness of fit for log-linear models relating Year (*Z*), Medical ward(*X*), and Outcome (*Y*)

Model	G^2	Df	P-value
(*ZX,ZY,XY*)	661	8	< 0.0001
(*ZY,XY*)	1337.86	16	< 0.0001
(*ZX,XY*)	724.09	12	< 0.0001
(*ZY,ZX*)	1081.89	10	< 0.0001
(*X,ZY*)	1755.26	18	< 0.0001
(*Y, ZX*)	1141.50	14	< 0.0001
(*Z, XY*)	1397.47	20	< 0.0001

From table 13, the models (*ZY, XY*), (*ZX, XY*) and (*ZY, ZX*) are conditionally independent. Also the models (*X, ZY*), (*Y, ZX*) and (*Z, XY*) are jointly independent.

Table 14: Test of nested models

Models Compared	Deviance	DF	P-value
(*ZX,ZY,XY*) –Saturated	661-0	8	<0.0001
(*ZY,XY*) - (*ZX,ZY,XY*)	676.86	8	<0.0001
(*ZX,XY*) - (*ZX,ZY,XY*)	63.01	4	<0.0001
(*ZY,ZX*) - (*ZX,ZY,XY*)	420.89	2	<0.0001
(*X,ZY*) - (*ZX,ZY,XY*)	1094.26	10	<0.0001
(*Y, ZY*) - (*ZX,ZY,XY*)	480.5	6	<0.0001
(*Z,XY*) - (*ZX,ZY,XY*)	736.47	12	<0.0001

The model with no three – factor interaction provides a good fit to the observed data. Thus, no pair of variables is conditionally independent. In this model, the conditional likelihood ratio between any two variable are identical. We therefore concluded that the model is three- factor interaction model.

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Summary

The study was on application of log-linear models analysis on hospital length of stay and outcome of admission. Central Regional Hospital- Cape Coast is a referral hospital for emergency cases. The Outcome of admission variables was categorical with two levels; the medical ward had three levels and the said year from 2006 to 2010. Variable had five levels and is ordinal. Two statistical approaches were used to analyze the data. The model approach based on log-linear models was used. In this case, the homogeneous association was tested by comparing the saturated model (SM) and a model assuming homogeneity (HAM). The conditional independence was checked by comparing the HAM model with different models. The best model was chosen to conduct further analysis on the effect of medical ward on the outcome of admission while controlling the year of admission.

The total number of patients admitted in the hospital was twelve thousand four hundred and twenty six (12,426) for the 5 year period. Ten thousand seven hundred and sixty one (10761) were discharged (alive); representing 86.6%. Also one thousand six hundred and sixty five (1665) died; representing 13.4% for the same five year period. It was observed that more patients were discharged or alive in the paediatric ward representing (91.19%) than those discharge in the male and female medical ward representing (87. 77%) and (75.58%) respectively.

It was observed that female medical ward recorded the highest number of death, (736) representing (24.71%).The paediatrics and male medical wards also recorded (429) and (500) representing (8.06%) and (12.23%) respectively.

It was realized that the year 2009 recorded the highest number of patients discharged (2337) representing (88.96%). Year 2006 recorded lest number of patients discharged. Meanwhile, year 2009 recorded least number of patients death (290) representing (11.03%). It was noted that, values obtained for both patients alive and death are evenly distributed within the five year period.

As shown in model 1b, the likelihood ratio statistic for testing the null hypothesis of independence of Year of admission and outcome of admission is ($G^2 = 60.70$). Therefore, there is clear evidence that the two variables are not independent. Year of admission is associated with outcome of admission. The main effect on the of Year of admission tests the null hypothesis and the subjects are evenly distributed over the levels of this variables. The strongly significant results of this tests ($G^2 = 18.72$, 4 df $P < 0.0009$) reflect the fact that 88.6% of the patients were alive and 13.4 of the patients died.

We observed that the models (ZY, XY), (ZX, XY) and (ZY, ZX) are conditionally independent. Also the models (X, ZY), (Y, ZX) and (Z, XY) are jointly independent as it can be seen in table 13 which was used to test for goodness of fit for log-linear models relating year (Z), medical ward (X) and outcome of admission (Y). The best model is the saturated model which contains both the two way pair of associations of outcome of admission, medical ward and year of admission and the three way pair of associations outcome, year and medical ward.

5.2 Conclusion

Based on the results of the research, we observed that the use of log-linear models is successfully employed to determine the associations between Year of admission (Z), Medical Ward(Y) and Outcome of admission(X). From the results, we can infer that the female medical ward recorded more death than the male and the paediatrics ward. Again the results reveal that more patients died in 2006 and year 2009 recorded least number of patients death. We further conclude that female medical ward recorded the highest number of death and paediatric ward recorded least number of death from 2006 to 2010

We can then conclude that there is association between medical ward and the outcome of admission, medical ward and the year, and year and outcome of admission. The three-way association tested was between category of medical ward, outcome of admission and year of admission (model 2d), and it was found to be significant. After that, a two-way association between medical ward, outcome of admission and year (models 1a, and 2a) were tested and all of them were found to be significant. This shows that there is an association between the three variables. Therefore, the best model is the saturated model.

5.3 Recommendations

Based on the findings from the log-linear model for outcome on admissions in Hospital from 2006 – 2010, the following recommendations have been made:

- The Hospital Authorities could use the log-linear modeling and likelihood ratio methods to analyze data periodically.

- Medical personnel should make maximum use of available facilities to help reduced mortality rate in the hospital. This is because current rate is not very good.
- Doctor to patient ratio must be improved fore store further death in the hospital.
- Further studies should be conducted to determine what actually causes the association between variables.

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APPENDIX (A)

Statistical Data

Outcome of admission at central Regional Hospital, Cape Coast (2006 – 2010)

Medical Wall	Outcome of Admission (2006)		
	Discharge	Death	Total
Male	558	164	722
Female	313	199	512
Paedics	1905	47	1081
Total	1843	312	2155

Medical	Outcome of Admission (2007)		
	Discharge	Death	Total
Male	889	44	933
Female	442	127	569
Paedics	512	141	653
Total	1843	312	2155

Medical	Outcome of Admission (2008)		
	Discharge	Death	Total
Male	1131	37	1168
Female	462	153	615
Paedics	622	146	768
Total	2215	336	2551

Medical	Outcome of Admission (2009)		Total
	Discharge	Death	
Male	479	121	600
Female	562	136	698
Paedics	1296	33	1329
Total	2337	290	2627

Medical	Outcome of Admission (2010)		Total
	Discharge	Death	
Male	532	134	666
Female	500	121	621
Paedics	1429	62	1491
Total	2461	317	2778