Cape Peninsula
University of Technology

Diagnostic radiology capacity and demand in Zimbabwe: trends and forecast

by

Lidion Sibanda

I.D.: 210115556

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Supervisor **:** Prof. P. Engel-Hills

External Supervisor: Prof. E. Hering

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DECLARATION

I, LidionSibanda, declare that the contents of this dissertation represent my own work, and that the dissertation has not previously been submitted for academic examination towards any qualification. It represents my own opinions and not necessarily those of the Cape Peninsula University of Technology (CPUT). Furthermore, this project was approved by the the research sites, CPUT Health and Wellness Sciences Research Ethics Committee (Ref. CPUT/HWS- 2014/H02) as well as the Medical Research Council of Zimbabwe (Ref. MRCZ/A/1875).

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Signed **Date**

ABSTRACT

Diagnostic radiology capacity and demand in Zimbabwe: Trends and forecast

The aim of this study was to provide evidence basedforecast for radiology demand in Zimbabwe that would support policies aimed at optimising radiology resource allocation and utilisation. This was upon the realisation that the Ministry of Health and Childcare required such forecast in order to ensure equitable, accessible and quality health services as prescribed in the 2009-2015 National Health Strategy as well as in Section 29 and 76 of the Zimbabwean constitution. On the international perspective, many researchers have reported stable high demand for radiology services giving rise to long waiting lists and backlogs. In the United Kingdom's National Health Services (NHS), there is general consensus that these waiting lists are caused by variation mismatches between capacity and demand for radiology services. Elsewhere, it has been reported that skill mix, role changes, dynamic nature of radiography teaching and learning, technology diffusion, service transaction time, overutilisation, and unjustified exposures are key drivers of high demand for radiology services. It has long been established that demand for radiology services is stochastic in nature, and therefore planning of future investments in radiology must be guided by an understanding of how these variables interact to model the criterion variable. However, there is paucity of information pertaining to key aspects of legitimate radiology demand forecasts. Formulation of these fundamental concepts formed the impetus of this study.

A document review, interviews and non-participatory observations revealed that justification of radiology examinations, dynamic nature of radiography teaching and learning, diffusion of extended roles and technology, equipment and personnel capacity, and most importantly service transaction time all had an impact on the demand for radiology services in Zimbabwe. Limited diffusion of extended roles and technology had increased over a ten year period. Observed role changes were informal additions to the procedures normally carried out by radiographers and these were not supported by formal education. Consistent with global concerns, over utilisation and unjustified requests were a national concern. In situations where capacity outweighed demand, there was evidence that internal management of radiology departments was responsible for most variation mismatches which then gave rise to long waiting times.

The relationship among pairs of predictor variables was investigated using Pearson product-moment correlation coefficient. Preliminary analysis was performed to rule out any significant violations of the assumptions of normality, linearity and homoscedasticity of the data. There

was a strong, positive paired correlation between variables [r=.836, n=132, p<.0005], with high numbers of appendicular examinations associated with high numbers of axial examinations for example. The associated coefficient of determination between these two variables was 0.699 which gave 69.9 per cent shared variance. There was an observed strong positive correlation among all predictor variables and the criterion variable. A multiple regression was run to predict Total number of patients examined (PAT) from Total number of chest examinations (CHE), Total number of axial skeleton examinations (AXI) and Total number of appendicular skeleton examinations (APP). These variables statistically significantly predicted (PAT), $F(3, 128) = 175.422$, $p < .0005$, $R^2 = .804$. All three variables added statistically significantly to the prediction, $p < .05$. The coefficient of determination was 0.804 which meant that the model accounted for 80.4% of the variance in the number of radiology patients that were observed. This was enough statistical evidence to conclude that the Linear Regression model was suitable for predicting the number of patients at the research sites.

The R-squared value for the chosen ARIMA model for predicting PAT was 0.848 while that for the Simple Seasonal Model was 0.566. The ARIMA model was able to account for 84.8 percent variance while the Simple Seasonal Model was able to account for 56.6 percent variance. The forecast error was 2% for ARIMA and 1% for Linear Regression. This represented a high accuracy (98% and 99% respectively). This meant that both models can be applied to explain variances in the observed PAT data, with the ARIMA model being the better performing model. Among the three models that were tested, the ARIMA model performed best followed by the Linear Regression model and then the Simple Seasonal Model. Model predictions and the actual value were within the error margins of each other and there was no significant difference ($p < .05$) among the three aforementioned data sets.

Regarding the trend, there was evidence of a trend that moved downwards and then upwards thereby representing a cycle in the data set. There was also evidence of an annual seasonal component in the time domain. This assertion was consistent with results of an analysis of the partial autocorrelation function. Further analysis in the frequency domain using Durbin-Watson test revealed that there was an independence of residuals (p>0.05 in all cases) which was enough statistical evidence for a seasonal pattern in the data. The Seasonal Adjustment Factors (SAF) showed that periods remained marginally at the same level of the series during the time horizon for the study. This was evidence that generally radiology demand remained at the same level during the time horizon.

A conclusion drawn from the statistical analysis was that generally, the central tendency regarding the number of radiology patients for the next ten years is likely to remain within 5% of the monthly predicted value. There was evidence that stake holders in radiology practice were aware of widespread inappropriate radiological exposures and that this impacted on the demand for radiology services. There was also enough evidence to conclude that a fragmented radiology resource management system was largely to blame for the observed considerable variation mismatches in capacity and demand. The developed theory did a good job in predicting the number of radiology patients as well as providing pertinent information in support of policy change with regards to the management of radiology resources.

With these research outcomes in mind, it is recommended that policy makers focus their efforts in evidence based resource redeployment, reinstating radiography rooms, reviewing the scope of practice of radiographers and reviewing radiography curricula. Further research may focus on needs assessments for the existing radiography curricular against the dynamic nature of radiography practice in which e-health is fast becoming a globally accepted practice.

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Prof. Engel-Hills and Mrs. Polly Davidson, you inspired me and you still inspire to keep going.

To policy makers I say, it is befitting for me at this point to quote the discoverer of X rays- a quote that sums up the process of philosophy and discovery presented in this thesis:

“It is very agreeable to have a broad knowledge, and it is sometimes useful, but after all it is only activity that brings real satisfaction.”

Wilhelm Conrad Röntgen 1845 - 1923

I thank you all.

DEDICATION

This thesis is dedicated to the radiography professionals in Zimbabwe for whom I quote *Sam Ewing:*

"It is not the hours you put into your work that counts, but the work that you put into your hours."

Be inspired to perfect the radiography profession!

GLOSSARY

Activity: All the work done but that does not necessarily reflect capacity or demand on a day to day basis. The activity is the work done on a particular day that may be the result of that day's demand and even some of the previous day's demand that has spilled over to the next day.

Capacity: Refers to resource time units available to do work. It is calculated as the number of resources multiplied by the number of time units each resource is available to the demand for services.

Demand: Patient demand at a stage in the patient care pathway is calculated by multiplying number of patients by the average time taken to attend to a patient.

SAF: Refers to the Seasonal Adjustment Factors. These values are particularly important in providing pointers regarding the effect of each period on the level of the series.

STC: Refers to the smoothed trend-cycle components. These values provide evidence regarding trend and cyclical behaviour in time series data.

ERR: Refers to the residual (error values). These values remain after the seasonal, trend, and cycle components are removed from the time series data.

SAS: These refer tothe seasonal adjusted series.

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CHAPTER ONE

THE PROBLEM AND ITS SETTING

It is Machiavelli (1469-1527) who wrote that, "...*There is nothing more difficult to take in hand, more perilous to conduct, or more uncertain in its success, than to take the lead in the introduction of a new order of things. Because the innovator has for enemies all those who have done well under the old conditions and lukewarm defenders in those who may do well under the new...*"

1.1 Purpose of the research

The Zimbabwe Ministry of Health and Child Care (ZMOHCC) wrote, in its 2009-2015 National Health Strategy (ZNHS) that its "vision will be attained through guaranteeing every Zimbabwean access to comprehensive and effective health services" (ZMOHCC, 2013). In the same document and in line with the Ministry's mandate and the current Results Based Management policy for Zimbabwe, the ministry outlines three Key Result Areas (KRAs) that were formulated to improve the health status of the population, improve the quality of care and to strengthen health systems. This, the Ministry says, was in order to further the mission of the Ministry of Health and Child Care:

MISSION STATEMENT

To provide, administer, coordinate, promote and advocate for the provision of equitable, appropriate, accessible, affordable and acceptable quality health services and care to Zimbabweans while maximizing the use of available resources, in line with the Primary Health Care Approach (ZMOHCC, 2009).

Important to this thesis is that in the vision and mission statements it is emphasised that equity, appropriateness, accessibility, quality of health services and optimised utilisation of available resources are fundamental to the fulfilment of the ministry's mandate. In line with the vision and mission of the Ministry, the overall aim in this research was to use patients', radiographers' and document review insights and foresights to create a comprehensive, strategic view of radiology examination processes that model utilisation trends and forecast in order to derive methods that could accelerate patients' journey on the path to the best care. Logically, this Care Pathway would provide insights and foresights regarding radiology resource deployment and utilisation by exposing consequences of intended and unintended radiological activities (labour drivers), as they impact upon efficiency in the practice of radiography as well as the mandate of the Zimbabwe Ministry of Health and Child Care. Faced with this scenario, the following research question was formulated:

“What predictive model can be used to forecast demand for diagnostic radiology services in Zimbabwe?”

The main outcome measure of the solution to this question was an evidence based forecast for radiology demand that would support policies aimed at optimising radiology resource allocation and utilisation by ensuring equitable, accessible and acceptable quality health services as prescribed in the National Health Strategy (ZMOHCC, 2013).

Mindful of the research question, the objectives of this study were:

i. To determine the nature of activities done across radiology patient care pathways;

ii. To determine those variables (predictor variables) that could be used to predict the number of patients examined across the research sites;

iii. To determine the variability of the aforementioned predictor variables (labour drivers) by establishing whether the key predictor variables were time-variant or not;

iv. To develop a theory to forecast the time-variant labour drivers and therefore demand for radiology utilisation.

Drawing from these research objectives, the following sub-questions were answered:

a). “What is the map of the radiology patient care pathway for Zimbabwe?”

b). “What are the predictor variables (labour drivers) for the observed frequency of radiology patients?”

c). “Why does the observed radiology utilisation follow the observed trend?”

d). “How can future utilisation of radiology services for Zimbabwe be predicted?”

1.2 Context of the problem

In healthcare, radiology departments are service departments for other clinical departments. Patients that visit radiology departments are examined based on referrals. In clinical practice, a referral to a radiology department is generally regarded as a request for a specialist opinion on the diagnosis of a patient (Sibanda, 2012; ECRP, 2008). Radiology departments prescribe the framework for requesting radiology examinations by designing request forms while referring departments use this framework (Request form) to request radiology examinations (IAEA, 2008). In so doing, it is the responsibility of the referrer to ensure that the radiology request is complete and justified while the radiology department has a duty to review the justification of all radiology requests before exposing patients to ionising radiation

(IAEA, 2008). Generally, upon arrival at a radiology department, the radiology department reviews the justification of a request and if appropriate, the patient is subsequently registered for a radiology examination and examined.

Radiology departments capture justification information as well as registration information from documented radiology request information complementing it with verbal information from patients (Sibanda, 2012). Together the request information, information captured into the radiology register, radiology reports and radiology images constitute radiology administrative data for a patient (WHO, 2007; Pelletier, Duffield & Donoghue, 2005). The accepted policy in clinical practice is that administrative data for each patient must be documented and must inform of the presenting condition, diagnosis, care provided and the outcome of that care as a continuous medico-legal record (WHO, 2007).

1.2.1 Justification of exposure for diagnostic purposes

Diagnostic radiology uses x-rays, among other forms of radiation, to further the diagnosis of patients. X-rays fall under a class of electromagnetic radiation which is ionising and termed a teratogen. The interaction of ionising radiation with human body atoms generates free radicals and ions which are potentially harmful. Therefore, because exposure of patients to ionising radiation can be harmful, its use is controlled such that, where its use is necessary, it must be used judiciously (IAEA, 2008).

Where ionising radiation is used for diagnostic purposes, the justification process is pivoted on the risk/benefit ratio to the patient as well as optimisation of exposures (IAEA, 2008; ICRP, 2007). In particular, the use of x-ray imaging is justified on it being able to demonstrate a wide range of pathologies. In this way, the wide range of applications of ionising radiation for diagnostic purposes makes x-ray imaging an indispensible tool in health care and therefore its justification is generally taken for granted (IAEA, 2008; Sibanda, 2012; ECRP, 2008). This is termed level 1 justification of radiological exposures.

Exposure of a region of a patient's body to ionising radiation for diagnostic purposes falls under level 2 justification. The justification of level 2 exposures depends on the general validity of the exposure in furthering diagnosis of a patient in that particular anatomical region. As an example, a skull radiograph may demonstrate skull fractures, intracranial pressure or calcifications. Skull radiographs are therefore justified in so far as furthering the diagnosis of a patient where fractures, intracranial pressure or calcifications are suspected. The examination is carried out with the intention to confirm or rule out pathology and therefore is justified.

Level 3 justification, on the other hand, involves exposure of an individual patient to ionising radiation. Justification of such exposure is patient specific (Sibanda, 2012; IAEA, 2008) and depends on the value of the exposure in furthering the diagnosis of an individual patient. This requires that the referrer and the radiographer make clinical decisions about appropriate radiological choices for specific clinical circumstances presented by the individual patient (WHO, 2007; WHO, 2000). In this regard, the assessment of justification considers a patient's individual needs, risks and benefits as well as the value of other examination options (Sibanda, 2012; IAEA, 2008). As an example, while abdominal radiographs may be justified under level 2, such an exposure is contra-indicated for a pregnant patient. Therefore, it is prudent in radiography practice that every radiographer is clear on these justification guidelines as they impact on the demand for diagnostic radiology and therefore, the potential harm caused by these exposures.

1.2.2 Diagnostic radiology exposure guidelines

Diagnostic radiology exposure guidelines are statements that are systematically developed to assist clinical decisions about appropriate radiological choices for specific clinical circumstances (Sibanda, 2012; ECRP, 2008). The ECRP (2008) explains that these statements spell out clinical situations for conducting a radiological examination, list some possible imaging techniques, give recommendation on the justification of the examination and further give explanations and radiation exposure bands involved. The fundamental purpose of these guidelines is to contribute towards the elimination of the main causes of unjustified exposures.

In this way, adherence to exposure guidelines reduces the frequency of unjustified radiological exposures and therefore, the demand for diagnostic radiology examinations (Sibanda, 2012). While ratios of patients that are wrongly turned away in an attempt to adhere to these guidelines have not been identified, causes of unjustified examinations are well documented (Sibanda, 2012; IAEA, 2008; ICRP, 2007). Causes of unjustified exposures that have been singled out as having the greatest impact on the demand for radiology services are repeating investigations which have already been done, doing an examination when the results are unlikely to affect patient management, doing the wrong procedure, failing to provide appropriate clinical information or raise questions that the examination should answer and over dependence on radiological examinations (Sibanda, 2012; ECRP, 2008; IAEA, 2008). However, despite the fact that these exposure guidelines are well documented (IAEA, 2008; ECRP, 2008), inappropriate diagnostic radiology exposures remain a cause of concern (Sibanda*,* 2012; Rehani, 2010; Emanuel & Fuchs, 2008; IAEA, 2008; Levin & Rao, 2004; Bosch, Hollingworth & Kinmonth, 2003; Khoo, Heron & Patel *et al.,* 2003; Eccles *et al.,* 2001).

Effects of inappropriate exposure to ionising radiation to affected patients have been documented as distress, financial burden and the risk of harm from the radiation (Sibanda, 2012; IAEA, 2008). Furthermore, inappropriate exposures add unnecessarily to demand for radiology services, to the population dose and to the workload (Sibanda, 2012). Again further to the aforementioned drivers of demand for radiology examinations, Sibanda (2012) investigated the impact of completeness of examination requests on the justification of diagnostic radiological exposures and found that generally, completeness had a significant impact on the number of justified requests. Sibanda (2012) was guided by literature in formulating the criteria for completeness and justification of diagnostic radiology requests (IAEA, 2010, IAEA, 2008). These criteria also guided knowledge building in this current study of *diagnostic radiology demand and capacity in Zimbabwe: trends and forecast.*

1.2.3 Variables that impact on demand for radiology services

Identifying and evaluating variables that impact on the demand for diagnostic radiology services is not a new concept as it dates back at least as far as 1993 (Maclaren, Ghoorahoo & Kirby, 1993). Since then many researchers have quantified the impact of various factors using different approaches (Sibanda, 2012; Triantopoulou, Tsalafoutas, Maniatis *et al.,* 2005; Eccles, Nick, Grimshaw *et al.,* 2001; Oakeshott, Kerry & Williams, 1994). Conclusions drawn from this literature pertain to over dependence on radiology examinations as well as inappropriate examinations, mainly but not limited to lack of awareness of exposure guidelines by referrers, thereby unnecessarily increasing the demand for radiology services. It also emerged that technological advancement especially the advent of a computer and image processing in the late 1970s, was singled out as one of the key drivers of demand for diagnostic radiology imaging that also enabled the capacity of imaging to significantly increase.

In Zimbabwe, a survey conducted by Sibanda (2012) in one radiology department reflected an exponential use of radiology services from 2006 to 2010. This background information shows that it remains imperative to elaborate on how much each one of the variables impacted on demand for radiology examinations. Furthermore, the Zimbabwe government had a National Health Strategies (ZMOHCC, 2009; ZMOHCC, 2013) which sought to regulate the patient care pathways thereby impacting on demand for radiology services. Supported by this background information Sibanda, Hering and Engel-Hills (2014) did a survey of demand and capacity for a radiology department in Zimbabwe in order to explain patient waiting times. They were able to make inferences that explained patient waiting times. The study by Sibanda *et al.,* (2014) was also pivotal for knowledge building in this current study of diagnostic radiology capacity and demand in Zimbabwe: trends and focus.

1.2.4 The Zimbabwe Ministry of Health and Child Care

Historically, the Zimbabwe Ministry of Health and Child Care services have been guided by five year Zimbabwe National Health Strategies (ZNHS) which are revised or replaced from time to time (ZMOHCC, 2009). The 2009-2015 National Health Strategy (ZMOHCC, 2013) titled “Equity and Quality in Health: Goals and Objectives” was preceded by the 2009-2013 National Health Strategy (ZMOHCC, 2013) titled “Equity and Quality in Health: A People’s Right”. In these two documents, the Ministry explains that “the main aim of the National Health Strategy 2009-2013 was to improve the health status of Zimbabweans and to put the country back on track towards achieving the Millennium Development Goals”. Consistent with a case study by Sibanda (2012), the Ministry further reports that utilisation rates for its services have been increasing over the years and that it was now prudent that the health sector moves “from the “emergency mode” of 2009-2010 to a planned health sector development strategy” (ZMOHCC, 2013). Accordingly, the ministry evaluated its performance under the 2009-2013 Zimbabwe National Health Strategy and identified gaps in its address of pivotal issues. The identified gaps necessitated that the ministry extend the preceding strategy to 2015 (ZMOHCC, 2013).

The 2009-2013 five year National Health Strategy (ZMOHCC, 2009) was designed to ensure provision of clinical services through an array of health facilities organised according to sophistication of the services they provide. In this system, patient referral up the referral chain was informed by the severity of the patient’s clinical condition. The referral chain consisted of primary, secondary, tertiary and central levels. Primary level comprised clinics and rural health centers. The secondary level was the first referral level and comprised district, mission and rural hospitals. The tertiary level was the second referral level and comprised provincial hospitals. The central level was the third referral level and comprised central hospital and infectious diseases hospitals. The research sites for this dissertation fell in the secondary, tertiary and central levels. According to this referral strategy, radiology requests that were received by central level centres were for those patients whose conditions required more sophisticated radiology resources than are found at primary level (ZMOHCC, 2009).

The traditional approach adopted by the Zimbabwe Ministry of Health and Child Care in developing National Health Strategies has always been to start with a review of old strategies (ZMOHCC, 2013). However, for the 2009-2015 Zimbabwe National Health Strategy, the Ministry alludes to the fact that the 2009-2013 Zimbabwe National Health Strategy was not reviewed but upgraded to add a major component that was missing from the ZNHS 2009-2013. The ministry further explains that this process was guided by the "Foreword" of the ZNHS 2009-2013:

Foreword of the ZNHS 2009-2013

Uncertainties over resources have made it difficult to set concrete targets to attain over the life of this strategy; however, a comprehensive Monitoring and Evaluation plan will be developed as an immediate first step to enable integrated monitoring of strategy implementation and impact. (ZMOHCC, 2009)

The ministry suggests that the missing link was a comprehensive Monitoring and Evaluation plan which necessitated the extension of the 2009-2013 Zimbabwe National Health Strategy to 2015. In the extended version, components that were identified as necessary for a successful evaluation of the 2009 - 2013 strategy were added in the 2009-2015 strategy. In particular, the process involved "looking at the 33 goals and several objectives in the 2009-2013 ZNHS and adding outputs, indicators, best available baselines and 2015 targets" (ZMOHCC, 2013). The updated version gave rise to a befitting extended title: "Zimbabwe National Health Strategy 2009 – 2015: Equity and Quality in Health: Goals and Objectives". In extending the 2009-2013 ZNHS, the ministry was particularly cognoscente of a number of programs that had developed specific program sub-strategies during the tenure of the 2009-2013 ZNHS and therefore had to include goals and objectives of these sub-strategies in the updated strategy. In this way, the 2009-2013 ZNHS formed the impetus of the 2009-2015 ZNHS thereby directing that any reference to this updated version be read in conjunction with its predecessor strategy as well as the program specific strategies.

The Ministry explains that the 2009-2013 strategy was pivotal in the formulation of important documents such as the “Government Medium Term Plan, the Zimbabwe United Nations Development Assistance Framework (ZUNDAF) and the Millennium Development Goal targets” (ZMOHCC, 2013). Therefore, because these documents all ran until the end of 2015, this saw the Ministry accordingly extending the 2009-2013 strategy to run in tandem with these documents. During the same period, it was also noted that the Government of Zimbabwe also formulated a new intervention programme known as the Zimbabwe Agenda for Sustainable Socio-Economic Transformation (ZIM ASSET): October 2013-December 2018 whose tenure overlaps with that of the two aforementioned strategies (ZMFED, 2013; ZMOHCC, 2013). According to the Ministry of Health and Child Care, the formulation of this intervention programme was informed by the 2009-2013 strategy (ZMOHCC, 2013). Quite intriguing is that this ZMFED (2013) document emphasises that Government ministries must formulate evidence based policies in order to optimise resource allocation and utilisation. Consistent with this requirement, the government prescribes the adoption of Results Based Budgeting (RBB) principles that focus on clear organisational visions and missions (ZMFED, 2013; ZMOHCC, 2013). This is in order to ensure resource availability, sustainability and to achieve equity in health by targeting resources in a way which enhanced access to health services as and when needed (ZMOHCC, 2013). These objectives formed the impetus of the current study of diagnostic radiology demand and capacity in Zimbabwe: trends and forecast. Furthermore, the Zimbabwe Ministry of Health and Child Care successfully lobbied the government to designate “Health as a Right” in sections 29 and 76 of the Zimbabwean constitution and captured into ZMOHCC (2013):

HEALTH AS A RIGHT

SECTION 29

... “The State must take all practical measures to ensure the provision of basic, accessible and adequate health services throughout Zimbabwe.”...

SECTION 76

...”Every citizen and permanent resident of Zimbabwe has the right to have access to basic health-care service, ... The State must take reasonable legislative and other measures, within limits of the resources available to it, to achieve the progressive realization of the rights set out in this section.”...

(ZMJLPA, 2013)

This background information was an exciting development for this dissertation as it impacted directly on the variables that formed the impetus of the study of *diagnostic radiology capacity and demand in Zimbabwe: trends and forecast.*

1.3 Radiology capacity for Zimbabwe

Zimbabwe has ten provinces with a total of 1533 health facilities of which 202 are referral hospitals. Referral health facilities offer, among other services, radiology services. The distribution of the 202 health facilities among the referral levels is such that secondary (181), tertiary (7) and central (14) referral levels (ZMOHCC, 2009). Referral hospitals that are in the same province share the same population of referrers. In this referral system, a patient referred for radiology has the prerogative to choose which radiology department (at a particular level) to go to. Consequently, these hospitals share the same population of referrers. Government referral hospitals that are at the same referral level also charge rates that aere determined by government from time to time. With respect to the fees charged, each of these radiology departments has an equal chance of receiving these patients.

Consistent with the 2009-2013 strategy, the Ministry explains that while there were some achievements recorded four years into 2009-2013 ZNHS, there remained a number of challenges in the health sector, chiefly due to shortage of resources (ZMOHCC, 2013). In the same document, the Ministry further explains that the success rate of its programmes was hinged upon adequate resources and appropriate working environment. According to ZMOHCC (2013), the Public Sector Human Resources for Health vacancy levels recorded in May 2013, were at an overall of 19 % with vacancy rates for specialist doctors of 73 % while that for radiographers was reported to be 50 %. The main reasons for these trends are cited as “poor conditions of service and the poor working environment” (ZMOHCC, 2013). In this regard, the Ministry says that the workload was on an upward trend owing to the aforementioned employment rates and further compounded by the use of “an establishment that was given thirty years ago”. The capacity of radiology departments has been singled out in the same document as an example of a critical area in need of recapitalisation. As an example, the Ministry points out that diagnostic radiology equipment was old, obsolete and in most cases non-functional in a number of institutions and that the situation was compounded by gross underfunding. The funding for these expensive resources has been heavily dependent on donor funding, a situation the Ministry says is not acceptable (ZMOHCC, 2013).

1.4 Organisation of radiology in Zimbabwe

Diagnostic radiology services in Zimbabwe are to a large extent provided by the government through its public health sector. The private sector generally represents stand alone departments that do not have a stratified referral system. The public health sector on the other hand, has a well established medical imaging system in all district, provincial and central hospitals (ZMOHCC, 2009). The referral system for the country requires that the patient be referred from primary to secondary, to tertiary hospital and then to central level as may be necessary. In all tertiary and central hospital radiology departments patient care is the responsibility of all staff. The management in radiology departments consists of a radiologist and a chief radiographer. Policy stipulates that each radiology department must have a radiation protection supervisor, a condition that is generally not observed by radiology departments. Government and private sector radiology departments complement each other in providing academic facilities for all health care personnel. These departments are an important research platform because they act as academic departments.

1.5 Diagnostic radiology resource structure for Zimbabwe

Radiology is a specialist area. The equipment used in radiology requires significant financial investments that have an impact on government fiscal. Therefore, matching demand and capacity was crucial for this sector. Public sector radiology departments receive their budget allocations from the ministry of health which in turn receives its budget from central government (ZMOHCC, 2009). The budget allocated for radiology services is historically donor dependent and not based on the stochastic nature of demand and required capacity (ZMOHCC, 2013). This approach renders the patient care pathways vulnerable to bottlenecks- those parts of the healthcare system with smallest capacity relative to demand on the system. Bottlenecks give rise to suboptimal radiology service (UKNHS, 2005).

1.5.1 The practice of diagnostic radiology in Zimbabwe

Diagnostic imaging has predominantly been the province of two groups of workers, diagnostic radiographers and radiologists who employ a range of sophisticated equipment to further the diagnosis of patients. To practice in Zimbabwe, these practitioners have to be registered with the Allied Health Professions Council (AHPC) and the Health Professions Council (HPC) of Zimbabwe, respectively. The expanded role of Radiologists is to diagnose, treat and monitor various disease processes. Consistent with global trends, in Zimbabwe, a referral for radiology is generally regarded as a request by a referrer for a specialist opinion on the patient’s clinical diagnosis (Sibanda, 2012; ECRP, 2008). The Statutory Instrument number 5 of 2004 (Zimbabwe) defines a referrer for radiology as a health professional. In this instrument, the term health professional means an individual who has been accredited through national procedures to practice a profession related to health. A referral for radiology, generally known as a radiology request, is normally made on a radiological request form, a patient’s clinical file or a patient’s clinical record book.

Diagnostic radiology departments perform both diagnostic imaging and image guided interventions thereby making diagnostic radiology an indispensable tool in clinical practice. In Zimbabwe, radiologist and radiographers are specially trained radiologic practitioners that handle cases that are considered too sophisticated for radiology equipment found at secondary level which are generally manned by x-ray operators (ZMOHCC, 2009). X-ray operators are specially trained to practice at secondary level although some secondary level radiological departments do employ radiographers mainly because of high radiology equipment capacity and sophistication of cases examined.

Across Zimbabwe, diagnostic imaging techniques include general radiology, magnetic resonance imaging, computed tomography, mammography, contrast studies, medical ultrasound, image guided interventions and nuclear medicine. Research carried out in 2012 in one central level diagnostic radiology centre showed that about 16 000 general radiography diagnostic procedures were carried out during the year 2010 alone (Sibanda, 2012). If this is taken to reflect the average for each of the 14 central level departments then the country carries out approximately 224 000 diagnostic radiology procedures at its public sector central level departments per year and in addition there are examinations at other levels of the system. This represents about two percent of Zimbabwe's thirteen million population.

1.6 The research problem

Radiology uses ionising radiation and other radiations, to further the diagnosis of patients. Ionising radiation is a teratogen (De Santis, Di Gianantonio, Straface *et al.,* 2005). While it is scientifically sound to hypothesise that there is a positive correlation between the proportion of exposed individuals in a population and cancer prevalence, gathering fundamental statistical data to support such an epidemiological study remains too cumbersome to achieve. Also of note is that radiology resources are generally so expensive that many economies consider them scarce resources and requiring efficient utilisation. While statistical data in respect of utilisation trends is invaluable in policy formulation aimed towards equitable distribution of scarce radiology resources, research that simplifies this process is yet to be identified in radiology practice. Variables that impact on the demand for radiology services are well documented yet while it is well documented that the frequency of radiological exposures impact on occupational dose, patient dose and population dose, studies that model interactions of radiology labour drivers in order to predict the number of patients that are exposed to radiation remains a researchable area.

The occurrence of long waiting times for radiology services is a major global concern for health systems and pressure on diagnostic radiology services has been evident from the number of imaging examinations undertaken annually. This has triggered policy makers to consider ways of managing patient waiting times and personnel workloads. Invariably, when faced with this problem policy makers always think of increasing personnel and equipment capacity. This is notwithstanding the fact that radiology resources require massive investments rendering this approach impractical for most low income economies.

While technological advancement, skill mix and role extension have emerged as integral practices for radiology departments in high income countries, role extension and skill mix (although being practiced) are yet to be formalised in Zimbabwe. It is widely accepted that, role changes involve complex processes that are influenced by a number of variables which include technological diffusion, government policy reforms, curricular and socialisation of new staff. These changes in the practice of radiography inevitably introduce new order of demands in the form of new working assignments. This has an impact on patient care pathways in a network of related disciplines.

When policy makers are faced with this problem, consistent with the line of thought exhibited by the Zimbabwe Ministry of Health and Child care in its National Health Strategy review, they invariably prescribe increased resources as a remedy. However, a more reasonable approach is to explore cheaper solutions first such as hypothesising that inefficiency in the delivery of health-care services is a result of variation mismatches between capacity and demand for radiology services. With reducing donor funding and the perceived impact of economic sanctions becoming more often talked about in Zimbabwe, there is growing internal pressure to align with global trends by employing evidence-based management policies. This requires a clear understanding of patient care pathways in order to direct resource allocation as well as optimise utilisation.

If the global approach is pursued, this brings with it the need to evaluate radiography curricular ability to match with these new demands. This is important because performing more complex tasks requires higher levels of decision making skill which normally would be outside routine training. High level curricular interventions as well as evidence based policies would build an informed workforce thereby increasing efficiency and reducing patient waiting times. There is also a school of thought that the radiology referral skills mix needs should be based on training that appropriately deals with the wide range of radiology tasks. This is particularly relevant to Zimbabwe because in the period preceding the onset of this study many health professionals were added to the list of accredited referrers (ZMOHCC, 2013). Alongside this development, there was a new requirement for Continuous Professional Development (CPD) as a pre-requisite for the renewal of practicing certificates. There was also an increasing demand for radiology services in tandem with reports of overutilization, incomplete and unjustified radiology requests as well as ignorance by referrers about exposure guidelines. In this regard, the nature of clinical radiology practice in Zimbabwe compels academic institutions to reflect on inter-professional roles and responsibilities against radiography curricular.

In spite of these problems, staff establishment, resource allocation and utilisation of material resources for Zimbabwe has remained supply driven and not demand driven. This has been compounded by the fact that most equipment is donor funded. Although, it is a fact that most equipment is donor funded, it can also be concluded that it is within the powers of decision makers to intervene from an informed point of view in the actual deployment of the donated resources. If unchecked, this scenario has the potential to reduce departments' capacity to efficiently respond to the stochastic nature of demand processes despite increased resources. Because there is a gap in health services resource management research, not only in Zimbabwe but also on a global perspective, policy formulation in this regard has remained largely depended on philosophies developed outside the health industry.

It is worth noting that while the Ministry was deprived of vital evidence based information necessary to efficiently deploy resources among radiology departments, new government policies such as ZMFED (2013) and ZMOHCC (2013) dictate that the Ministry use evidence based approaches. These policies are essentially aimed at optimising available resource allocation and utilisation in order to realise the Vision and Mission of the ministry. Fundamental to this background and to the Vision and Mission of the parent ministry, there was a need to map the radiology patient care pathway, evaluate variation mismatches between capacity and demand and then forecast future demand for radiology services. This was vital in informing policy formulation in the deployment and utilisation of both human and equipment resources in radiology departments. Further compelling evidence to conduct this research was:

(a) According to global statistics, diagnostic radiology exposures contribute the most towards artificial exposure to ionising radiation,

(b) It is common knowledge that technology and practices in diagnostic radiology are changing rapidly,

(c) The frequency of diagnostic radiology exposures was a thematic priority of the United Nations Scientific Committee's strategic plan (2009-2013) and

(d) The request for the UNSCEAR "secretariat to prepare a detailed plan for a report on this subject".

Importantly, the Committee had also requested for a Global Survey of Medical Radiation Usage and Exposures and was calling for close cooperation with international researchers in this regard. In conclusion, scenarios identified in this problem have led to a compelling need for the research objectives that this thesis addresses. Furthermore, consistent with a case study by Sibanda (2012), the Ministry reports that utilisation rates for its services have been increasing over the years and that it is now prudent that the health sector moves "from the "emergency mode" of 2009-2010 to a planned health sector development strategy". This research could not have come at a better time than this and because of the diversity of factors impacting on capacity and demand trends, motivation was pivotal in maintaining focus to the objectives of this study.

1.7 Motivation

The period preceeding the data collection involved important deliberations in Zimbabwe regarding Continued Professional Development (CPD) for radiographers, upgrading of diploma radiography graduates to degreed radiography graduates and establishment of post graduate radiography degrees in Zimbabwe. Numerous meetings were organised by the Radiographers Association of Zimbabwe (RAZ). In these meetings, radiographers presented their experiences which included issues that impacted on radiology patient care pathways in the practice of radiography. In particular, radiographers indicated that their departments experienced long patient waiting times, overutilisation of radiology, incomplete and unjustified requests. However, there was no mention of how these labour drivers individually contributed to the problem except for one study which quantified the proportion of justified requests for one radiology department (Sibanda, 2012). With this background information, there was no doubt that these issues would best be understood by mapping the radiology patient care pathway. This would in turn require focus on the synergy among stake holders in the radiology patient care as it impacted on the demand and capacity for radiology services. There was much to consider regarding this proposed approach which included rigorous ethics evaluation. On the other hand, getting radiology staff to accept operations research required not only academic knowledge, but also knowledge about people's perceptions about potential impact of policy change emanating from this research.

There were other factors that played a role in the demand for radiology services in Zimbabwe. The radiography education developments up to 2012 were accompanied by a period of rapid entrepreneurship in imaging with the adoption and diffusion of many new technologies. Browsing the research data base for Zimbabwe revealed little evidence of high level research activity by radiographers. In this regard, there was no doubt that the Radiography Association of Zimbabwe was still in its infancy with regards peer reviewed research. As a result of the aforementioned, it was clear that the research base within the radiography profession in Zimbabwe was not well developed to reflect the impact of both exogenous and endogenous labour drivers on referrals. Further to the aforementioned factors, it was possible that other factors which included; technology diffusion, training content, socialisation of new employees into the system, impact of new technology on role extension, the critical shortage of radiologists (ZMOHCC, 2013) and the adoption of new technologies that drew radiologists away from their traditional roles increased the demand for radiographers.

In 2014 role extension meetings that sought to formalise radiographers' roles by formally taking some of the tasks previously undertaken by radiologists were conducted by the association of radiographers under the initiative of the Allied Professions Council of Zimbabwe. It was inevitable that this move would increase work load for radiographers but the rationale was that there were more radiographers and their training was shorter than that of radiologists thus making this a cost effective solution. Importantly, if there was to be a role change and therefore policy shift in radiology human resource structure, questions regarding the capacity of the radiology departments to accommodate the demand for radiographer services in the new role structure needed to be answered.

It was practically, impossible then to lobby for a role change for radiographers without first providing this key understanding. Coincidentally, finalised role change proposals still remain pending as if waiting for more evidence from this study to support this change. This environmental reality was therefore a motivation to choose a research approach informed by the impact on the demand for radiology services of variation mismatches in the practice of radiology. Therefore, before embarking on the program of research, deep insights into the practice of radiography in Zimbabwe as well as an impression of factors that impacted on the practice of radiography had been developed. This background provided the foundation necessary to pursue the study of *diagnostic radiology demand and capacity: trends and forecast.*

1.8 The program of research

The research focused on three key aspects: map of the radiology patient care pathway, labour drivers for radiology demand and forecasting demand for radiology services. Chapter two of the thesis evaluates previous research that formed the impetus of this study while chapter three details the overall research methodology drawing from the reviewed literature. The results section comprises three chapters. These chapters are presented according to the research objectives (and therefore research questions): chapter 4 of the report evaluates the radiology patient care pathway for Zimbabwe, chapter 5 identifies and evaluates drivers for radiology demand and chapter 6 is concerned with forecasting demand for radiology services. Chapter 7 of the thesis is an overall discussion of the research process while chapter 8 evaluates the outcomes.

CHAPTER TWO

DIAGNOSTIC RADIOLOGY DEMAND, CAPACITY, TRENDS AND FORECAST A LITERATURE REVIEW

2.1 Introduction

There is overwhelming global evidence that radiology utilisation has increased in high income countries (Borretzen, Lysdahl & Olerud, 2007; Chrysanthopoulou, Kalogeropoulos, Terzis *et al.,* 2007; Matin, Bates, Sussman *et al.,* 2006; Semin, Demiral & Dicle, 2006; Bhargavan & Sunshine, 2002). This has forced policy makers to consider evidence based policy formulation as a solution to this demand. The use of evidence based healthcare to inform the way management decisions are made has been a consistent global theme in healthcare policy formulation for many years now (ZMFED, 2013; ZMOHCC, 2013; UKNHS, 2006). However, there is evidence of a gap between radiography research and radiography practice particularly with respect to improvement methodologies (Gahan, 2010; Berwick, 2003). Over the years, this gap has largely contributed to a slow shift towards evidence based healthcare resource management policy in the global perspective (Berwick, 2003; Walshe & Rundall, 2001). This is despite the fact that health delivery systems are processes and, being processes, possess characteristics that are central to the concepts of improvement methodologies that are well documented for non health industries. Consistent with this notion Gahan, (2010) noted that where a shift towards evidence based practice has been identified, it has largely been on the basis of management philosophies formulated and tested outside healthcare industries.

Many researchers have given examples of improvement philosophies: Lean Thinking, Queuing Theory, Theory of Constraints, Six Sigma and System Dynamics (De Feo & Barnard, 2004; Bicheno, 2000; Goldratt & Cox, 2004; Womack & Jones, 1996). Drawing from this literature, inferences have also been made from maps of patient care pathways implying that safe, high quality and cost effective radiology healthcare is possible through application of the aforementioned improvement methodologies (Gahan, 2010; UKNHS, 2005; Lodge & Bamford, 2008; Hobson, 2007; Spear, 2005). In this chapter reviews of the foundations of these improvement paradigms, specifically, variation mismatches of demand and capacity with a view to explain how a broader view of utilisation trends can help in forecasting utilisation. Because the retrospective document review was for 2004-2014 window period, researches carried out from ten years prior to the period the research carried out were deemed important in informing the research process (Matin, Bates, Sussman *et al.,* 2006; Rosenberg, 1997). This review formed the impetus for the study of *diagnostic radiology demand and capacity for Zimbabwe: trends and forecasting.*

2.2 Management of patient throughput in radiology departments

Consistent with the definition of clinical patient care pathway, radiology patient care pathways refers to the process a patient follows from the time he or she is referred for a radiology examination until a time he/she is dismissed from a radiology department (Daniel & Alan, 2006). These clinical care processes are used internationally to guide evidence-based radiology healthcare (Daniel & Alan, 2006). In general, a clinical care pathway is defined for an examination process thereby leading to varied points of view among researchers and healthcare workers regarding what constitutes a clinical pathway (Daniel & Alan, 2006). This alone shows that this area remains open to lot of knew knowledge yet to be explored. However, when it comes to the United Kingdom's National health Services, work done to clear bottlenecks in patient care pathways, to understand the magnitude and variation mismatches in demand and capacity and to smooth these variations where possible. The overall objective of this work was to prepare the ground for Lean thinking. This work by the UKNHS (2005) explains how evidence based approaches can be used to map radiology clinical care pathways and how to use the relationship between demand and capacity to explain workloads and therefore patient waiting times. This literature formed the impetus of this research.

Consistent with UKNHS (2005), Daniel and Alan (2006) allude that in non healthcare industries, waiting times (or queuing as is widely known) and workload have for a long time been most widely managed using Lean Thinking. They explain that Lean Thinking is a client service improvement paradigm that was muted by Toyota manufacturing company over half a century ago (Daniel & Alan, 2006). The same authors further explain that Lean Thinking has been spreading inevitably from industry to industry for over half a century and, in the process, its principles were fine-tuned and tested. Drawing from literature, an important documented observation about Lean Thinking is improvement of quality of services to clients by redeployment of resources without necessarily having to invest more in resources (Langley, Nolan, Nolan *et al.,* 2009; Daniel & Alan, 2006; UKNHS, 2006; UKNHS, 2005). Problems identified by ZMOHCC (2013), require an understanding of mismatches in demand and capacity variation as they impact on Lean management of radiology resources (Langley *et al.,* 2009; Daniel & Alan, 2006).

Langley *et al.* (2009) and the National Health Services of the United Kingdom explain how individual quality improvement initiatives are interlinked to model the performance of Lean (Langley *et al.,* 2009; UKNHS, 2006; UKNHS, 2005). They further explain that Total Quality Management (TQM) and Six Sigma Management (SSM) approaches are handy in measuring the root causes of variation mismatches in capacity and demand. Further to these improvement methodologies, Total Productive Maintenance (TPM) is identified by the Langley *et al.* (2009) as vital in improving material capacity while the Theory of Constraints (TOC) is identified as pivotal in the management of bottlenecks. An intriguing aspect drawn from these authors is the recognition that Systems Dynamics (SD) may provide for general optimization of the whole patient care process rather than optimising individual activities. However, despite these recommendations, the UKNHS (2006) reports that despite this evidence, all too often, organizational restructuring and re-organisation does not always result in improvement to the work people do but often interferes in the way in which the work should be carried out. This, according to UKNHS (2006), is because while the general rule of thumb is that restructuring should happen after the basic work problems have been identified and solved, all too often restructuring is done before this evidence based knowledge is acquired. This analysis is consistent with evidence drawn from the ZMOHCC (2013) where operations research in radiology is not visible to support policy formulation.

Many researchers have reported on basic work problems for radiology departments: over utilisation, high demand and/or long waiting times for radiology services (Sibanda, 2012; Gahan, 2010, Rehani, 2010; Emanuel & Fuchs, 2008). Consistent with the UKNHS (2006), Gahan, (2010) also alludes to the fact that, all too often, where high demand for radiology services have been identified, inevitably, policy makers embark on increasing capacity in order to match demand. However, all too often again, limited budgets and expensive human and equipment resources for radiology departments have been cited as constraints for increasing capacity for radiology departments (Gahan, 2010). Lessons drawn from this literature are particularly important for small economies. This assertion is supported by the fact that, in the case of the United Kingdom, it is rare to encounter situations where demand generally exceeds capacity (Langley *et al.,* 2009). This suggests that for big economies general lack of capacity is rarely a cause of any observed inefficiencies and any observed long waiting lists and times (Martin, Sterne & Gunnell, 2003; Audit Commission, 2002; Murray, 2000). This evidence suggests that the solution for this particular case lies in the Theory of Constraints which states that all processes have an associated bottleneck step (Langley *et al.,* 2009; Gahan, 2010; UKNHS, 2006; UKNHS, 2005). In this regard and because of high cost of radiology resources, the Theory of Constraints approach should be the method of choice for low income economies.

A bottleneck step is defined as a rate limiting step in a patient care pathway (UKNHS, 2005) because, inevitably, patient flow is restricted at this step. In this way it can be inferred from this philosophy that increasing capacity to a part of the patient care pathway, other than a bottleneck part, will not in any way improve the net flow of patients. However, on the contrary and logically, increasing capacity at a bottleneck part is a fundamental way of improving net flow of patients (Gahan, 2010; UKNHS, 2005). An important scenario arises when capacity and demand variations are matched as this arrangement optimises utilisation of resources by ensuring that all resources are utilised to their fullest at any given time and stage in the patient care pathway (Langley *et al.,* 2009; UKNHS, 2006; Lee & Silvester, 2004; Silvester, Lendon & Bevan, 2004). This represents a situation where demand to capacity ratio equals one. This understanding is very important from a management point of view because in situations where demand exceeds capacity a waiting list, patients' queue or backload of work is created but on the contrary when capacity exceeds demand, and cannot be filled by waiting lists, this spells inefficiency due to under-utilisation of these cost intensive radiology resources (Langley *et al.,* 2009; UKNHS, 2005; Silvester & Walley, 2005; Lee & Silvester, 2004; Silvester *et al.,* 2004).

2.3 Radiology exposures: important lessons

Growing global radiology capacity as well as growing demand for radiology services has brought with it growing global concerns over healthcare costs and radiation hazards (Sibanda, 2012; Emanuel & Fuchs, 2008; IAEA, 2008; Matin *et al.,* 2006). In particular, ionising radiation hazards have been a global concern dating back to the nineteen nineties (UNSCEAR, 1996). This concern drove many researchers to investigate key drivers of high demand for radiology services. In this pursuit, overutilisation, unjustified examinations, patient demands, technology diffusion and role extension were identified as key drivers to high frequencies of inappropriate radiology exposures (Sibanda, 2012; Rehani, 2010; IAEA. 2008; UNSCEAR, 2008). Any unnecessary radiology examinations add to radiology demand thereby impacting on waiting times and workloads (Sibanda, 2012; Gahan, 2010; ECRP, 2008; UKNHS, 2006). Apart from identifying under resourced areas in the patient care pathway, an analysis of demand trends for diagnostic radiology services is pivotal in identifying inappropriate radiology practices (Matin *et al.,* 2006; UKNHS, 2006). This school of thought requires mapping the radiology patient care pathway in order to identify and understand variables that impact on demand for radiology services and the flow of patients (UKNHS, 2006).

2.4 Demand for diagnostic radiology services

In a radiology perspective, the term "demand for diagnostic radiology services" refers to all requests and referrals for radiology services coming in from all sources to a bottleneck step (UKNHS, 2005). A bottleneck step itself is defined by the same author as that part in a patient's clinical pathway that has the smallest capacity relative to the demand on the system. In the same document, the author classifies bottlenecks into two types: process bottlenecks and functional bottlenecks. A process bottleneck being that stage in a process that takes the longest time to complete and is therefore referred to as the 'rate limiting step or task' in a radiology patient care pathway (UKNHS, 2005). This could be a radiographer conducting the examination, or a radiologist reporting on the images for example. On the other hand, functional bottlenecks are caused by services that have to cope with demand from several sources (UKNHS, 2005). Typically, in the radiology patient care clinical pathway, image reporting for example is all too often a functional bottleneck process that causes waits and delays for patients from several sources thereby causing disruption to the natural flow of radiology patient care processes. According to UKNHS, (2005) radiology demand is measured at each step by multiplying the number of patients referred by the time it takes to process or examine a patient at that step. Therefore, on the same note, the term radiology demand signifies the need for radiology services at any given point in time at a particular step in the patient care pathway.

Elsewhere, economists record demand on a demand schedule and plot it on a graph as a demand curve that usually reflects a negative or inverse relationship between price and quantity demanded (Mohr, Fourie & Associates, 2008). In this perspective therefore, each radiology patient has a demand curve for any radiology service that he or she is willing and able to access assuming full information and the lack of frictions that would perturb the patient's choice (Mohr *et al.,* 2008). Using the same author's line of thought, when the demand curves of all radiology patients are added up, the result is a market demand curve for radiology services which should also indicate a negative or inverse relationship between the cost for a radiology service and quantity demanded.

2.4.1 Radiology demand function

There is no literature that was identified with respect to radiology demand function. However, the use of well documented operations research/economics demand function methodologies as a framework for developing radiology demand function was considered logical in ensuring the validity of this study. Therefore, consistent with literature (Mohr *et al.,* 2008), a radiology demand equation may be defined as the mathematical expression of the relationship between the number of radiology examinations demanded and those factors that affect the willingness and ability of a patient to access the examination (Equation 2.1). In this equation, on the left side is the utilisation or demand for radiology services (Q_d) while on the right side is a function that manipulates labour drivers to give the observed demand for radiology services. As an example, if Q_d denotes the number of radiology examinations demanded, E the amount charged for the examination, P_{rg} the amount charged for a substitute or complementary examination, and Y the income of a patient then we can write:

$Q_d = f(E; P_{rg}, Y)$……………………………………………………………Eqn 2.1

Consistent with economics methodologies, equation 2.1 denotes a demand equation. The function on the right side of the equation is called the demand function, commonly referred to as labour drivers (Mohr *et al.,* 2008). In this example, the semi-colon in the list of arguments for this demand function means that the variables to the right of the semi-colon are being held constant as one plots the demand curve in (number of examinations, price) space. Using this line of thought, a demand equation (Mohr *et al.,* 2008) may be written as:

$Q_d = 1.1Y- 4P_{rg}$ - E -constant. …………………………………………………….Eqn 2.2

In this example, the constant is the repository of all relevant non-specified factors that affect demand for radiology examinations, **E** is the fee for the examination and the coefficient for the cost is negative in accordance with the law of demand (Mohr *et al.,* 2008). According to this approach, if P_{rg} examination were a complement, the coefficient of its fee would be negative as shown in equation 2.2. However, if it were a substitute examination, the coefficient of its price would be positive (Mohr *et al.,* 2008). On the contrary, income (Y) has a positive coefficient. This is illustrative of a requested examination being routine, normal or indicated for the presenting condition. If the requested examination was inappropriate or unjustified, the coefficient would be negative meaning that the demand for the examination would fall as the patient's income increased (Mohr *et al.,* 2008). In essence, this literature review shows that in a demand equation, these coefficients will be positive whenever a variable is known to have a positive impact on demand and negative otherwise.

2.5 Radiology utilisation trends: methodology and sources of data

The United Nations Scientific Committee on the Effects of Atomic Radiation (UNSCEAR) has, for years, been evaluating global trends in radiology demand by assessing annual frequency and types of procedures being undertaken. The committee also evaluated radiation doses for each type of radiology procedure. UNSCEAR, (2008) defined this process of establishing radiation doses for each type of procedure from an evaluation of annual frequencies as an evaluation of radiology exposures. The 1982 UNSCEAR report which used a survey developed by WHO in co-operation with UNSCEAR, to establish capacity and demand for radiology services in various countries is an important indicator that the desire to optimise radiology resource management is not a new concept. However, the Committee acknowledges that its radiology demand estimates were limited in that surveys were only conducted in a few countries (mostly high income countries) and this was followed by extrapolation of the data to other similar environments.

In the 2008 Committee's report, annual frequency and dose data were derived from three main sources namely, "peer-reviewed scientific literature, official reports provided by member States, and Surveys of Medical Radiation Usage and exposures conducted by the secretariat on behalf of the Committee" (UNSCEAR, 2008). An important lesson drawn from this literature is that the number of physicians per head of population is well correlated with radiology demand for a given research site (UNSCEAR, 2008). In this regard, this correlated behaviour allowed for an extrapolation of data to those research sites for which there was limited or no data (UNSCEAR, 2008). It is not surprising then that the approach used by many researchers to evaluate demand for radiology services involves annual frequency data on procedures stratified by health-care level (level I, II, III or IV) as defined in this literature. Table 2.1 illustrates this stratification model. As an example, in the UNSCEAR (1988) report, this four-level health-care model was successfully used to stratify countries according to the number of physicians per head of population.

Table 2.1: Radiology capacity stratification model (UNSCEAR, 1988; UNSCEAR, 2008)

Level	Number of Physicians	Number of people in the general population per physician
I	1	1 000
II	1	1 000-2 999
III	1	3 000-10 000
IV	Less than one	10 000

Consistent with the Committee, many researchers have conducted surveys to establish demand and capacity trends for radiology services (Matin *et al.,* 2006; Maitino, Levin, Parker *et al.,* 2003; Henley, Mann, Holt *et al.,* 2001; Khorasani Goel, Ma'luf *et al.,* 1998). It emerges from literature that other approaches that have been used to explore the radiology demand include classification of health-care levels by health-care expenditure, number of hospital beds, Case Mix Index (CMI) and Case-Mix-Adjusted Admission (CMAA). However, it was found that there was poor correlation between values for these latter parameters and the number of medical radiation procedures as opposed to the four tier stratification reported in Table 2.1. As a result, this four tier approach was considered unparalleled and robust in estimating medical radiation exposures and therefore, has remained the basis for many studies (UNSCEAR, 2008, UNSCEAR, 2000; UNSCEAR, 1996). This is understandable because the approach has an important advantage that provides a consistent foundation for extrapolation of practice in a small sample to the entire population (UNSCEAR, 2008) and further facilitates the comparison of trends in medical exposures over time (UNSCEAR, 1988).

Another important observation from literature is that further analysis of frequency data may lead to data on doses. In this analysis, to calculate dose due to each procedure, the product of the number of procedures per head of population, the effective dose per procedure and the relevant population size for the respective health-care level is calculated. This means that the analysis of exposure frequency data may be taken a step further to determine collective effective dose (which is also called population dose) for a country's population by adding together dose due to all radiological procedures. The 2008 survey report on radiology frequencies by the UNSCEAR, covered the period 1997-2007. This report includes frequency data on Zimbabwe. Of particular note is that the basis of the Committee's estimation of medical exposures was upon an analysis of limited questionnaire returns which were mostly from high income countries. This approach by UNSCEAR provided important literature that guided the research methodology for the study of *Radiology demand and Capacity in Zimbabwe: Trends and Forecast.*

2.5.1 Radiology utilisation trends: achievements and gaps from previous research

The last decade has seen many researchers publish work on trends in the demand for diagnostic radiology services (Matin *et al.,* 2006; Maitino *et al.,* 2003; Henley *et al.,* 2001; Khorasani *et al.,* 1998). Unfortunately, all these aforementioned researches were limited to the United States of America. Research on work load has evolved around the development of claim coding using Relative Value Unit (RVU) assigned to a claim which, when multiplied by the conversion factor (CF) and a geographical adjustment (GPCI), creates the compensation level for a particular service. This code takes care of the relative level of time, skill, training and intensity a physician would take to provide a given service. This data is readily available from medical aid schemes that have adopted this coding system.

The Case Mix Index (CMI) can be used to adjust the average cost per patient (or day) for a given hospital relative to the adjusted average cost for other hospitals by dividing the average cost per patient (or day) by the hospital's calculated CMI. The adjusted average cost per patient would reflect the charges reported for the types of cases treated in that year in the form of case-mix-adjusted admission (CMAA). With these variables in mind, Matin *et al.,* (2006) assessed workload trends using relative value units (RVUs) and linear regression analysis to assess the significance of trends for the number of examinations and RVUs per case-mix-adjusted admission (CMAA). Earlier on, Henley *et al.,* (2001), set out to test the significance of Relative Value Units (RVU) after adjusting for case-mix-adjusted admission (CMAA). These researchers concluded that the increase in inpatient imaging RVUs between 1993 and 1998 in America was no longer significant after accounting for changes in case mix and that only the increase in magnetic resonance imaging RVUs was significant.

Khorasani *et al.,* (1998), also report for America that total imaging per patient admission declined over a decade (1984-1993) upon an adjustment for the severity of illness. They further report a significant increase in total inpatient imaging RVUs even after adjustment for case mix brought about by the increases in Computer Tomography (CT) and Magnetic Resonance Imaging (MRI) rates. This is in contrast to Henley *et al.,* (2001), who report an increase in total imaging per patient admission for the same host country. Maitino *et al*., (2003), reported that the demand for conventional studies among the Medicare population in America declined significantly nationwide between 1993 and 1999, whereas the use of all other imaging techniques increased. The work by Maitino *et al.,* (2003) is consistent with that of Khorasani *et al*., (1998) who concluded that the newer imaging technologies were replacing conventional studies. Khorasani *et al.,* (1998) recommend that to control further increase in overall imaging costs, priority should be placed on understanding trends in the demand for CT and MR imaging techniques and curbing their inappropriate use.

In a book written for the United States of America Department of Health and Human Services, Rosenberg, (1997), explains key concepts and methods in trend analysis, interpretation and predictive modelling. Rosenberg (1997), similar to Martin *et al.,* (2003), proposes a time series period of ten years. Martin *et al.,* (2003) realised that most published research on the demand for radiology were based on a 3-6 year period. In this regard, they identified two studies that calculated imaging rates adjusted for changes in disease severity among the patient population over their study interval. They then conducted a ten year radiology demand trend analysis for diagnostic radiography services in the United Kingdom in order to assess the significance of trends for the number of examinations and RVUs per case-mix-adjusted admission (CMAA). Their study comprised a retrospective review of administrative data of adult inpatients for fiscal years 1993-2002 in a 721-bed tertiary care institution.

Consistent with Martin *et al.* (2003), Maitino *et al.* (2003), Henley *et al.* (2001) and Khorasani *et al.* (1998) coded examinations according to imaging technique: conventional, sonography, nuclear medicine, CT or MRI. They went further to assess workload trends using relative value units (RVUs). Again, consistent with previous researchers, their results show a significant decrease in the total number of examinations per CMAA, which they account to significant decrease in the use of conventional studies and sonograms. This decrease is despite significant increase in the number of nuclear medicine, CT and MR imaging examinations per CMAA. They further report that the RVUs per CMAA increased significantly during the study period.

2.6 The focus of high demand for radiology services

Drawing from literature, global trends in the utilisation of radiology services has over the years remained technology specific (Matin *et al.,* 2006; Maitino *et al.,* 2003; Henley *et al.,* 2001; Khorasani *et al.,* 1998) and dependent on healthcare level (UNSCEAR, 2008). Global demand for diagnostic radiology services remains increasing partly because of the dynamic nature of technological innovation by equipment supply companies (UNSCEAR, 2008; Matin *et al.,* 2006; Maitino *et al.,* 2003; Henley *et al.,* 2001; Khorasani *et al.,* 1998). This technological innovation resulted in the introduction of new imaging techniques such as MRI, multislice CT and digital imaging. Collective dose due to CT examinations is generally a cause of concern in health care level I in which it is responsible for 34% of the collective dose due to medical exposures (UNSCEAR, 2000). In this regard, any increasing trend in annual CT demand and therefore the associated significant dose per examination have an important impact on the overall population dose due to radiological exposures.

The reduction of scan times brought about by the introduction of helical and multislice scanning (ICRP, 2007) has introduced a number of factors that impact on demand and capacity for diagnostic radiology services. As an example, this technological innovation made it possible to perform “more examinations in a given time, to extend the scope of some examinations and to introduce new techniques and examinations” (UNSCEAR, 2008). It has been reported that this ease of acquisition of images together with an increased number of such machines has a great impact on unnecessary diagnostic radiology exposures and therefore on population doses (UNSCEAR, 2008). This positions an accurate assessment of high demand radiological technologies (which on level I healthcare systems happens to be CT scan) as an important step in collective dose surveys.

2.6.1 Diagnostic radiology labour drivers: a global perspective

Exposure of patients to ionising radiation for diagnostic purposes is an indispensable part of healthcare (Sibanda, 2012; IAEA, 2008; ICRP, 2007). However, because ionising radiation is a teratogen as well as carcinogenic, these exposures are not without harm. Harm resulting from medical exposures has been cited in the report by the United Nations (UNSCEAR, 2008). Of particular importance in this study are those reports on carcinogenesis which were reported in annexure A of the report on "Epidemiological studies of radiation and cancer" (UNSCEAR, 2008) and those on accidental exposures reported on annexure C of the report "Radiation exposures in accidents" (UNSCEAR, 2008).

Benefits associated with exposures to ionising radiations have also been documented on a global perspective (IAEA, 2008; WHO, 1990). Generally, exposures to ionising radiations are on an understanding that the principles of justification and optimisation are adhered to. In practice area, day to day optimisation is a shared responsibility between a Medical Physist and a Radiographer and is hinged on the concept of doses that are "As Low As Reasonable Achievable" (ALARA) while justification is hinged on ensuring that the benefit to a patient outweighs the risk. It is however noted that cases of inappropriate exposure of diagnostic radiology patients to ionising radiation are well documented (WHO, 2016; Sibanda, 2012; Rehani, 2010; Emanuel & Fuchs 2008; IAEA, 2008; Levin & Rao, 2004; Bosch, Hollingworth, Kinmonth *et al.,* 2003; Khoo *et al.,* 2003; Taragin, Feng & Ruzal-Shapiro, 2003; Eccles *et al.,* 2001). Inappropriate exposure to ionising radiation can cause a lot of distress to the affected patient notwithstanding financial burden and the risk of harm from the radiation (Sibanda, 2012; IAEA, 2008; ICRP, 2007). Furthermore, these inappropriate exposures add unnecessarily to radiology demand (Sibanda, 2012; IAEA, 2008).

There are many drivers for radiology demand that have been identified in literature. Most of these have investigated to establish their impact on the demand for diagnostic radiology services. Eccles *et al.,* (2001) observed that referrers tend to rely too much on radiological tests such that most of the examinations contribute very little to the clinical management of patients. They noticed that these exposures were contrary to documented exposure guidelines so they set out to identify and assess two methods of reducing general practitioner referrals in accordance with referral guidelines for lumbar spine and knee radiographs. Their approach involved a cluster randomised controlled trial with audit and feedback, as well as educational reminder messages in six radiology departments involving 204 general practitioners. They were able to conclude that awareness of exposure guidelines by referrers was one of the important variables that modelled the demand for radiology services. This was after an observation that routine attachment of reminder messages about exposure guidelines to radiographs reduced the number requested by 20%. This result was consistent with that of Oakeshott, Kerry and Williams, (1994) who investigated the effect of guidelines for General Practitioner (GP) referrals to the radiology department.

Consistent with Eccles *et al.,* (2001) results, in a study by Oakeshott *et al.*, (1994) 62 practices and 170 GPs were enrolled. They stratified practices by number of radiographic examinations requested and then randomised them into two groups; the intervention group and the control group. They then conducted a prospective study of the request forms over seven weeks after which guidelines and an introductory letter were sent to the intervention group of practices. After a time lapse of three weeks request forms were further prospectively analysed for conformity spanned over a period of nine weeks. Their result was consistent with that of Eccles *et al.,* (2001), in that conformity was enhanced by the introduction of guidelines. However their approach had cohort effect implications. Triantopoulou *et al.,* (2005) and Maclaren *et al.*, (1993) agree that errors made by referrers in the justification of examinations can be avoided by constantly referring to exposure guidelines.

2.6.1.1 Exposure guidelines: what are these?

Radiation protection authorities, where they exist, are the overall custodians of exposure guidelines. At local level a Medical Physicists in synergy with radiologic clinician are accountable for the day to day optimisation. Diagnostic radiology exposure guidelines are statements that are systematically developed to assist clinical decisions about appropriate radiological choices for specific clinical circumstances (Sibanda, 2012; ECRP, 2008). Specifically, diagnostic radiology exposure guidelines are a documentation of clinical situations for requesting an examination, possible imaging techniques for the examination, recommendation on the justification of the examination, explanations for the examination and radiation exposure bands involved (Sibanda, 2012; ECRP, 2008: 11). The advent of Image Wisely campaign by The Joint Comission (TJC, 2015) has seen these regulations being adhered to by more and more clinicians thereby minimising unjustified ionising radiation exposures. Common causes of unjustified exposures are repeating investigations which have already been done, doing an investigation when the results are unlikely to further the diagnosis, doing the wrong procedure, failing to provide appropriate clinical information and questions that the imaging investigation should answer and relying too much on diagnostic radiology investigations (ECRP, 2008). Therefore, drawing from literature awareness, availability and adherence to these guidelines present an important aspect in the study of radiology demand.

2.6.2 Impact of technology on demand: past, present and the future

The impact of technological innovation on the demand for radiology services has been reported, particularly that of digital imaging. As early as 1980s, digital imaging using photostimulable storage phosphor devices was introduced to level I health care followed by new types of digital imaging systems that utilised a large-area direct digital detector (UNSCEAR, 2008). The advantage of these new systems include, in principle, lower dose per image compared with analogue devices (IAEA, 2014; UNSCEAR, 2008) which is an added radiation protection advantage. The publication by the IAEA (2014) examines issues regarding digital image acquisition, storage, display and distribution. It is an important publication that provides a pragmatic guide for those considering implementation of digital imaging, including teleradiology. It should also be helpful to those users who are considering an upgrade of their existing imaging facility. All things being equal, it is logical to expect that before this publication wide spread technological diffusion will initially influence health-care level I countries before the practice widely influences radiology demand in other health-care levels (UNSCEAR, 2008). Again, consistent with reports on CT demand, it is logical to hypothesise that collective doses due to this digital radiology revolution will increase as a result of an increasing capacity for radiology.

Technological diffusion is a slow process and therefore, a better understanding of technological impact can be established if events are traced as far back as the early eighties when most of these technologies were introduced (Rose & Gallivan, 1991). It is not surprising then that arguments about the impact of technology on the demand and capacity for radiology services dates back as far as nineteen eighties. Brindle (1996) and Craig (1989) were of the opinion that radiology departments were significantly under-resourced. Consistent with these researchers, Rose and Gallivan (1991) predicted that: “it would take an increase of 71% in the radiological staffing level to achieve the capacity of 3.6 radiologists per 100 000 populations recommended by the Royal College of Radiologists”. Drawing from this literature, the integration of computers and image processing into radiology in the late 1970s introduced key drivers for change in diagnostic radiology imaging. This notion is indeed consistent with other researchers in that it recognises that the developments enabled the capacity of imaging to significantly increase. The author reports that Computed

Tomography (CT), Magnetic Resonance Imaging (MRI), Digital Radiography (DR) and the subsequent development of Ultra Sound Scan (USS) immensely benefited from this development thereby resulting in these modalities being leaders in technological innovation. With reference to this perspective, the overall growth in examinations from 1995 to 2000, as reported in the Department of Health's (2000) own statistics for imaging in England, shows that there was a 17% increase in radiology demand. In Zimbabwe, a survey conducted by Sibanda (2012) for one radiology department reflected an intriguing exponential use of radiology services from 2006 to 2010. The aforementioned researchers however do not indicate a direct link between the dynamic nature of technology and the impact on radiology utilisation trends thereby leaving a gap for further research. When it comes to the case of Zimbabwe (the host country), in parallel with this technological revolution, the Zimbabwe government had National Health Strategies (ZMOHCC, 2013; ZMOHCC, 2009) which sought to regulate the patient care pathways. The impact of these strategies on utilisation trends is yet to be evaluated.

On a global perspective, there is also a school of thought that considers skill mix as an important variable impacting on demand trends. This approach focuses upon key drivers for change in respect of work roles (Buchan, Ball & O'May*,* 2000). This researcher evaluates the practice of radiology, explains the changes taking place within imaging sector and concludes that studies on skill mix were limited in that they largely focused on one profession in the United States of America and therefore recommends a broader research in this field. This notion was consistent with the definition presented by Friedenberg (2000) that the term skill mix as applied to clinical practice implies the utilization of all types of expertise available to a patient.

Global trends show that reasons for the observed increase in the demand for diagnostic radiology services can be generalised into five categories (Sibanda, 2012; IAEA, 2008; Levin & Rao, 2004; Bhargavan & Sunshine, 2002). These categories are: repeating investigations which have already been done, doing an investigation when the results are unlikely to affect patient management, doing the wrong procedure, failing to provide appropriate clinical information and questions that the imaging investigation should answer and over investigating (Sibanda, 2012; ECRP, 2008). These can further be summarised into overutilization of radiology and unjustified examinations (Sibanda, 2012; Maarse, 2006). This kind of practice impacts negatively on the effective delivery of radiology services (Maarse, 2006; IAEA, 2008). Elsewhere, many western countries are shifting the health care delivery system from public to (semi) private health care systems in an effort to manage increased demand for healthcare services (Maarse, 2006). This policy shift requires that departments engage evidence based decision making approaches in order to optimise patient care. However, the Zimbabwean situation has remained supply driven (ZMOHCC, 2009) and silent on optimisation presumably because of lack of home grown fundamental research that forecasts demand for radiology services.

The need to optimise radiology patient care is however not a new concept (IAEA, 2008). Matching capacity and demand for diagnostic radiology services has emerged as an important approach in optimisation of patient care (UKNHS, 2005). Variables that impact on demand (referral rates) for diagnostic radiology services have been identified as important aspects in optimisation of radiology patient care particularly with respect to resource allocation (Sibanda *et al.,* 2014; Sibanda, 2012; IAEA, 2008; Maarse, 2006; Siciliani & Hurst, 2005). Demand for radiology services is stochastic in nature and therefore any quoted value must be evidence based. On the other hand, radiology equipment comprises long term investment and therefore radiology resource allocation must be hinged on forecasted demand (Brown, Rappert & Burlington, 2013). The forecasts must offer opportunity for a pragmatic demand driven resource management system that aligns the stochastic nature of radiology demand to personnel and material capacity (UKNHS, 2005). Drawing from the United Kingdom's National Health Services:

"...Improvement of a patient's healthcare journey will not necessarily improve with just more staff, more equipment and more facilities. It has been proved that our valuable resources are not always used wisely and if there is a need for investment, the location of that investment should be carefully considered..." (UKNHS, 2005)

It is therefore, paramount for decision makers to be regularly appraised of this important aspect because lack of this knowledge creates a macro-economic gap in the match between capacity and demand in that,

"....as long as we think we already know, we don't bother to rethink the situation...." (UKNHS, 2005).

2.7 Frequency of radiological exposures: distribution by healthcare level

Global surveys estimate that there are 3.6 billion diagnostic radiology X-ray examinations undertaken annually (UNSCEAR, 2008). In this estimate, 24% of the population living in health-care level I countries received approximately two thirds of these examinations. Of particular note is that the annual frequency of diagnostic medical examinations in health-care level I countries was estimated to have increased from 820 per 1,000 people in the general population per physician in 1970–1979 to 1,332 in the 1997-2007 survey while that of health-care level II countries exhibited an even greater relative increase, from 26 per 1,000 people in the general population per physician in 1970–1979 to 332 per 1,000 in the 1997–2007 survey. However, in the case of health-care level III/IV, UNSCEAR (2008) reports that the figures remained fairly constant over the same period although there was considerable uncertainty associated with this estimate in respect of limited data for these countries.

Zimbabwe is positioned in healthcare level III and as a result this makes data for health care level III of particular importance in this study. According to this report, the contribution of CT scanning to the total collective effective dose due to diagnostic radiology examinations was approximately 65% in health-care level III/IV countries. However, the report notes that "there is great uncertainty in the doses and frequencies for health-care level III/IV countries" (UNSCEAR, 2008). Furthermore, the frequency of diagnostic radiology examinations is reported to be over 66 times more frequent in health-care level I than in health-care level III and IV. This is contrary to population indicators predicting that where 24% of the global population lives (health care level I) the frequency of examinations should be less than where 27% of the global population lives (health care level III/IV). The committee explains that the "change in annual frequency of diagnostic medical examinations reflects changes in population demographics, as most medical exposures are performed on older individuals". However, a closer look at conclusions from this literature shows that the wide imbalance in health-care radiology examinations frequencies is also reflected in the capacity of radiology departments and availability of physicians.

2.7.1 Frequency of radiological exposures: Distribution of dose

Further to the frequency distribution of radiological exposures, UNSCEAR (2008) report that on average, over "70% of the total collective effective dose is received by the 1.54 billion individuals living in health-care level I countries". The annual collective effective dose to the populations of health-care level I to IV countries was estimated to be 2 900 000 man Sv, 1 000 000 man Sv, 33 000 man Sv and 24 000 man Sv respectively (UNSCEAR, 2008).

Adding these figures gave the total annual collective effective dose to the global population from diagnostic radiology to be 4 000 000 man Sv as reported by UNSCEAR (2008). These statistics also formed the basis for calculating the annual per capita effective dose for the various health-care levels and the average value across the global population from diagnostic radiology examinations as published by the United Nations (UNSCEAR, 2008).

The challenge associated with extrapolation of these statistics across countries and practices is hinged upon evidence of inconsistencies inherent in day to day exposures. Evidence put forward by Smith-Bindman (2009), for example, shows that “radiation doses from commonly performed diagnostic CT examinations are higher and more variable than generally quoted, highlighting the need for greater standardization across institutions.” This example and statistics from UNSCEAR (2008) stimulate the need for a closer look at the impact of radiation on humans.

Information posted by the IAEA in its website on Diagnostic Reference Levels (DRLs) in medical imaging highlights substantial variations in dose across different imaging modalities, between some healthcare facilities for same examination and between similar patient groups (patients of defined sizes) (IAEA, 2013). This presents overwhelming evidence towards the need for standardisation of dose and minimisation of variation in dose without compromising the clinical purpose of each examination. This school of thought is forms the impitus of examination-specific DRLs presented by IAEA for various patient groups as a stimulus for monitoring practice to promote improvements in patient protection. The numbers and the variety of diagnostic exposures call for a more forecused attention on diagnostic reference levels. In accordance with Basic Safety Standards prescribed by the IAEA, the regulatory body (RPAZ) established regulations and guides for protection and safety as well as a system to ensure their implementation. The primary goal of the IAEA Basic Safety Standards initiative on quality assurance (QA), for example, is to improve patient care in order to maximise the effect of clinical care while at the same time minimising harm to individuals and to society as a whole (IAEA, 2010). The approaches presented by the latter are essentially fact finding and interpretation and therefore are in synchrony with the the study of “diagnostic radiology demand and capacity: trends and forecast.”

2.8 Summary of reviewed literature

Diagnostic radiology administrative documents are information rich documents out of which trend data can be obtained. Previous researchers were able to identify radiological technique, justification of requests, awareness to exposure guidelines, cost of examinations, health level stratification, case mix adjusted ratio and technology diffusion as labour drivers. These have been classified into repeating investigations which have already been done, doing an investigation when the results are unlikely to affect patient management, doing the wrong procedure, failing to provide appropriate clinical information and questions that the imaging investigation should answer and over investigating. Previous researchers successfully used regression analysis to compare categorical data. However, these researchers did not take the research a step further to derive a demand equation and also engage in predictive modelling to forecast radiological demand. What is very clear in literature is that the demand for diagnostic radiology has increased significantly over the past two decades. Furthermore, there is overwhelming evidence in literature that during the same period, radiology practice saw more sophisticated and more costly technology being introduced.

Despite numerous advantages associated with these newer technologies, there was a reported time lag in the uptake of these technologies by developing countries which was largely attributed to a slow pace of technological diffusion from level I and II countries to level III /IV countries (UNSCEAR, 2008). Consistent with this observation Borretzen *et al.,* (2007) and Espeland, Natvig, Loge *et al.,* (2007) both report on the dependence of the frequency of utilisation for radiology services on geographic location.

On the other hand, the observed overall global growth in the demand for radiology services may well be understood by noting that factors such as advances in diagnostic radiology equipment resulted in newer radiology equipment being indicated in more clinical conditions (Chrysanthopoulou *et al.,* 2007). There was also a cascade of other factors such as, increasing number of radiologists and increased availability of radiology equipment (Langley *et al.,* 2009; Fisher & Welch, 1999). However, these studies were in contrast to the Zimbabwean situation which actually saw reduced capacity over the same period (ZMOHCC, 2013). Consistent with this literature, the UNSCEAR (2008) reported a correlation between the number of referring physicians and the frequency of radiological exposures thereby positioning physicians centrally in the modelling of demand trends for diagnostic radiological services. Following this school of thought, a number of factors have been identified in literature as impacting on physicians' referral behaviour. These include lack of exposure guidelines awareness or compliance (Sibanda, 2012; IAEA, 2008; Wright & Wilkinson, 1996), defensive medicine (Studdert, Mello, Sage *et al.,* 2005), prolonged working hours resulting in stress due to workloads and challenges arising from demands of emergency cases (Kristin and Bjorn, 2009), financial re-imbursements (Moskowitz, Sunshine, Grossman *et al.,* 2000), patients' expectations (ECRP, 2008; Wilson, Dukes, Greenfield et al., 2001; Wright &

Wilkinson, 1996), and physicians' self-referral (Gazelle, Halpern, Ryan *et al.,* 2007; Levin & Rao, 2004).

In persuit of this line of thought, many of these researchers focused on the impact of individual factors on radiology utilisation (Espeland, Natvig, Loge *et al.,* 2007; Gazelle *et al.,* 2007; Borretzen *et al.,* 2007; Verstappen, ter Riet, Weijden *et al.,* 2005; Wilson *et al.,* 2001) while some focused on establishing and explaining clinicians' points of view regarding the drivers for demand of radiology services (Wright & Wilkinson, 1996). On the other hand, the United Nations has, over the years, focused a lot of resources towards establishing global sources and biological hazards of ionising radiation (UNSCEAR, 2013; UNSCEAR, 2012; UNSCEAR, 2010; UNSCEAR, 2008). The results of these studies have fuelled global concerns over justification of radiology examinations as well as overutilization of radiology (Sibanda, 2012; Rehani, 2010; IAEA, 2008; Otero, Ondategui-Parra, Nathanson *et al.,* 2006). It has been reported that the significance of these individual factors in modelling demand for radiology examinations and therefore ionising radiation hazards varies depending on institutional structures and health-care level of a country (UNSCEAR, 2008; Levin & Rao, 2004).

Over-utilisation of radiology means wasteful investigations defined by the European Referral guidelines for imaging (ECRP, 2008) and echoed by Sibanda (2012) as comprising unnecessarily repeating investigations, investigating when the results are unlikely to affect patient management, investigating too often, doing the wrong investigation, incomplete request information and over-investigation (for reassurance of clinicians and patients). Literature points to the fact that the bid to increase capacity of radiological services all too often significantly impacts on health care costs, quality of health care services and also on health care risks (UNSCEAR, 2008; Otero *et al.,* 2006; Iglehart, 2006; Fisher & Welch, 1999). It is not surprising then that the risk of radiation exposure, health care costs and the quality of healthcare services in respect of diagnostic exposures has attracted growing global attention (UNSCEAR, 2013; UNSCEAR, 2012; IAEA, 2010; IAEA, 2008; UNSCEAR, 2008).

Compelling evidence to conduct this research can be summarized as:

(a) According to global statistics, diagnostic radiology exposures contribute the most towards artificial exposure to ionizing radiation (a teratogen and cacinogen),

(b) Technology and practices in diagnostic radiology are changing rapidly thereby impacting on justification requirements and the frequency of exposures,

(c) Because ionising radiation is a teratogen, frequency of diagnostic radiology exposures was a thematic priority of the United Nations Scientific Committee's strategic plan (2009-2013),

(d) The scientific committee of the United Nations had particularly requested the secretariat to prepare a detailed plan for a report on the frequency of exposures thereby making the scope of this study globally relevant and

(e) The aforementioned Committee had also requested for a Global Survey of Medical Radiation Usage and Exposures and has called for close cooperation with international researchers in this regard.

This literature review may best be summarised by noting that, although labour drivers for radiology services have been suggested in a global perspective, few studies have explored and quantified their interactions and therefore, their relative impact on the number of patients (diagnostic radiology demand) attending radiology departments. This analysis would essentially require time variant labour drivers. Intuitively, because labour drivers identified in cited literature were time invariant in the respective time horisons, none of these researchers went a step further to use this knowledge to model and forecast utilisation of radiology services. Reviewed literature also explains that there is limited research in respect of the subject from radiographers' perspective on their capacity as radiology service providers. This is despite the fact that as radiology service providers, radiographers hold key information as their perceptions are continuously refined through experiences with a multitude of referrals, interaction with a variety of clinicians and patients, and their vast knowledge of indications for radiology examinations. Radiographers' as well as patients' perceptions of the mechanisms behind observed usage of radiological investigations are invaluable in policy formulation aimed at optimally managing radiology resources. Therefore, this literature review formed the impetus of this study by informing on how the diversity of these factors could be categorised, ranked and interrelated when the patients' and radiographers' perspective alongside document review information were considered with the intention to forecast radiology demand.

CHAPTER THREE

RESEARCH METHODOLOGY

> The question of reliability has to do with the consistency of observations: whether a research instrument yields the same results every time it is applied. If it does yield the same results time after time then it can be said that the instrument is dependable for the purpose at hand. **(Lindlof &Taylor, 2002: 238).**

3.1 Introduction

In this chapter, an explaination of the positivist methodological paradigm that defines the way investigations were carried out in order to answer the research questions for this study (Saunders, Lewis & Thornhill, 2007; Welman & Kruger, 2001; Haralambos & Holborn, 2000; Gill & Johnson, 1991). A review of the research objectives, questions and design are given at the onset of this chapter. The population, the sample, inclusion and exclusion criteria are also discussed. The description of the document review and the survey methods, inferential and descriptive statistics as applied to the practices and techniques used to sample, collect, process, analyse and interpret data for this study are also presented. Philosophies upon which the document review, observational and questionnaire research approaches were based are explained (Hopkins, 2008**;** Grimes & Schulz, 2002; Hulley, Cummings, Browner *et al.,* 2001; Haralambos & Holborn, 2000; Howard & Borland, 1999). Furthermore, issues that relate to the validity and reliability of the study are discussed followed by issues pertaining to research ethics. This discussion was guided by literature (Bowling, 2009; Hopkins, 2008; Eng, 2003; Hulley *et al.,* 2001; Welman & Kruger, 2001; Haralambos & Holborn, 2000**)**.

3.2 Research question

Therefore, mindful of the main research question "What predictive model can be used to forecast demand for diagnostic radiology services in Zimbabwe?" the the following sub questions were answered:

a). "What is the map of the radiology patient care pathway for Zimbabwe?"
b). "What are the predictor variables (labour drivers) for the observed frequency of radiology patients?"
c). "Why does the observed radiology utilisation follow the observed trend?"
d). "How can future utilisation of radiology services for Zimbabwe be predicted?"

3.3 Research objectives

The objectives of this study were:

i. To determine the nature of activities done across radiology patient care pathways;

ii. To determine those variables (predictor variables) that could be used to predict the number of patients examined across the research sites;

iii. To determine the variability of the aforementioned predictor variables (labour drivers) to demonstrate whether the key predictor variables were time-variant or not;

iv. To develop a theory to forecast the time-variant labour drivers and therefore time variant radiology utilization.

3.4 Research philosophy

The key idea in this study was that the observations made were not inferred subjectively through sensation, reflection or intuition but through objective measurements. This necessitated that the research methodology be structured and the instruments validated (Burton & Mazerolle, 2011; Gill & Johnson, 1991). In this study, data was collected (the researcher) as a non participant observer and this was an important consideration towards eliminating research bias in that the researcher had no obvious vested interests in the outcome of the study (Haralambos & Holborn, 2000). This philosophical approach was therefore positivist (Ritchie & Lewis, 2003; Haralambos & Holborn, 2000; Smith & Hunt, 1997).

3.5 Research design

The researcher visited the data collection sites solely for the purposes of data collection and was therefore a non participant observer. The data collection was cross sectional and the analysis was descriptive as well as inferential. Data collection involved a questionnaire survey and a document review of radiology administrative documents from consenting departments across Zimbabwe (Hopkins, 2008; Creswell, 2003; Grimes & Schulz, 2002; Howard & Borland, 1999). The adopted research approach made it possible to identify and measure the impact of variables without engaging intervention methods or a pilot study to determine baseline data (Rosenberg, 1997). This was an important consideration because the approach had no control over which variable were implemented or when they were implemented. A documented weakness of this design is that change brought about by variables cannot be separated from change that would have happened naturally or change brought about by other unknown variables introduced at the same time (Rosenberg, 1997). Logically, this weakness is particularly problematic in the analysis of variances if the variable has a relatively small impact compared to the change that happens naturally. To minimise the possible effect of this problem, the a ten year study period was employed in order to identify an interruption of the trend at the time the variables were introduced and then checked that the interruption was sustained over time (Rosenberg, 1997). The research culminated in mathematical modelling to forecast radiology demand for Zimbabwe. The predictive model was aimed at making sense of observations by inductive reasoning on how the observations fitted into a trend. The predictive model was produced after observations were made and therefore the study was ex post facto theorising (Rosenberg, 1997).

3.5.1 Document review method

A self designed instrument was used to review radiology administrative documents in order to identify radiology utilization trends. A document review method was considered suitable for this study because of its relative non reactivity with the researcher (Bowling, 2009). Consistent with Bowling (2009), with respect to validity and reliability, data collected using a document review method was verifiable thereby ensuring repeatability of the study. Data was collected from filed documents thereby ensuring that the data collection process did not interrupt the routine processes of the radiology department and because at each centre documents were at a central location, the document review was cost effective and efficient (Sibanda, 2012). Consistent with literature, a problem that was encountered with the document review process was that documented information was often not complete thereby limiting the event rates of those sources with complete critical data required for the analysis (Sibanda, 2012; Bowling, 2009; Hopkins, 2008; Creswell, 2003; Grimes & Schulz, 2002; Howard & Borland, 1999). Furthermore, event rates varied seasonally and during the course of each year, so much that the denominator used to calculate working averages had to be varied from month to month and from year to year, a concept known as moving averages.

3.5.2 Survey method

A self designed checklist was used to map the radiology patient care path way for Zimbabwe while a survey questionnaire as well as interview questions were used to provide important data regarding how radiographers and patients perceived the delivery of radiology services in the country (Bowling, 2009; Haralombos and Holborn, 2000). The survey questionnaire provided important data about how radiographers thought and acted thereby providing insights on the trend data (Haralombos & Holborn, 2000). Consistent with literature, the weakness of this approach was that questionnaire information often did not reflect what actually happened on the ground. To minimise the impact of this weakness the questionnaire data was complemented by interview and observational survey data. The researcher and four research assistants (radiographers) administered and received back the questionnaire during the data collection period. This was in order to obtain a high return rate for the questionnaire, reduce mailing costs and to ensure respondents did not discuss the questions within the research site since this could affect their answers. The use of a questionnaire enabled the collection of large quantities of data from considerable numbers of radiographers and patients over a relatively short period of time (Haralombos & Holborn, 2000). The questionnaire had a mixed type of questions which included open ended questions in order to allow respondents to compose their own answers thereby providing valid data (Haralambos & Holborn, 2000). This combination of structured and unstructured approach enabled the identification of a wide range of variables that had an impact on the number of patients attended to at the research sites.

3.5.3 Forecasting

Forecasting radiology demand involved regression and time series analyses. There were two main goals of the regression and time series analyses: to identify the nature of the phenomenon represented by the sequence of observations and to predict future values of the time series variables (monthly frequencies of examinations as well as monthly frequencies of patients). The latter aim is called forecasting (Rosenberg, 1997). Both of these aims required that the data trends be identified and formally described. Consistent with literature and the aims of this study, the steps to solve the research question followed the sequence: trend establishment, identification of labour drivers and extrapolation of identified pattern to predict future events using time series forecasting and multiple regression.

Multiple regression analysis was used to establish a quantitative relationship between the predictor variables and the dependent variable (SPSS, 2010; Brown *et al.,* 2013; Richard, 2000). Important in this approach was aware that, unless checks and balances were put in place, predictive modelling was typically limited by the tendency to produce a plausible explanation of a set of observations which is frequently just one of a number of possible explanations that fit the data (SPSS, 2010; Brown *et al.,* 2013; Richard, 2000; Rosenberg, 1997). In order to guard against this shortcoming, the protocol involved systematical testing of the data to specifically evaluate how well the explanation held when subjected to a range of competing possibilities as they emerged from the study. This was made possible by dividing the data set into estimation period which was used to develop the model and evaluation period which was used to evaluate the model (SPSS, 2010). Furthermore, predictions made using the time series approach were weighed against those made using multiple regression approach.

3.6 Instrument development

The instrument development process was intended to objectively answer the questions:

i. *What is the minimum information consistently documented in radiology patient registers across the country?*

ii. *What is the general map of radiology patient care path way across the research sites?*

iii. *In the radiology patient care pathway, what resources (equipment and human resources) and how are these resources involved?*

iv. *What can be learnt from radiographers' and patients' perceptions about the observed utilisation trends?*

Initially, a blank radiology patient register was used to draft the data collection instrument for trend analysis data. The list was subsequently refined upon visiting four radiology departments in Bulawayo and Matabeleland south provinces. This analysis came up with an answer to the instrument development sub-question (i.) in the form of a check list. The framework to answer instrument development sub-questions (ii.) and (iii.) was derived from literature (Langley *et al.,* 2009; UKNHS, 2006; UKNHS, 2005) and to refine this framework, the patient care path way for a pilot sample of 20 patients derived from the aforementioned four sites. This was in order to identify activities performed, equipment used and the staff involved. To answer instrument development sub-question (iv.), the framework for this instrument was derived from literature. In this case commonly documented labour drivers were identified and because there were too many labour drivers to analyse during the research time horizon, structured and open ended questions were combined to accommodate diverse views from participants (Burton & Mazerolle, 2011). The instrument was refined using logic in which those drivers perceived to have greatest potential impact were singled out into structured questions.

3.6.1 Reliability and validity of measures

In the instrument development stage, key indicators selected as measures of quality for the measuring instruments were the reliability and validity of the measures. Primarily, the process of developing and validating instruments was aimed at reducing error in the measurement process. Important in this process was that everything possible to strengthen the reliability and validity of the instruments was done. At the onset, to ensure the validity of measurement, face validity of the instrument was considered. This essentially, ensured that the questions were phrased appropriately and that options for responding were appropriate so much so that the questionnaire measured what it was intended to measure (Burton & Mazerolle, 2011). In order to have content validity, the questionnaire adopted for this study included items about known labour drivers (Burton & Mazerolle, 2011). This was complemented by criterion validity in which a check of how well the results from the regression analysis compared with those from time series analysis. To further pursue validity issues, the models were tested on validation data (the "gold standard") that was already known and the estimation data. Comparison of the two outputs gave the extent of validity of the findings. To ensure construct validity of the questionnaire, radiographers were given a questionnaire to measure similar constructs (justified requests and indicated requests) in which related results were expected. However, a questionnaire on different constructs (unjustified requests and indicated examination) was expected to give opposite results (Burton & Mazerolle, 2011).

Reliability of measurements was tested by repeating the questionnaire to the pilot sample in a space of one week with the same radiographers. Consistent with Burton and Mazerolle (2011), the criterion was that high "repeatability" of the questionnaire was indicative of test-retest reliability. In this regard it was paramount that validation ensured that measures were actually reflective of what was intended to be measured and that reliability tests ensured that measurements were consistent. Therefore, reliability estimates were used to evaluate stability of measures (Burton & Mazerolle, 2011). This entailed ensuring that the measures were verifiable and that these pragmatic quantities were measured by objective and structured instruments. Furthermore, statistical means to demonstrate the extent to which the interpretations of the results of the tests were warranted were applied.

Consistent with literature, the problem associated with the document review method is inconsistencies in the documented data (Burton & Mazerolle, 2011; Hopkins, 2008; Hope *et al.*, 2003). As these authors explain, social desirability biases surface if self-reporting of subjects is used in an attempt to ensure completeness of collected data. Filed documents were used as sources of data such that data that were originally compiled for a different purpose were used as primary sources of data to answer the research question. This approach took care of social desirability biases but did not take care of the adequacy of the source documents. In some cases the completeness of this data in respect of completed form fields identified in some research sites was not consistent and this affected the applicability to the study at hand and therefore further refinement of the instruments was conducted as the need arose during the data collection process.

To summarise the instrument development process, variables of interest and their outcomes were not abstract concepts which are otherwise known as theoretical constructs. The variables were pragmatic quantities that were measured by objective and validated instruments. To be able to do this, the design of the data collection instruments was a process hinged upon the research questions, the literature review and the background information from the research sites. In this study, the use of validated reliable instruments to measure pragmatic variables raised the research quality (Burton and Mazerolle, 2011; Hopkins, 2008; Hope *et al.*, 2003).

3.7 The research site

The number of research sites used in this study was determined by those that responded positively to the request to collect data. In this way, all departments had an equal chance of being selected provided they consented to participate in the study. Data collection application letters were sent to the population of radiology departments in the country that were identified from the telephone directories as well as those identified from the data base for departments used for student attachment found at the National University of Science and Technology (NUST). In this way, the number of letters sent out was guided by this availability of contact details. Delivery of the letters involved postal and where possible hand delivery. In this way, the researcher had no control over which departments were enrolled for the study. Because radiology departments are essentially service departments, the task was to ensure that the catchment area for the research sites had secondary, tertiary and central level radiology department representation, located across the country as well as private and public departments' representation. Each of these central departments handled referrals from at least 20 external referring centres while the provincial department handled referrals from 10 departments (primary and secondary departments) thus giving coverage of patients arising from 90 referring sites.

3.8 Study population

The population for this study comprised all radiology examinations from across the districts of Zimbabwe from the time Zimbabwe started offering radiology services to date. This population of radiological examinations for Zimbabwe as a country was too large to study directly. The accessible population (Yount, 2006) therefore, comprised all radiology examinations falling between January 2004 and December 2014 for which documentation could still be accessed. This period was of particular interest because it was characterised by activities that had a bearing on the day to day running of Zimbabwe's health sector (ZMOHCC, 2009, ZMOHCC, 2013). Figure 3.1 summarises the model that was used to identify the population of examinations for this study.

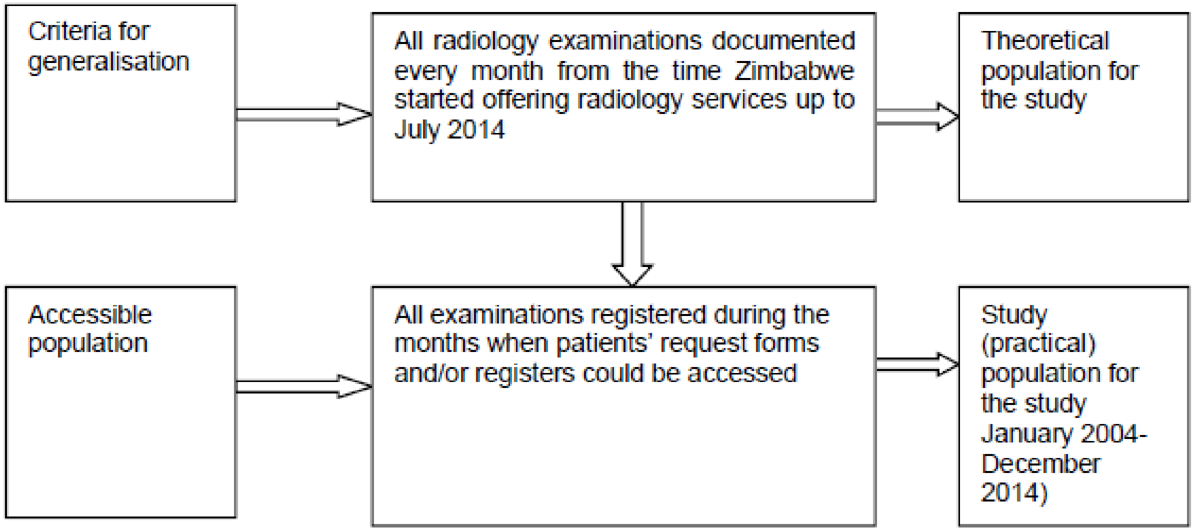

Figure 3.1: Model for identifying the study population

3.8.1 The sample

Consistent with published research on trend analysis, this study on the demand and capacity for diagnostic radiology services was carried out at the ecologic level (Rosenberg, 1997) in which the units of analysis were time periods (months) as well as individual examinations (Matin *et al.,* 2006; Maitino *et al.,* 2003; Bhargavan & Sunshine, 2002; Henley *et al.,* 2001; Khorasani *et al.,* 1998; Alexander *et al.,* 1996). The monthly data comprised the whole population of monthly radiology examinations from which moving averages were established. This type of sampling increased the precision of the sample (Bowling, 2009) in that it allowed the consistent sampling frequency (i.e., constant number of samples per period, equally spaced across the period) in order to minimise variance as was the requirement for the statistic.

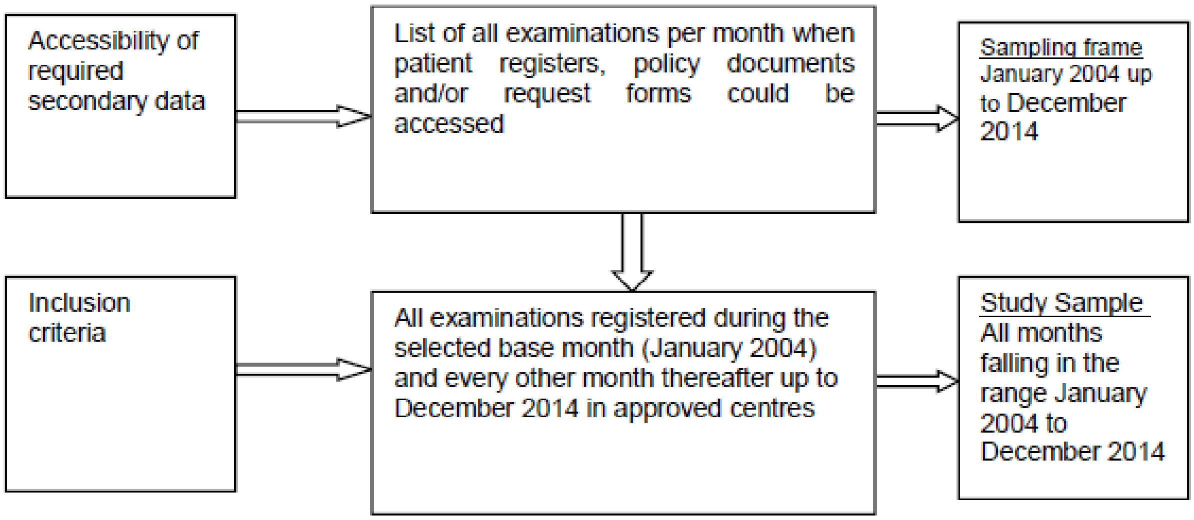

Figure 3.2: Model for identifying the sample

Figure 3.2 illustrates the model used to identify the sample for this study. During this sampling process, there were 4 missing sample units from the reviewed documents. These values were imputed using evidence based statistical approaches. This was in order to ensure that when it came to analysis stage there were no missing observations because such an occurrence would invalidate the time series analysis by changing variance. This was also true for outliers. The nature of the collected data was such that each result was independent of other samples across time and space. This was an important consideration for serial correlation of the data.

3.8.2 Sample size calculation

In the dataset for trend analysis, there were 132 (11 years x 12 months per year) observations. In statistical terms, each of these 132 observations comprised a sample in time. Therefore, in this study 132 was the sample size for analysis regardless of the size of the population denominators for each month. The strength of this approach was that the longer the time period, the more information and therefore the more likely it was to precisely identify patterns of change (Rosenberg, 1997). The concept of moving averages was used to determine monthly averages followed by exponential smoothing which represented final sample units that were used in the analysis (Rosenberg, 1997).

3.8.3 Inclusion and exclusion criteria

The inclusion and exclusion criteria for this study were an important consideration because it enabled the enhancement of the validity of the study. The radiological examinations that were finally included in this study were all examination documented at the research sites for the period January 2004 to December 2014. This was on condition that the examinations fulfilled the two additional inclusion criteria.

a) Inclusion criteria

- The examinations were documented on the radiology patients' register for the research site and
- The research site had approved the data collection.

These inclusion criteria were chosen because:

- Examinations documented in the registers could be consistently and reliably measured using the data collection instrument.
- Examinations documented in the registers represented the framework for documenting radiological examinations typical for the research site

b) Exclusion criteria

Radiological examinations were excluded from the study if they showed the following characteristics:

- All radiology examinations documented outside the selected referral centres and
- All examinations documented in any other document other than the official register.

3.9 Data capturing

In all the data collection sites, the researcher was a nonparticipant observer meaning that the presence of the researcher at the research site was solely to collect research data. Retrospective quantitative data was used as primary data. The overall data emanated from radiology registers, request forms, organisational policy documents and surveys (interview and questionnaire). In the document review, the time series frequency data was collected in respect of the number of patients, number of examinations per anatomical region. Radiographers' and patients' views about radiology demand were also recorded. This was through systematic and objective identification and counting of specified information in individual documents against the checklists designed and tested by the for this study. To ensure confidentiality, data could only be identified with the source documents by use of a pass worded master link list. This master link list was generated for the purposes of data verification that could be required during the data analysis phase.

3.10 Preparatory procedures for statistical analysis

The data collection instruments were designed for this study in order to map the radiology patient care pathway, assess the distribution of radiology demand and capacity, and subsequently forecast demand for radiology. In respect of the distribution of the demand for radiology services, the organisation of the data involved frequencies of radiology patients per sample unit (month). The spread sheet was prepared to enable forecasting time variant labour drivers as well as the dependent variable (number of patients examined per month). The concept of moving averages and exponential smoothing was used to minimise random variances in the observed frequencies for the 132 months data. These calculations helped normalise the data **(**Rosenberg, 1997).

3.11 Data analysis

The strategy adopted for analysing data was hinged upon the specific objectives of the study and the criteria used to accomplish the aforementioned specific objectives are subsequently described in subsections **3.11.1** through **3.11.4**.

3.11.1 Determining the nature of activities in radiology patient care pathway

The determination of radiology departmental activities involved an account of activities that were performed at any time (e.g. damp dusting, filling and replenishing of drugs and accessories) as well as activities that were performed upon demand (e.g., examining a patient, disinfection after examination, image evaluation and interpretation). Consistent with literature (Sibanda *et al.,* 2014; Schneider, 2011), these were categorised as "controllable work" (activities that were flexible in their timing) and "uncontrollable work" (activities that were rigid in their timing). Consistent with the aforementioned definition, controllable work afforded radiographers time latitude in which they could perform such activities but this had to be performed within certain window periods. Logically, controllable-work windows could therefore vary in length depending on the nature of the activity.

The criterion was that if a patient’s clinical journey in the radiology department had a mixture of controllable and uncontrollable characteristics, essentially this activity was uncontrollable. This was an important consideration aimed at ensuring that whenever it was necessary, patients were always advantaged. Importantly, in a busy radiology department, as is the norm, services were essentially offered immediately to the next arriving patient and therefore, no window period was defined for such instances. Using this framework, the task was to map the radiology patient care pathway noting activities. This was essential in forecasting both uncontrollable and controllable work that was likely to be generated by various labour drivers in the system but first these labour drivers had to be identified (Sibanda *et al.,* 2014; UKNHS, 2006; UKNHS, 2005; Rosenberg, 1997).

3.11.2 Identifying Labour Drivers

The second step in forecasting demand for radiology services was to identify those variables (activities) that affected the efficient flow of patients in radiology departments (Sibanda *et al.,* 2014; UKNHS, 2006; UKNHS, 2005). Consistent with these researchers, this involved analysis of resources needed to deliver radiology services. Individual activity measurements were used to determine how service characteristics affected the duration and nature of the service transaction for patients. First, brainstorming was conducted to identify characteristics of each examination that could affect its duration prior to the aforementioned measurements.

Regression analysis was then used to determine the precise effect of each activity characteristic on the service transaction time for each patient. At this stage labour drivers that could reasonably be assumed to be independent of each other were identified. This was crucial because any such relation would imply that over and above interaction with the dependent variable, these independent variables interacted with each other. Statistically, elimination of related labour drivers simplifies statistical analyses (SPSS. 2010). It was logical to consider that patient factors, number of exposures or films used on each patient and the total amount of money paid by each patient could be used to predict demand for radiology services. This was reasonable because these variables were reflective of the time taken by radiographers attending to patients. It was also logical to assume an association (correlation) between the amount paid by each patient and the number of exposures or films per patient. Furthermore, for this particular example, it was logical to expect a causal relationship between the cost of the service and the number of exposures. In all such cases, the researcher substantiated the proposition by statistically testing the relationship among the labour drivers (Schneider, 2011).

Therefore, in summary, laboure drivers were identified and analysed before forecasting because it was pertinent to be parsimonious when selecting relevant drivers. Correlation analysis was fundamental in identifying relationships among labour drivers (Schneider, 2011). The criteria were that any labour drivers with correlations below 0.4 were considered to be independent where as those above 0.4 were considered to be dependent. Having identified the set of independent labour drivers, the next step in the analysis of the objectives was to determine whether the drivers were time-variant or time-invariant (Sibanda *et al.,* 2014; Schneider, 2011; Rosenberg, 1997).

3.11.3 Determining whether Labour Drivers were Time-Variant

To fulfil this objective, an analysis of labour drivers to determine whether their individual effects varied over the course of the planning horizon or remained constant was conducted. During this process, it was appreciated that over sufficiently long time, every labour driver becomes time variant but how long a time depended on time horizon for the individual drivers (Schneider, 2011; Rosenberg, 1997). With this information in mind, graphical tracking the observed labour drivers over time by use of trend lines was conducted in order to distinguish between time-variant and time-invariant labour drivers (SPSS, 2010). Essentially, the this sought to identify any well defined cyclical changes over time and random variations superimposed on them. This was a unique feature defining graphs for time-variant labour drivers (SPSS, 2010). On the contrary, time-invariant labour drivers would remain relatively constant with superimposed random variations over the time horizon. As an example, a graph of the time taken to perform chest radiography per patient was a relatively constant relationship over a period of months suggesting a time-invariant labour driver. However, an important time-variant labour driver for chest radiography was essentially the frequency of patients examined across the time series data horizon.

To derive statistical conclusions about variability of the many identified labour drivers, a lagged correlation analysis was applied, results of which were used to distinguish between time variant and time-invariant labour drivers (SPSS, 2010; Rosenberg, 1997). Consistent with Rosenberg (1997), correlation for labour drivers was measured with the data lagged one period (i.e. comparing each period with the period before it). Using manual approach, the time interval for tracking time-variant labour drivers was logically set at one year, one month and then quarterly. This analysis was essentially a trial and error approach in that many trials were made until a suitable time interval for tracking time-variant labour drivers was obtained. The choices of intervals to test were based on logic guided by practical issues applicable to the research sites particularly holiday times, national economics and political situations as they were expected to model periodicity.

3.11.4 Introduction: Forecasting work generated by Time-Variant Labour Drivers

As the final step towards fulfilling the objectives of this study, forecasts of the level of each time-variant labour driver for every time interval for the entire work study period were conducted. Two approaches were explored using the observed data: forecasting individual labour drivers in each period independently and forecasting labour drivers using aggregation-disaggregation approaches (SPSS, 2010; Rosenberg, 1997).

The selection of how to analyse and present the data involved ascertaining that the data met the data quality objectives as detected by the statistical tests (SPSS. 2010). The time series patterns for this study were described in terms of two basic classes of components: trend and seasonality. Consistent with the aforementioned literature, trend represented a general systematic component that changed smoothly over time and did not systematically repeat within the data collection time horizon (year 2004- 2014). On the other hand, seasonality patterns represented those that repeated themselves in systematic intervals over time during the aforementioned time range. Naturally, these two general classes of time series patterns coexisted and therefore, to satisfy the objectives of this study, the chosen statistic was in order to describe the trend as well as the variable effects on the observed demand for radiology services (SPSS, 2010, Rosenberg, 1997). For this reason, the chosen statistical approach was nonparametric. The selected statistical tests requirements were reviewed to satisfaction before applying the tool (SPSS, 2010).

3.11.4.1 Statistical analysis: independent labour driver forecasting

The objective of this part of the study was to predict the future number of radiology patients by inductively reasoning from observed trends. Based on the observed time interval (periodicity) predicted in the preceding subsections for the time variant labour drivers, periodicity was factored in order to bring clarity in forecasts. Key labour drivers (time variant) were the monthly frequency of examinations for each anatomical region and the workload due to each patient was generally time-invariant (Schneider, 2011). Consistent with Schneider (2011), variances in the observed service transaction for patients that were introduced by the number of examinations per patient as well as competencies of radiographers were considered random.

3.11.4.2 Statistical analysis: aggregation-disaggregation labour driver forecasting

An important pre-requisite for the application of aggregation-disaggregation forecasting model was that the behaviour of the observed labour drivers be consistent. This requirement was qualified by visual (graphical) displays as well as correlation tests (SPSS, 2010; Rosenberg, 1997). The observed (historical) data were collected for an eleven year period. The object was to establish whether the data clearly exhibited consistency necessary for an aggregation- disaggregation approach to forecasting. A correlation test was run on the data to add statistical evidence to qualify the consistency status of the data (SPSS, 2010; Rosenberg, 1997). The criteria for significance was that high correlation values (greater than 0.4) indicated that monthly demand for radiology services were significant. The object of this analysis was to establish whether the data showed similar demand patterns period after period so that an aggregation-disaggregation forecasting approach could be used to within the observed time period demand. Furtheremore graphs were used to strengthen the validity of the conclusions regard consistency and trends in the data.

3.11.4.3 Statistical analysis: smoothing of graphs

The use of the statistic was to fascilitate the process of drawing scientific conclusions about the distribution of the data as well as inferences about the unique features of the data. However, because of the compounding random variables such as rampage equipment failures and supply of consumables, the time series radiology demand data inevitably contained considerable random variations. With this in mind, it was logical to expect that some variations in the demand for radiology services would be predictable while some would be random and therefore, unpredictable.

The main outcome measure of this study was to establish demand trend for radiology services and then go a step further by predicting future demand trend for the same. Mindful of the fact that a trend line is a smooth curve representing the observed data, the objective of the smoothing process was to enable explaination as to why the demand peaked and lagged at the times and volumes they did while at the same time ensuring that the explanation was not shrouded by unpredictable (random or noise component) variations (SPSS, 2010). Therefore, the first step in the statistical process of trend identification was smoothing the data so that none systematic components of individual observations cancelled each other out. To achieve this, moving average technique together with the negative exponentially weighted smoothing technique were chosen (SPSS, 2010). This method was chosen because it filtered out the noise and converted the data into a smooth curve that was relatively unbiased by outliers. This process retained the general shape of the original forecast while at the same time eliminating the randomness by making up for erratic data (SPSS, 2010).

In moving averages approach, each element of the series (month) was replaced by a weighted average of surrounding months (SPSS, 2010; Rosenberg, 1997). This is not to say this process was not without disadvantages. This approach however was more biased by outliers than the use of medians within the smoothing window (SPSS, 2010). However, the main disadvantage of median smoothing was that in the absence of clear outliers it produced more "jagged" curves than moving averages and furthermore, it did not allow for weighting.

Generally, an important disadvantage of smoothing was that it knew no boundaries between spikes and valleys of demand that were caused by real phenomena such as those due to inadequacy of the data (SPSS, 2010; Rosenberg, 1997). This was problematic in that logically radiology department from referral hospitals occasionally experience large but short-lived increases in the demand for radiology services following, for example, major bus disasters. Inevitably, therefore, application of smoothing to the aforementioned data resulted in the short-duration peak caused by such incidents to disappear. Consequently, forecasting of resources based on such a smoothed output required consideration of additional staff when such an incident happened again. In summary, the determination of whether smoothing was appropriate was born from an understanding of the various labour drivers encountered in the delivery of radiology service.

3.11.4.3 Statistical analysis: The forecast equation

The main outcome measure of this study was a forecast for radiology demand. The Kendall test as explained by Rosenberg (1997) was used to test for the presence of a consistent trend and to measure the magnitude of trend (Sen slope test) by inferring from the slope. The Wilcoxon-Mann-Whitney step trend analysis was used to determine variable effects while Hodges-Lehmann estimator (SPSS, 2010) was used to determine the magnitude of the step due to a variable (variable effect). These steps were pivotal in the identification of a function associated with the smoothed monotonous time series data.

Identification of the period for seasonal variations in the demand for radiology was fundamental to forecasting (SPSS, 2010; Rosenberg, 1997). Drawing from Rosenberg (1997), the data was analysed for seasonality by measuring correlation between two measurements separated by a lag *k* in the time series radiology demand data. In statistical format, this essentially meant correlation dependency of order *k* between each i'^{th} element of the radiology time series data and the $(i\text{-}k)'^{th}$ element. This correlation dependency was measured by autocorrelation (i.e., a correlation between these two terms). The criterion was that if the measurement error was not too large, seasonality could be visually identified in the series as a pattern that repeated every k^{th} elements (Rosenbrg, 1997).

In order to give visual perception of the seasonal patterns, autocorrelation correlograms were used to display graphically and numerically the autocorrelation function (*ACF*), that is, serial correlation coefficients (and their standard errors) for consecutive lags in specified range of lags. In these correlograms, the size of auto correlation was more important than its reliability because the criterion was that of very strong and therefore highly significant autocorrelations. The rationale for examining these correlograms was that since autocorrelation for consecutive lags are formally dependent; this implied that the pattern of serial dependencies would change considerably after removing the first order auto correlation, which in statistical terms means after differencing the series with a lag of 1 for example (SPSS, 2010; Rosenberg, 1997). This logic of statistical treatment was vital for this study in removing serial dependency and therefore further transforming the time series data.

Consistent with explanations advanced by Rosenbrg (1997), serial dependency for a lag of *k* was removed by differencing the series, that is converting each *i*'th element of the series into its difference from the (*i-k*)''th element in the time series data. The reason for engaging such transformations were that by so doing the hidden nature of seasonal dependencies in the series could be identified (SPSS, 2010). This is because autocorrelations for consecutive lags are interdependent such that removing some of the autocorrelations, all too often eliminates them or it may make some other seasonalities more apparent. This was an important consideration because removal of seasonal dependencies also made the time series data stationary which was an important requirement for the subsequent statistical analysis (SPSS, 2010; Rosenberg, 1997).

3.11.4.4 Statistical analysis: Tracking Forecast Accuracy

Literature evidence that forecasts are rarely perfect was an important consideration in the methodology section of this dissertation (SPSS, 2010; Mentzer & Moon, 2004; Brocklebank & Dickey, 2003; Chatfield, 2000; Rosenberg, 1997; Makridakis & Wheelwright, 1989). Therefore, drawing from this literature, measurement and tracking of forecast accuracy was fundamental to ensure that the forecasting method was appropriate and valid. To accomplish this specific objective in a speciality deprived of such research, forecasting knowledge was drawn from economics operations research in which a lot of research has been done in respect of validation steps of forecasting models (Agnolucci, 2009; Cheong, 2009; Cortazar & Schwartz, 2005; Costello *et al.,* 2008; Mentzer & Moon, 2004; Brocklebank & Dickey, 2003; Chatfield, 2000; Makridakis & Wheelwright, 1989).Two yardsticks for measuring forecast accuracy that was common in the reviewed literature were engaged in this study. These were the mean absolute percentage error (MAPE) and the coefficient of variation of the forecast error (COV).

Calculation of MAPE and COV was explicitly explained in the SPSS (2010) users' guide- the statistical software that was used in this dissertation. Adapting these formulae to the *diagnostic radiology capacity and demand: trends and forecasts*, this meant that "actual demand" formed the denominator of both measures. This meant that, both MAPE and COV measured relative error (Agnolucci, 2009; Cheong, 2009; Costello *et al.,* 2008; Cortazar & Schwartz, 2005). Consistent with general statistics, MAPE was found by calculating the mean of the absolute value of the error, dividing by the actual demand and then multiplying the outcome by 100 percent (to convert to a percentage). On the other hand, COV was found by calculating the standard deviation of the error and dividing it by the average demand. Great care was taken to ensure that the forecast errors were all tracked using the time intervals (periods or season) used for tracking the labour drivers as was defined by periodicity in the data.

3.12 Distribution of the data

Skewness was used as a preliminary indicator of asymmetry and deviation from a normal distribution while kurtosis was used as a preliminary indicator for peakedness of the distribution for the data (SPSS, 2010; Decoursey, 2003; Intercapital, 1995). Interpretation of skewness was:

- Skewness> 0: This demonstrated a right skewed distribution of data such that most values were concentrated on left of the sample mean, with extreme values to the right.
- Skewness< 0: This demonstrated a left skewed distribution in which most values were concentrated on the right of the sample mean, with extreme values to the left.
- Skewness = 0: In this class of data, the mean was equal to the median and therefore the distribution was symmetrical around the mean.

The kurtosis statistical indicator was used to determine the flattening (peakedness) of the distribution for the data. The interpretation for kurtosis was:

- Kurtosis >0: This demonstrated a leptokurtic distribution in which the peak was sharper than in a normal distribution. Values were concentrated around the mean and distribution tail was thicker than for normal distribution. This implied a high probability for extreme values.
- Kurtosis < 0: This demonstrated a platykurtic distribution in which the distribution was flatter than a normal distribution with a wider peak. In this case, the probability for extreme values was less than for a normal distribution and the values were wider spread around the mean.
- Kurtosis = 0: This demonstrated a mesokurtic distribution in which data was normally distributed.

To test the skewness and kurtosis for significance, the numerical values for skewness and those of kurtosis were compared with twice the standard error of skewness and kurtosis respectively. Values of skewness and kurtosis that fell within this range were considered insignificant.

3.13 Ethical issues

The promotion and protection of the dignity, privacy, anonymity and confidentiality of all participants and their next of keen was an important part of this research process. This was guided by the 1964 World Medical Associations Declaration of Helsinki incoooperating amendments by the 59th WMA General Assembly held in Seoul October 2008 (WMA-GA. 2008), guidelines from the Medical Research Council of South Africa (MRCSA) and guidelines from the Medical Research Council of Zimbabwe (MRCZ). Competent participants were informed of the aims, methods, sources of funding, possible conflicts of interest, institutional affiliations, anticipated benefits, potential risks of the study, the discomfort it may entail and where to report any ill treatment related to the research. All participants were given the opportunity to ask questions as and when they wanted to. All potential participants were informed of the right to refuse to participate in the study or to withdraw consent to participate at any time without reprisal so much so that participation was voluntary. It was only after ensuring that the potential participants had understood the information, that their freely-given informed consent was sought in writing. In the case of incompetent potential participants, the ability and competence of the participant to assent was established. All such participants were given information in a way to make them understand and give their assent or dissent. Importantly, the informed assent process did not replace consent signed by parents, guardians or next of keen. In this way, ensuring that participants got adequate information about the research before seeking their consent formed the impetus of adherence to ethical research process in this study (Picano, 2004).

In order to minimise any interference with the routine processes of the research site, the issue was approached using a survey and a non participatory document review method. The collected data did not include biographic data associated with the examinations or respondents. The document review process reviewed filed documents only. It was ensured that all reviewed documents had no messages attached to them indicating that the patient was not willing to have the data used for research purposes (Hope, Savulescu & Hendrick, 2003). Throughout the research process confidentiality of source documents was observed. Furthermore, a pass worded coding system was used to ensure that row data could not be identifiable with the participants or source documents except through the pass worded master link list. This identification process was a contingency measure to allow for any data verification where necessary. Throughout the study, care was taken that the research process did not negatively interfere with the medical management of patients or with the day to day running of the department. Permission from the selected research sites as well as ethics approval from the Medical Research Council of Zimbabwe ethics committee and the Cape Peninsula University of Technology Research Ethics Committee was granted before the study began. These committees were independent of the research and the sponsor. During the research process, the protocol was not chaged so that there was no need to resubmit the protocol for consideration and approval by the committee. Throughout the study, constant touch with the research sites with regards to feedback on the outcome of the research was maintained.

Consistent with WMA-GA (2008), every effort was made to fulfill his ethical obligation regarding making publicly available the results of the research, completeness and accuracy of the thesis report. Every effort was made regarding adherence to accepted guidelines for ethical reporting explained by WMA-GA (2008). Dissemination of the research outcomes involved the final thesis, seminars and articles. All participants were offered a post-study access to the research outcome. Disseminated information encompassed an explanation of how the research was conducted, report of the results, highlighted limitations of the research, drawn out main conclusions as well as recommendations made for practice and for further research. This was in order to make accessible to relevant research community so that findings are open to critical examination by others and so that they are accessible to all who might benefit.

3.14 Chapter conclusion

A reflection on chapter 3 shows the steps taken to fulfil specific objectives of the study. The research questions were reviewed and research philosophy explained, research design and the study population and sample were explained. This is followed by data capturing, data analysis and validity of the study. The chapter closes with a discussion on the ethical consideration and chapter conclusion. The following chapters (Chapter 4, 5 &6) are the results chapters while chapter 7 reviews the research process. The three results chapters are arranged in sequence according to research sub-questions (specific objectives) and are presented alongside supporting statistical evidence. Each of these subsequent chapters ends with a conclusion and a list of recommendations.

CHAPTER FOUR
DIAGNOSTIC RADIOLOGY PATIENT CARE PATHWAY

Abstract

In this chapter, the radiology patient care pathway for the research sites is addressed. Related literature was explored to derive a care pathway checklist which was refined for the observation of practice. The work performed in this chapter formed an exploratory study to guide methodology for forecasting radiology demand. The study focused on the activities that diagnostic radiology departments did in their quest to offer plain radiography services. The main outcome measure of this chapter was a theoretical basis for a pragmatic study on a plain radiology care pathway for Zimbabwe. Measuring the time associated with each activity required an appreciation of the characteristics of each radiology procedure that could affect its duration. This was the underlying concept in identifying those variables that had an effect on the number and skills of human resources needed to serve patients attending for plain radiology procedures. A comprehensive literature search on CPUT post graduate library guide and Google Scholar, for example, using key words: radiology care pathway, radiology clinical pathway and plain radiology was conducted. Prominent in the search results was the International Journal of Care Pathways. Articles related to this chapter found in this journal formed the impetus of this investigation.

The global problem encountered in this search was that often a clinical care pathway was defined for a single examination process and because there are many clinical examinations this element of confusion lead to paucity of knowledge regarding what constitutes a clinical pathway . As a result, this research area had remained open to lot of knew knowledge yet to be explored in respect of what constitutes the radiology care pathway. This part of the study employed survey and observational approaches. There was consistency in the activities done by radiology departments across research sites. Conclusions drawn from this part of the study were that the main activities performed in plain radiology patient care pathways by radiographers were consistent with global expectations as detailed in the checklist designed and tested for this study from literature.

4.1 Introduction

The policy prescribed in the Zimbabwe Agenda for Sustainable Economic Transformation (ZMFED, 2013) specifically requires that policy makers engage evidence based decision making approaches so that efficiency and cost-effectiveness can be realised. Elsewhere, efficient and effective utilisation of valuable radiology resources have been realised through an understanding that investment policies ought to be guided by capacity and demand. However, to appreciate this concept it is pertinent that respective patient care pathways be explicitly defined.

A radiology patient care pathway may be loosely defined as the process a patient follows from the time of referral for a radiology examination until a time the patient is dismissed from a radiology department (Vanhaecht *et al.,* 2007; Daniel & Alan, 2006). Vanhaecht *et al.,* (2007) as well as Daniel and Alan (2006), explain that processes that comprise patient care pathways are used internationally to guide evidence-based healthcare to provide efficient services. Both authors go on to concur that all too often, a clinical care pathway is defined for single examination process thereby leading to an element of confusion regards what constitutes a clinical pathway in respect of activities and personnel involved. Hypothetically and logically, activities that form radiology care pathways may differ from patient to patient because patient demands and therefore flow times, equipment used, radiographer experience as well as institutional exposure guidelines may differ across sites. Logically, patient factors may lead to variances in the specific path a patient would follow within a radiology department. As an example, there is a difference between patient factors associated with acute and those associated with elective care pathways. Using the same example, because elective care is not in the medium term life threatening, elective care allows some planning latitude so that the radiographer can control the start time of care within reasonable reliability margins.

Vanhaecht *et al.,* (2007) outlines defining characteristics of care pathways as embracing appropriately sequenced, patient specific and evidence based goals and key elements of care that recognises synergy among team members. With respect to plain radiology patient care pathway, the aforementioned defining characteristics of care pathways are indeed consistent with the main outcome measure of a radiology care pathway because radiology care is aimed at enhancing care across the continuum. This analysis as well as the aforementioned characteristics is consistent with concepts from the field of Health Operations Management (HOM), defined by Vissers and Beech (2005) as the analysis, design, planning and control of all activities necessary to provide a (radiology) service to (patients as) clients. Vissers and Beech (2005) as echoed by Schrijvers (2009) as well as Schrijvers and Hoorn (2012) explains that challenges are bound to arise if care pathways are not based on capacity planning of resources. This is logical because demand to capacity ratio is a scientific way of defining workload. It is not surprising then that, mapping patient care pathways has been identified by UKNHS (2005), as pre-requisite for any policy formulation aimed at optimising resource deployment and utilisation. Work done to clear bottlenecks in patients' care pathways; to understand the magnitude and variation mismatches in demand and capacity and to smooth these variations, where possible, has been reported for the United Kingdom's NHS using the aforementioned approach (UKNHS, 2005). In respect of UKNHS (2005), work was done in order to prepare the ground for Lean thinking. Work done by the UKNHS (2005) explains how evidence based approaches can be used to map radiology clinical care pathways and also how to use the relationship between demand and capacity to explain workloads and therefore patient waiting times. Figure 4.1, 4.2 and 4.3 are illustrative displays for a bottleneck activity, process activity and a functional activity as defined by UKNHS (2005).

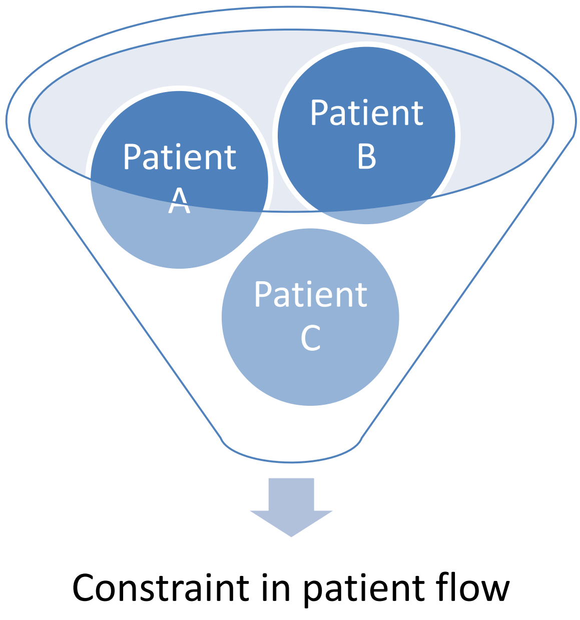

Figure 4.1: Illustrative display of a bottleneck activity

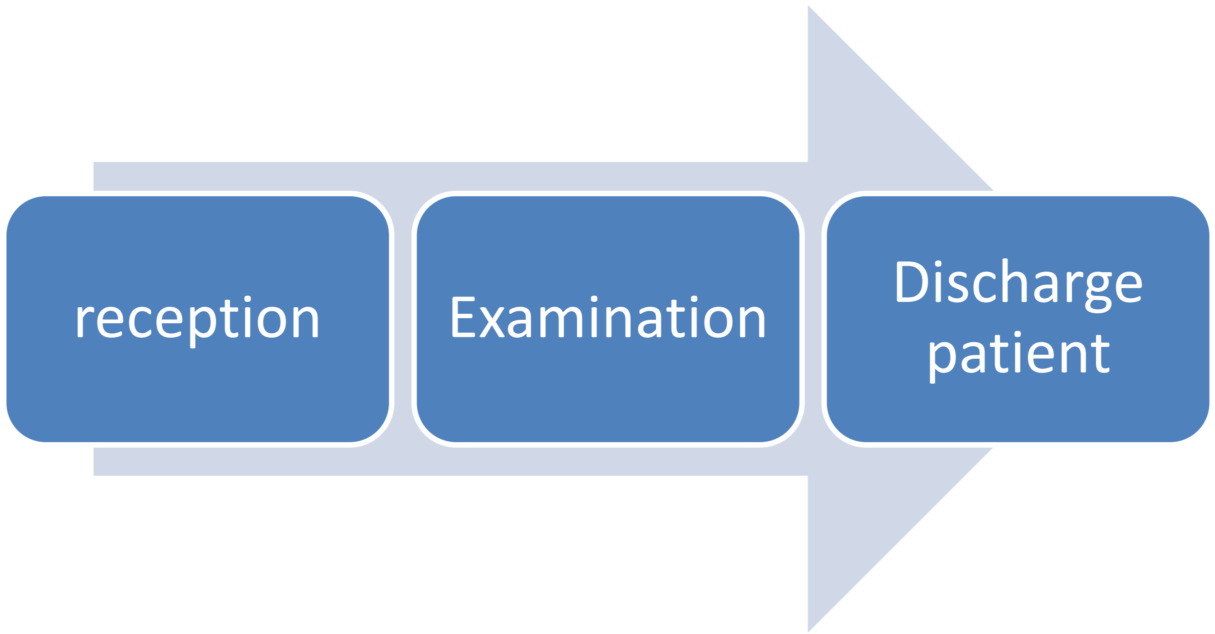

Figure 4.2: Illustrative display of process activities

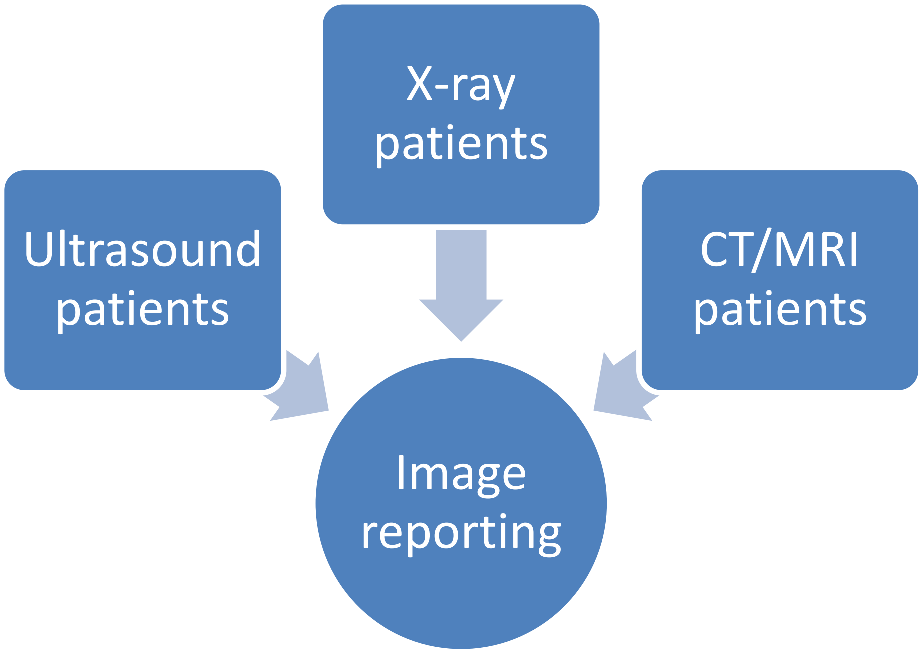

Figure 4.3: Illustrative display of a functional activity

The objective of this exploratory study was "to determine the nature of activities in plain radiology patient care pathway"**.** The main outcome measure for this objective was a map of the radiology patient care pathway giving a clear picture of the nature of activities performed by radiographers in their quest to deliver plain radiology care. The aforementioned literature review formed the impetus for this study.

4.2 Data collection procedures

Guided by an abundance of literature on patient care pathways, patiens were observed from the time they arrived at the radiology reception area until they were dismissed from the radiology department (Schrijvers & Hoorn*,* 2012; Vanhaecht *et al.,* 2007; Daniel & Alan, 2006; Vissers & Beech, 2005, UKNHS, 2005). Consistent with this literature, the objective was to document all instances where the patient moved from one personnel to another (handoffs) and activities performed by radiology staff in respect of patients at each handoff (Sibanda *et al.,* 2014; Schneider, 2011). At each stage in the patient care pathway, documentation involved activities that patients were involved in, with who, equipment involved and amount of time taken for the activities (Sibanda *et al.,* 2014; Schrijvers and Hoorn*,* 2012; Schneider, 2011; Vanhaecht *et al.,* 2007; Daniel & Alan, 2006; Vissers & Beech, 2005, UKNHS, 2005). Documentation also included the total number of radiology referrals coming in from all sources at each of these stages (UKNHS, 2005). These observations were triangulated by questionnaire and interview data which further sought to explain the observations.Interview questions were administerd by the researcher prospectively.

The data collection process was complex in that there were huge variances in anatomical regions involved, the examination techniques, expertise and curricular background of radiographers, type of equipment and patient/pathological characteristics as well as diversity of activities done by radiographers. Care was taken regarding inter-equipment, inter patient, inter-operator and inter-pathology variability in the measurements. To accomplish this task, the anatomy was divided into four categories namely: appendicular, axial and skull, chest region and others. Times associated with these regions were measured from a calculated quota sample of patients examined by various radiographers on various available x-ray machines (Sibanda *et al.,* 2014; Schneider, 2011; UKNHS, 2005). These measurements were collaborated by interview results in respect of views of radiographers about the time estimates per patient as well as explanations for the observed data. Weighting these times across examinations, equipment, patients and radiographers allowed the determination of how service characteristics affected the duration and nature of the service transaction time for patients per anatomical region.

4.3 Data Analysis protocols

The determination of radiology departmental activities involved an account of activities that were performed at any time (e.g. damp dusting, filling and replenishing of drugs and accessories) as well as activities that were performed upon demand (e.g., examining a patient, disinfection after examination, image evaluation and interpretation). Consistent with Sibanda *et al.* (2014) and Schneider (2011), these were categorised as controllable work- activities that were flexible in their timing and uncontrollable work- activities that were rigid in their timing. By this definition it was therefore, logical to consider controllable activities as activities that afforded radiographers time latitude to perform the activity (Schneider, 2011). Notably, though, this latitude did not mean an open ended window period. With this in mind, controllable-work windows were variable in length depending on the nature of the activity (Schneider, 2011).

The criterion adopted for this study was that if a patient's clinical journey in the radiology department had a mixture of controllable and uncontrollable characteristics, this essentially meant the journey was uncontrollable. Using this framework, the task was to map the plain radiology patient care pathway noting activities done, equipment and personnel capacity (Sibanda *et al.,* 2014; Schneider, 2011; UKNHS, 2006; UKNHS, 2005). The equipment and personnel involved as well as the number of patients entered to calculate demand was based on the central tendency for the five sites. Activity time used in this study was an arithmetic mean for the research sites obtained by a survey approach. These activity time values for individual activities represent an average of values obtained by observational and interview approaches per examination. The final mean activity service transaction time together with associated standard error of the mean were calculated by adding the aforementioned activity times associated with each examination and averaging across examinations.

Calculated staff and equipment capacities represented the total number of resources available at any given time for the five sites. With no official time series records on staff and equipment numbers, observed numbers for year 2014 and year 2015 were used. When it came to time series data, the number of patients used for the calculations was the total number of patients for the five sites. Annual demand, defined as all radiology referrals coming in from all sources to a step in a patient care pathway (Schneider, 2011; UKNHS,2006), was measured at the identified step by multiplying the patient numbers by the time in years it took to handle a patient at each step (UKNHS, 2006). Again consistent with the aforementioned literature, capacity was defined as the resources available to do work at each of the steps in a patient care pathway. This included all equipment and staff hours available to care for patients. Annual x-ray equipment capacity was obtained by multiplying the number of pieces of equipment by the time available to personnel with the necessary competencies to offer radiology care to patients (UKNHS, 2005). In order to ensure consistency and comparability as outlined by UKNHS (2005), demand and capacity were both measured in the same units (per year). This analysis was therefore such that:

*a). Annual demand= patients attended to per year *service transaction time (in minutes) per patient / (60 minutes per hr*24hrs per day*365days per year)*

b). Annual X-ray equipment capacity= 9machines 8 hours per day* 5 normal days per week* 52weeks per year/ (24*365 hrs per year).*

These calculations were done using the Statistical Package for Social Sciences (Version 21). The same statistical package was used to describe interview data by establishing central tendencies necessary to support inferential analyses.

4.4 Results

In this set of results, an outline of observed activities (labour drivers) performed at the research sites radiography departments in the quest to deliver radiology services is given. There were eleven distinct activities that were identified and observed using the check list (Appendix B). Table 4.1 is an illustration of a process template describing the process in terms of what happened to a patient at one point in time in the radiology department.

Table 4.1: identified activities in radiology patient care pathway

Who was involved?	Personnel involved	Equipment involved	Activity (Doing what?)	Service transaction time in minutes
Reception part & registration	Clerk		i. Information about examination costs ii. Registration for radiology examination	6.4 ±0.4
Accounts (accounts clerk)	Clerk		Receiving payment for radiology services	12.6±0.7
Waiting area		Chairs	Waiting for a radiology examination	9.3±0.2
Examination process (radiographer)	Radiographers	X-ray equipment	i. Reviewing justification of examinations ii. Room preparation iii. Equipment iv. Patient preparation v. Radiology examination vi. On demand Infection control	29.6±0.8
Image processing	Darkroom technician	i. Actinic printer ii. Film processor	i. Film I.D ii. Processing iii. Evaluation of image	9.98±0.09
Dismissal of patient	Radiographers	Nil	Assuring patient and directing patient back to referrer	6.66±0.08
Routine infection control	Radiographers & infection control nurse	Nil	All round damp dusting	20±4
Archiving	Radiographers	Information technology/ shelving	Storage of radiology images for future use	20±6
Restocking	Radiographer	Nil	Identifying stocks that need replenishment and ordering from stores	20±7
Replenishing	Darkroom technician	Nil	Changing processing chemicals	40±8

Items 8, 9, 10 and 11 were recorded to help explain observed personnel capacities although these were certainly outside the individual patient care pathway. Observed compliance levels of the research sites as measured using the checklist is shown in Table 4.2. Observed discontinuities regarding day to day records of examinations in patient registers were noted for the purpose of explaining spikes in the data.

Table 4.2: Activities checklist site by site

	Expectation	**Observations from Site No.**						**% compliance**
		1	**2**	**3**	**4**	**5**		
1	Information about examination (Reception part i.)	√	√	√	√	√		100
2	Payment for examination (Accounts)	√	√	√	√	√		100
3	Registration for examination (Reception part ii.)	√	√	√	√	√		100
4	Waiting to be examined (Waiting area)	√	√	√	√	√		100
5	i. Review of justification (Radiologist/Radiographer)	×	×	×	×	×	60%	0
	ii. Viewing of previous radiographs (Radiographer)	×	×	×	×	×		0
	ii. Room preparation (Radiographer)	√	√	√	√	√		100
	iii. Patient preparation (Radiographer)	√	√	√	√	√		100
	iv. Examination process (Radiographer)	√	√	√	√	√		100
6	i. Image identification marker (Radiographer)	√	√	√	√	√	100%	100
	ii. Image processing (dark room technician/radiographer)	√	√	√	√	√		100
7	i. Image evaluation (Radiographer)	√	√	√	√	√	55%	100
	ii. Image reporting (radiologist)	×	√	×	×	×		20
	iii. Communication of findings (Radiologist/Radiographer)	×	√	×	×	×		20
	iv. Dismissal of patient (Radiographer)	√	√	√	√	√		100
8	Infection control (radiographer/x-ray operator or infection control nurse)	√	√	√	√	√		100
9	Archiving (radiographer)	√	√	√	√	√		100
10	Restocking (radiographer)	√	√	√	√	√		100
11	Replenishing (radiographer)	√	√	√	√	√		100

All centres had no resident radiologist and out of the 5 radiology departments observed, there was only one centre that reported on images. Patients would leave their images behind and these would be delivered to a radiologist who, upon finishing the reporting process, would forward the report and images to the referring clinician. Waiting time for these reports was no less than one day.

At the time of this research the research sites had a total of 9 general radiography x-ray machines that were working among all the research sites. Again, among them all, the total number of filled staff posts (in service staff numbers) was: 41 radiographers but 20 radiographers on duty per session and 15 darkroom technicians/clerks but 11 on duty per session. It was also observed that darkroom technicians doubled as reception clerks. For the purpose of calculation of staff capacity, this observed total number of darkroom technicians and reception clerks was equally distributed between the two categories. Generally, when a patient arrived for radiology services, financial accounting issues were attended to first. The process itself took an average 12.57 minutes. The accounts department served the entire hospital and there was generally a queue at any given time across research sites. Some departments had an alternative cashier at the radiology department such that there were two personnel serving this queue. Out of a 118 patients observed, 108 were able to pay and proceed back to radiology reception area to register for a radiology examination. This means that 9.2% of patients were not examined because of financial issues and therefore, the number of patients recorded on the register represented 90.8% of the actual demand seen at the accounts and reception areas. Upon arrival at the radiology reception, the patients would join the queue and await their turn. For each patient, a total (including registration time for examination) service transaction time at the reception desk was on average 6.39 minutes. After the registration process, the patient would then join the queue in the waiting area for an average 9.34 minutes. The total service transaction time for plain radiology patients was 74.55minutes. The examination process accounted for 39.7% of the service transaction time which was therefore, the bulk of this service transaction time (29.61 minutes out of 74.55 minutes).

With respect to sites 1, 3, 4, and 5, it was observed that radiographers started work at 0800Hrs and that each radiographer had 30 minutes tea break and one hour lunch break on each normal working day. Normal working hours ended at 1600Hrs. In this regard, each radiographer was available to deliver services for six and a half hours on each normal working day. However, with respect to site 2, radiographers had eight working hours. They would only break for tea or lunch when there were no patients. The centre was generally not busy and this arrangement seemed to work very well. The number of radiographers per shift is indicated as rostered radiographers in Table 4.3.

Table 4.3: Staff and equipment numbers

	Site 1	**Site 2**	**Site 3**	**Site 4**	**Site 5**
Radiographer complement	**11**	**2**	**10**	**3**	**15**
Rostered number of Radiographers	5	1	5	1	8
Darkroom tech. & Reception Clerk complement	**5**	**1**	**3**	**1**	**6**
Rostered staff (clerks/tech)	3	1	3	1	3
Functioning plain x-ray rooms	**2**	**1**	**2**	**1**	**3**
Functioning processors	**1**	**1**	**1**	**1**	**2**
Shift hours	6.5	8	6.5	6.5	6.5

Information displayed in Table 4.3 together with overall yearly number of patients enabled a calculation of demand to capacity ratios (**DC^R**).

Overall demand to capacity ratios (**DC^R**) for the five research sites is displayed in Table 4.5. It was observed that 90.8% of patients initially seen at the radiology reception desk managed to return from the accounts department for radiology examinations. Reasons for the fallout were not investigated and it was logical that this was due to financial reasons. Based on the pilot statistics in which out of 118 originally seen at the reception and 108 who finally registered for the examination, this means that the percentage number of patients seen at the reception and accounts departments as compared to registered number of patients documented in patient registers as having undergone radiology examinations was 109.3% [(118x100)/108]. .

Table 4.4: Overall year on year demand/capacity ratio (DCR)

Table 4.4 Overall year on year demand/capacity ratio (DC^R)

		2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Compensated number of patients		**50321**	**55685**	**38089**	**43630**	**25379**	**16495**	**41080**	**38117**	**54171**	**50169**	**48550**
Accounts	Demand	1.20	1.33	0.91	1.04	0.61	0.39	0.98	0.91	1.30	1.20	1.16
Reception desk	Demand	0.61	0.68	0.46	0.53	0.31	0.20	0.50	0.46	0.66	0.61	0.59
	Staff Capacity	1.54	1.54	1.54	1.54	1.54	1.54	1.54	1.54	1.54	1.54	1.54
	DC^R	*0.40*	*0.44*	*0.30*	*0.34*	*0.20*	*0.13*	*0.32*	*030*	*0.43*	*0.40*	*0.38*
Actual Number of patients		**45746**	**50623**	**34626**	**39664**	**23072**	**14995**	**37345**	**34652**	**49246**	**45608**	**44136**
Waiting	Demand	0.81	0.90	0.62	0.70	0.41	0.27	0.66	0.62	0.88	0.81	0.78
	Sitting Capacity	4.75	4.75	4.75	4.75	4.75	4.75	4.75	4.75	4.75	4.75	4.75
	DC^R	0.17	0.19	0.13	0.15	0.09	0.06	0.14	0.13	0.18	0.17	0.17
Examination	Demand	2.58	2.85	1.95	2.23	1.30	0.84	2.10	1.95	2.77	2.57	2.49
	Equipment Capacity	2.14	2.14	2.14	2.14	2.14	2.14	2.14	2.14	2.14	2.14	2.14
	Staff capacity	7.91	7.91	7.91	7.91	7.91	7.91	7.91	7.91	7.91	7.91	7.91
	Staff capacity roistered	3.86	3.86	3.86	3.86	3.86	3.86	3.86	3.86	3.86	3.86	3.86
	DC^R Staff	0.33	0.36	0.25	0.28	0.16	0.11	0.27	0.25	0.35	0.32	0.31
	DC^R Roistered Staff	0.67	0.74	0.51	0.58	0.34	0.22	0.55	0.51	0.72	0.67	0.64
	DC^R Equipment[¥]	*1.21*	*1.33*	*0.91*	*1.05*	*0.61*	*0.40*	*0.98*	*0.91*	*1.30*	*1.20*	*1.16*
Image processing	Demand	0.87	0.96	0.66	0.75	0.44	0.28	0.71	0.66	0.94	0.87	0.84
	Equipment Capacity	1.42	1.42	1.42	1.42	1.42	1.42	1.42	1.42	1.42	1.42	1.42
	Staff capacity	1.54	1.54	1.54	1.54	1.54	1.54	1.54	1.54	1.54	1.54	1.54
	DC^R Staff	*0.56*	*0.62*	*0.43*	*0.49*	*0.28*	*0.18*	*0.46*	*0.43*	*0.61*	*0.56*	*0.54*
	DC^R Equipment	*0.61*	*0.68*	*0.46*	*0.53*	*0.31*	*0.20*	*0.50*	*0.46*	*0.66*	*0.61*	*0.59*

[¥]Denotes demand greater than capacity

Table 4.5: Descriptive Statistics: Demand to capacity ratios for radiology services

	Minimum	Maximum	Mean	
	Statistic	Statistic	Statistic	Std. Error
Demand/Capacity ratioWaiting area	.06	.19	.1414	.0003
Demand/Capacity ratio Staff in Examination room	.11	.36	.2690	.0006
Demand/Capacity ratio Reception area	.13	.44	.3273	.0008
Demand/Capacity ratio Staff in Processing area	.18	.62	.465	.001
Demand/Capacity ratio Equipment in Processing area	.20	.68	.504	.001
Demand/Capacity ratio Staff Rostered Examination room	.22	.74	.552	.001
Demand/Capacity ratio Equipment Examination room	.40	1.33	.996	.002

From Table 4.5, the maximum demand to capacity ratios for all the stages are lower than expectation. Minimum that are below 0.5 are also shown. For all activity stages the central tendency of demand to capacity ratio as mearsured by the mean value was lower than expected (1.00) except in respect of demand to capacity ratio for examination equipment (0.996+/-0.002).

In order to provide supporting evidence to explain the observed demand to capacity ratios, 400 request forms spanning from 2004 to 2014 were analysed. The distribution was however, affected by availability of these documents. It was also observed that 22% of the request forms were complete in respect of both clinical history and diagnosis. The central tendency (78%) was that referrers would indicate the examination question without supporting clinical history. Furthermore, survey results established that generally, radiographers' perspectives were that, for a long time since about year 2000, there was a cascade of artificial negative pressures on radiology patient care pathway. According to the interviewed (84%) radiographers, these pressures (perceived artificial) included economic sanctions, a weakening economy, equipment breakdowns and staff exodus were always used by policy makers to explain long waiting times for radiology services. However, it also emerged from some radiographers (15%) that waiting times were presumed consistent with epidemiological trends as well as overutilisation (76%) of radiology by referrers.

Generally, radiographers concurred (94%) that there was an unofficial role extension which saw radiographers assuming some roles that were officially done by radiologists. However, none of the interviewed radiographers acknowledged having been formally trained to offer life support services, to inject patients, nor to interpret radiology images. Furthermore, there were no continuous development programmes recorded by radiographers in line with these aforementioned activities except that radiographers were in-house "trained". It was generally, accepted (98%) that all radiographers were academically competent to do obstetrics and gynaecology ultrasound scans and reporting. The Radiation Protection Authority of Zimbabwe was in existence throughout the data collection window period. Regulatory requirements such as ionising radiation signs, pregnancy alert and pilot exposure lamps were observed in all centres. However, justification and optimisation of exposures documents were not identified in all sites.

4.5 Discussion

In this study, a map of the radiology patient care pathways and quantification of the demand for radiology from all participating departments was managed. A sustained demand for radiology examinations was observed. Small but random variations were associated with missing values that pointed to equipment breakdowns. Long patient waiting times that were evident at reception areas, accounts and patient waiting areas were avoidable. Many handoffs and bottlenecks observed in the patient pathways, although consistent across departments, could be reduced by introducing an online patient tracking system. Consistent with literature, the concept of utilising radiographers to undertake tasks which previously had been the role of radiologists had continued to diffuse slowly (though unofficially) across the country. Although the practice by radiographers to identify pathology/abnormality by placing a dot where it is observed on images (red doting) was acknowledged by radiographers as part of their activities, such evidence was however not observed across all research sites, and therefore cannot be used to explain observed service transaction times.

Observations made in this study indicate that role extensions existed across Zimbabwe but there was no evidence to suggest that implementation was official, systematic or centrally organised by the regulatory body - the government through the Allied Health Professions Council (AHPC). However, with the Zimbabwe National Health Services hard hit by a shortage of radiologists and these unofficially extended roles not in conflict with radiologists, these activities by radiographers may as well be an available solution to long patient waiting times for the research sites. However, caution must be exercised to ensure that the impact of this role extension on the demand for radiology services, while easing an existing bottleneck (on radiologists) dose not introduce an even worse new bottleneck on radiographer services. Overall, the observed pattern and rate of adoption of extended role and activities fits the observations made by Stevens, Robert and Gabbay (1997). These researchers claimed that, firstly there is a tendency for new health care technologies to be introduced somewhat haphazardly in the first event. It must be emphasised here that while the observed interview outcomes seem to support Stevens *et al.* (1997), second suggestion that first technological diffusion is typically unorganised and that it occurs at different rates, factors that influenced this are subject to further investigation for these research sites.

Another issue that was investigated was the impact of completeness, accuracy and justification of radiology examinations on the demand for radiology services. There was wide spread non compliance (78%) with the completion of radiology examinations request forms. Non compliance potentially compromised the continuity of patient care in radiology departments in that it potentially compromised accuracy of the requested examinations. Consistent with literature, most important was the fact that, by virtue of being incomplete and therefore not indicated in so far as documented request information was concerned, these examinations were not justified and unnecessarily added 78% examinations to radiology demand. The impact on occupational dose and patient dose cannot be over emphasised. The impact of exposure guidelines as well as technology diffusion was not visible in the collected data from individual sites and neither was it visible in the overall data because of the time horizon for the data.

While the outcome of this study has illustrated a rather moderate shift in practice for radiographers and that the extended roles now have a real potential to be officially embedded into practice, it would appear that a great deal of work still remains. In particular, because there were different radiographer entry level qualifications offered across Zimbabwe (Bachelors degree, Diploma and certificate level), matching the skills available with practice demands across different staff groups requires review of radiography curricula. The current scenario inevitably provided a challenge to manpower planning for delivery of an effective service. Consistent with this observation, by the time of writing this report, the National University of Science and Technology (NUST) as well as the Zimbabwe Council for Higher Education (ZIMCHE) were engaged with the process of reviewing curricula. In this endeavour, the Allied Health Professions Council (AHPC) of Zimbabwe and the Radiographers' Association of Zimbabwe (RAZ) have also initiated the process to redefine scope of practice boundaries for radiographers. In this regard, it would seem that the adoption and diffusion of extended roles in radiography will continue for some time until these institutional policies are well aligned to each other. If this does not happen, the pressure is bound to continue together with a growing demand for radiology services (Department of Health, 2000). Suffice it to say, if the scope of practice is not redefined soon in Zimbabwe, these factors will play a pivotal role in accelerating the introduction of ad hoc extended role activities rather than reducing them.

It is acknowledged that the aforementioned activities at NUST, ZIMCHE and AHPC are indeed testimony that the scope of practice for radiographers has found itself as topical in Zimbabwe. It was evident that blurring role boundaries within multidisciplinary environments required that the Zimbabwe radiography education be responsive to the observed demands of practice in order to meet changing priorities. However, ways will have to be defined to cater for those radiographers already in practice, possibly by developing their skills over and above those developed during pre-registration education and training. With respect to training institutions, opportunities also exist for supporting and enabling the widening scope of practice. Suffice it to say, institutions will have to be proactive in modernising and developing the scope of pre and post registration education.

Turning focus to improvement methodologies, in a radiology perspective and consistent with previous research in other disciplines, activities done by radiographers were looked at using a "bottleneck" concept (UKNHS, 2005) in which identification of areas where patients' natural flow was constrained was a prerequisite to prescribing efficient and equitable distribution of resources as well as their utilisation. Using this concept, calculated demand to capacity ratios for the research site revealed that all but one of the observed activity stages were significantly over capacitated. Based on statistical evidence, for the majority of handoff stages there was under utilisation of resources. Consistent with literature, the patient care pathway itself had activities that fell into two types: process activities and functional activities. The examination process took the longest time to complete and was therefore referred to as the 'rate limiting step or task' in a radiology patient care pathway (UKNHS, 2005).

Statistical evidence showed that despite reports by the ministry regarding poor staffing levels (ZMOHCC, 2009), the radiology sector was actually over capacitated in so far as demand to capacity ratios can show. This was made more evident by noting that even when staff capacity was calculated based on half the observed established number of radiographers manning the department, (where half the number of radiographers in the establishment was available to offer services at any given time) the staff capacity was found to be still above demand. This statistical analysis is evidence that even when half this number was in service, the sector was still over staffed. However, the results show that for most of the years, there was under-capacity in respect of X-ray equipment and this could provide answers to explain the existence of observed long waiting times. This was enough statistical evidence to recommend that the ministry should, at least in the short to medium term, focus its investment on radiology equipment and, instead of increasing radiographic staff capacity, focus on redeployment to solve observed variation mismatches in demand and capacity. Consistent with literature (UKNHS, 2005), activities such as image processing were typically functional bottlenecks with a potential to cause waits and delays for patients from several sources (radiographers) thereby causing disruption to the natural flow of radiology patient care processes. This delay was however not visible, possibly because the processing area had over-capacity relative to the demand for processing services. Image reporting being another example of a process activity was however not assessable using this criterion because images were delivered to a radiologist who had over a day to report on them.

Literature explains that such circumstances result in demand that is not promptly dealt with thereby resulting in a backlog (UKNHS, 2006) so much that when it comes to execution of activities latitude windows for the individual activities would be oversubscribed. In this study, it was observed that when departments started work, patients were already waiting and because queues would build up during tea and lunch breaks, despite the fact that capacity generally surpassed demand, it can be concluded that these queues were mostly as a result of a mismatch between variation in demand and capacity. Elsewhere, it has been shown by many researchers that under similar conditions queues are as a result of the right people not always being available to deal with the demand in a timely manner (Brown et al., 2013; Gahan, 2010; Hobson, 2007; Lodge & Bamford, 2008; Taylor & Shouls, 2008; Silvester & Walley, 2005; Lee & Silvester, 2004; Silvester *et al.,* 2004; Martin *et al.,* 2003). Drawing from this literature, this means that every time demand exceeded capacity, a queue resulted and demand was subsequently carried forward. However, on the contrary, every time capacity exceeded demand, the extra capacity was either lost in the fixed session or was filled from the backlog and this may explain the observed intermittent queues (Silvester & Walley, 2005; Silvester *et al.,* 2004; Martin *et al.,* 2003).

Generally, throughout the plain radiography patient care pathway, capacity remained higher than demand for plain radiology services. In this study, the central tendency for equipment demand/capacity ratio was 0.996+/-0.002 which was not significantly different from expectation (1.00). This means that there was no enough room to accommodate flash variations in demand. This observation is despite the concerns by the Ministry of Health and Child care in which concerns were raised regarding the capacity of radiology human resources (ZMOHCC, 2009). The observed waiting time for radiology examinations was consistent with literature where these times were cited as the source of patient dissatisfaction (Taylor & Shouls, 2008).

The methodological approach adopted in this study took account of the variability of activity time as an indicator of demand by averaging activity time based on the variability of patient factors, personnel proficiency and examinations at the research site. This approach compensated for the fact that activity time varies depending on variables such as co-operation of the patient, age of the patient, the radiographer and the pathology investigated. Furthermore, the research focus was general radiography patients and observed patients placed similar demands on departmental resources. Gathering both the number of patients and the number of examinations was a plus for this study as previous researchers had recommended that this approach provides a more accurate estimate of activity and therefore demand (Brown *et al.,* 2013; Gahan, 2010; Hobson, 2007; Lodge & Bamford, 2008; Taylor & Shouls, 2008; Silvester & Walley, 2005; Lee & Silvester, 2004; Silvester *et al.,* 2004; Martin *et al.,* 2003). Although radiographers were assumed to be “interchangeable”, it is acknowledged that the use of activity time gathered in one year, as a basis for calculations for all the years, introduced cohort errors. Again, this study did not include demand encountered outside normal working hours although contrary to other researchers, the data set did provide the ability to determine whether a drop in demand for one research site was picked up by other providers in the same catchment area (Sibanda *et al.,* 2014).

In order to provide more insights into the observed labour scheduling, observed activities were further classified based on timing. The nature of observed activities was such that some activities were performed at any time while some activities were performed upon demand. Of particular note is that radiographers were involved in occupational health and safety activities which were extra to what was measured in this study. This included routine hazards prevention measures such as daily damp dusting (disinfecting door handles, cassettes and equipments for example) as well as on demand infection control. The observed protocols were that routine infection control was done first thing in the morning or at the end of the day’s work or in between examinations when demand allowed. This means that the scheduling of such activities was essentially controllable by radiographers. In other words, it allowed time latitude so that it could be done at the radiographers’ convenient time. Some of these controllable activities were those done monthly. Further examples of such activities were archiving and replenishing of emergency drugs and accessories. By this definition, controllable work afforded radiographers time latitude in which they could perform the activity. Importantly, though, these activities had to be performed within the aforementioned window period. As such, controllable-work windows could therefore vary in length depending on the nature of the activity: replenishing of emergency drugs at the research sites had documented latitude of months which was quite reasonable when considering expiry dates and rates of usage. It is strongly recommends that these activities be investigated to see if they can account for the balance human resource capacity.

There were other activities that did not allow radiographers to be flexible in their scheduling. These were particularly elaborate on busy examination schedules. As an example, examining a patient, disinfection after examining patients with open wounds, image evaluation and interpretation as well as communication of findings were certainly "uncontrollable work" as they were rigid in their timing. Importantly, when a patient had been examined and there was another patient waiting for the services, room preparation was mandatory at the end of the examination. Therefore, the criteria was that if a patient's clinical journey had a mixture of controllable and uncontrollable characteristics, the journey was uncontrollable was befitting in that once the examination process for the patient had been initiated, with all due respect to the patients' time, it had to be finished forthwith. There was also some evidence from literature that the duration of a patients' stay in a radiology department can be shortened by starting activities sooner or increasing parallelism (Mould *et al*., 2009, Tennat, 2001).The approach adopted in this study can best be described by The Theory of Constraints (Cox & Schleier, 2010;Goldratt & Cox, 2004).Consistent with Goldratt and Cox (2004) as well as UKNHS (2006), the focus of this study was on the fact that radiology patient care being a process, bottlenecks occurred that had to be passed before the process could continue. Because bottlenecks created rate determining stages on the capacity of a system, it was therefore befitting to embrace Goldratt and Cox's (2004) view that a bottleneck solution was an overall process solution.This view was also shared by many other researchers who went a step further to indentify the actual problems in patient care pathways(Brown *et al.,* 2013; Gahan, 2010; Hobson, 2007; Lodge & Bamford, 2008; Taylor & Shouls, 2008; Silvester & Walley, 2005; Lee & Silvester, 2004; Silvester *et al.,* 2004; Martin *et al.,* 2003).

4.6 Conclusions

Generally, observed radiology departments were over capacitated in respect of human resources with demand to capacity ratio significantly less than one for all steps in the patient care pathway. However, equipment resources for conducting examinations were under capacity. The observed queues and waiting times allowed the radiology departments to appear busy and in need of more resources yet in the actual fact virtually all stages had capacity that surpassed demand. Continued requests by the Zimbabwe Ministry of Health and Childcare for more radiology staff was without evidence from this research. Because plain radiography formed the bulk of the work for radiographers in the host country, Zimbabwe, it can be concluded that an observed reserve staff equivalent to the number of radiographers manning the department at any one time was rather too high for the struggling economy even when other hidden duties are taken into consideration. Guided by interview and questionnaire results, it can be concluded that inconsistencies between demand and capacity was evidence that, beginning with lack of evidence to guide policy formulation; there was a cascade of negative beliefs pressuring on radiology patient care pathway which included beliefs that economic sanctions, a weakening economy, overutilization of radiology and staff exodus were responsible for long waiting times for radiology services. Conclusions regarding service transaction times are summarised in Tables 4.6 and 4.7.

Table 4.6: Controllable process activities in radiology patient care pathway

Observed Activity	Equipment involved	Description of activity
Infection control (radiographer/x-ray operator or infection control nurse)	Nil	All round damp dusting
Archiving (radiographer/x-ray operator)	Information technology/ shelving	Storage of radiology images for future use
Restocking (radiographer/x-ray operator)	Nil	Identifying stocks that need replenishment and ordering from stores
Replenishing (radiographer/x-ray operator)	Nil	Changing processing chemicals

Also important in the findings of this study is that, role extension is now unavoidable, curricula and AHPC must respond by aligning themselves to this development. Because activities that happened in the examination rooms had the greatest negative impact on service transaction time for radiology patients, it can be concluded that directing future research into this focal point may have the greatest impact in service transaction time.

Table 4.7: Uncontrollable activities in radiology patient care pathway

Hand off	Description	Doing what?
1. Reception part i. (receptionist)	Functional activity	Information about examination costs
2. Accounts (accounts clerk)	Functional activity	Payment for radiology services
3. Reception part ii.(clerk)	Functional activity)	Registration for radiology examination
4. Waiting area	Process activity	Waiting for a radiology examination
5. Examination process (radiographer/x-ray operator)	Process activity	i. Reviewing justification of examinations
		ii. Room preparation
		iii. Equipment preparation
		iv. Radiology examination
		v. Infection control
6. Image processing (dark room technician, radiographer or x-ray operator)	Functional activity i. Actinic printer ii. Film processor iii. Viewing box iv. Computer monitor	i. Film I.D ii. Processing iii. Evaluation of image
7. Dismissal of patient (Radiographer/ x-ray operator)	Process activity	Assuring patient and communicating findings

Generally, the observed plain radiology patient care pathway for Zimbabwe had four functional activities and seven process activities. Out of an observed eleven activities, four were controllable while seven were uncontrollable.

4.7 Recommendations

In light of these research findings, it is recommended that Health Operations Management concept of care pathways described in literature as the analysis, design, planning and control of all steps necessary to provide a service to a patient (Vissers & Beech, 2005), be considered by the ministry. It is envisaged that in their quest for background literature, policy makers will inevitably be exposed to the output of this dissertation and be guided accordingly. Furthermore, the care plan for individual patients will require the managers to look at patient examination planning, protocols, patient group planning and control some of which is already being practiced in the National Health Services. However, because this would still leave a gap in capacity planning of professionals, equipment and space, it is recommended that forecast from this study regarding prediction and planning ahead for the number of patients to be treated and care activities be carried out as well as utilisation of long-term strategic planning by policy makers to improve service transaction times for radiology patients. Connecting all activities within the patient care pathway, this study has shown how the duration of a patients' stay in a radiology department can be shortened by starting activities sooner. Consistent with literature, (Brown *et al.,* 2013; Gahan, 2010; Hobson, 2007; Lodge & Bamford, 2008; Taylor & Shouls, 2008; Silvester & Walley, 2005; Lee & Silvester, 2004; Silvester *et al.,* 2004; Martin *et al.,* 2003; Goldratt & Cox, 2004), it is recommended that policy makers focus on the fact that in any process bottlenecks occur that must be passed before the process can be continued.

It is also recommended that the ministry of health focus its efforts on reducing the variation mismatches in the system by managing the capacity to meet the peaks and troughs in demand (Brown *et al.,* 2013; Gahan, 2010; Hobson, 2007; Lodge & Bamford, 2008; Taylor & Shouls, 2008; Silvester & Walley, 2005; Lee & Silvester, 2004; Silvester *et al.,* 2004; Martin *et al.,* 2003). Consistent with lessons drawn from the aforementioned literature, this can be achieved through evidence based redeployment of resources before even thinking of new acquisitions or raising staff establishments. Investment should focus on reinstating existing x-ray examination rooms and human resource management. Further research must focus on what is causing the peaks and troughs in the demand and capacity in order to redeploy radiology staff to match the variations. Evidence based selection of Continuous Professional Development (CPD) activities is strongly recommended in order to foster immediate academic and technical skills of radiology staff towards an understanding of time management and reflective practice. There is a need for the radiology staff to appreciate what they can do as radiology departments to solve the problems before even looking beyond to the ministry for external solutions.

Observed service transaction times as well as demand to capacity ratios demonstrated that the radiology sector could still take up an increased numbers of patients without the need for additional staff. However, it remains a researchable issue to project the timeline for this window period in which the status quo of staffing levels can remain valid. Exploration of variables that model radiology demand (those that have a correlation or causal relationship with patient numbers) be explored in order to establish foundations for a model to estimate the associated time line that the radiology sector would require to review staff establishments. The main outcome measure of this proposed study would be a statistically substantiated proposition regarding a relationship among those identified labour drivers as well as whether the aforementioned drivers are themselves time-variant or time-invariant (Malkowski *et al.,* 2007).

CHAPTER FIVE
PREDICTOR VARIABLES AND THEIR CHARACTERISTIC TRENDS

Abstract

This chapter addresses labour drivers for radiology. The focus was on the identification and characterisation of labour drivers consistent with the assumptions dictated by the Time and Frequency domain statistical analyses for forecasting plain radiology utilisation.The main outcome measure of this chapter was a statistical conclusion regarding the relationship among the observed labour drivers. This was an important consideration for this study because these variable interactions impacted on the complexity of the chosen statistical analysis approach. Because there was a wide range of prospective predictor variables for forecasting utilisation, the process was parsimonious in selecting relevant drivers by including only those that revealed strong associations with the criterion variable.

Observations from the findings presented in chapter 4 revealed that service transaction times for the examination area was the highest among the steps in the patient care pathway meaning that the examination room was the rate limiting stage in the patients' radiology patient care pathway. This essentially means that this bottleneck stage had the highest impact on the service transaction time and therefore a significant impact in the number of examined patients for all timing horizons. Consistent with this theory, observations showed that there was an association between the number of examinations and in particular the number of examinations per anatomical region with the number of patients examined thereby qualifying the number of examinations per anatomical region to be listed as labour drivers. There was enough statistical evidence to conclude that the number of Axial, appendicular and chest examinations had strong statistical interactions with the number of examined patients thereby qualifying these three regions to be listed as predictor variables for the number of plain radiology patients.

5.1 Introduction

The specific objectives of this component of the study were:

i. To determine those variables (predictor variables) that could be used to predict the number of patients examined across the research sites;

ii. To determine the variability of the aforementioned predictor variables (labour drivers) i.e. whether the key predictor variables were time-variant or not;

To fulfil the above specific objectives, it was important to preview concepts for the approach adopted for this part of the study. By definition, a correlation coefficient was a single summary statistical number that was used to tell whether a relationship existed between variables, how strong that relationship was and whether the relationship was positive or negative (Decoursey, 2003). Drawing from literature, interpretation of the strength of an association was simplified as shown in Table 5.1.

Table 5.1: Interpretation of the strength and direction of a correlation

Numerical value of the correlation factor									
Perfect	+1								-1
Strong		+0.9						-0.9	
		+0.8						-0.8	
		+0.7						-0.7	
Moderate			+0.6				-0.6		
			+0.5				-0.5		
			+0.4				-0.4		
Weak				+0.3		-0.3			
				+0.2		-0.2			
				+0.1		-0.1			
Zero					0.0				

The criterion drawn from literature (SPSS, 2010; Decoursey, 2003) was that the sign of a correlation indicated whether the tested variables were synchronous (where correlation was positive) or anti-synchronous (where correlation was negative). Multiple regression, being an extension of simple linear regression, was used to predict the value of a dependent variable based on the value of the independent variables (SPSS, 2010). Consistent with this literature, the variable that was being predicted was called the dependent variable, the outcome, the target or criterion variable whereas the variables used to predict the value of the dependent variable were called the independent, the predictor, the explanatory or the regressor variables. These names were used interchangeably throughout this dissertation. When applied to labour scheduling, the aforementioned dependent and independent variables are also called demand and labour drivers respectively (Sibanda *et al.,* 2014; Brown *et al.,* 2013; Schneider, 2011; Gahan, 2010; Hobson, 2007; Lodge & Bamford, 2008; Taylor & Shouls, 2008; Silvester & Walley, 2005; Lee & Silvester, 2004; Silvester *et al.,* 2004; Martin *et al.,* 2003).The determination of whether labour drivers (predictor variables) were time-variant was a basic requirement for the application of statistical tools in forecasting demand. In fact, drawing from operations research, aggregation-disaggregation forecasting approach specifically required that labour drivers were essentially consistent (SPSS, 2010; Agnolucci, 2009; Cheong, 2009; Costello *et al.,* 2008; Cortazar & Schwartz, 2005; UKNHS, 2006).

5.2 Data collection procedure

Equipped with knowledge from the patient care pathway presented in Chapter 4, brainstorming the characteristics of variables that affected the natural flow of patients with particular focus at the identified bottleneck stage (examination rooms) was conducted. This was because this step had been identified as having the greatest impact on the number of examined patients and evidence from literature indicated that a solution targeted at a bottleneck stage is a solution for the patient care pathway (UKNHS, 2006). A self designed check list was used to extract time series (monthly) data in the form of frequencies of patients as well as frequency of selected radiology examinations for each research site. For each research site, plain radiology monthly examinations were listed under chest, axial skeleton, appendicular skeleton and others (abdomen, foreign body e.t.c.). Further to these records, any dates that were not accounted for in the observed documents (patient registers and statistical registers) were recorded alongside any observed reasons for the event. This was in order to facilitate “missingness” analysis. In order to minimise problems of missing data, data from statistical records for the individual departments was used to complement data collected from patient registers.

5.3 Data analysis

Drawing from the approaches advanced by Schneider (2011), SPSS (2010) and Rosenberg (1997), the observed data earmarked for forecasting using this statistical approach were analysed to determine whether their individual effects varied (time variant) over the course of the planning horizon or remained constant (time invariant). The assertion by Schneider (2011) that every labour driver becomes time variant when given a sufficiently long time was considered important for this study. In this study a time horizon for the data set was fixed at 11 years which was one year more that proposed by Rosenberg (1997). The extra one year was included for the validation process (SPSS, 2010). The main outcome measure of this part of the research process was a distinction between time-variant and time-invariant labour drivers.

In the backdrop of the above information, the first task in data analysis was to establish data quality in respect of missing values (SPSS, 2010). “Missing Value Analysis” was used to explore patterns of missing values in the observed data and to determine whether multiple imputation was necessary (SPSS, 2010; Pigott, 2001). This was achieved by producing “Missing Value Pattern” from the spreadsheet so that analysis of variables and patterns revealed monotonicity where it existed (SPSS, 2010). Drawing from SPSS (2010) users guide, variables were ordered from left to right of the spreadsheet in increasing order of missing values. Patterns were then sorted first by the last variable (non-missing values first, then missing values), then by the second to last variable, working from right to left. In this way, the produced figure revealed whether the monotone imputation method could be used for the data and, where it could not be used, the figure revealed how closely the data approximated a monotone pattern (SPSS, 2010; Fay, 1996).

The criteria was that, for monotone data, all missing cells and nonmissing cells in the figure were contiguous meaning that, there would be no “islands” of nonmissing cells in the lower right portion of the figure and no “islands” of missing cells in the upper left portion of the figure (SPSS, 2010). This analysis was reinforced by a companion bar graph displaying the percentage of cases for each pattern. Having established monotonicity, this was followed by the command “Impute Missing Data Values” to multiply impute missing values. Imputation method was set on “automatic”, number of imputations 4 and the model for scale variables was “Linear Regression”. Analysis of “complete data” followed. This complete data was, also earmarked for multiple regression analysis.

The use of multiple regression to analyse the data required that the data analysis process included verifying to make sure that the data could actually be analysed using multiple regression (SPSS, 2010; Agnolucci, 2009; Cheong, 2009; Cortazar & Schwartz, 2005; Costello *et al.,* 2008; Mentzer & Moon, 2004; Brocklebank & Dickey, 2003; Chatfield, 2000; Makridakis & Wheelwright, 1989). This involved verifying that the data satisfied assumptions that were required for multiple regression to give a valid result (SPSS, 2010; Mentzer & Moon, 2004). This was done using SPSS Statistics. Observed violations were attended to using scientific methods drawing from literature (SPSS, 2010; Agnolucci, 2009; Cheong, 2009; Cortazar & Schwartz, 2005; Costello *et al.,* 2008; Mentzer & Moon, 2004; Brocklebank and Dickey, 2003; Chatfield, 2000; Makridakis & Wheelwright, 1989). These violations were expected because the data emanated from real-world (pragmatic) data rather than theoretical (book) examples that often only show how to carry out multiple regression when everything goes well. Drawing from this literature, protocols used in this dissertation to address violations of assumptions are itemised forthwith (SPSS, 2010):

- ✓ **Assumption number one:** This involved ensuring that the dependent variable was measured on a continuous scale.
- ✓ **Assumption number two:** This involved ensuring that the data comprised two or more predictor variables, which were either continuous (i.e., an interval or ratio variable) or categorical (i.e., an ordinal or nominal variable).
- ✓ **Assumption number three:** This involved checking that the data exhibited independence of observations. Adherence to this assumption was checked using Durbin-Watson statistic.
- ✓ **Assumption number four:** This involved checking that there was a linear relationship between (a) the dependent variable and each of the independent variables, and (b) the dependent variable and the independent variables collectively. The analysis involved creating scatter plots and partial regression plots using SPSS Statistics. Logarithmic and moving averages data "transformation" were applied to enhance compliance.
- ✓ **Assumption number five:** This involved checking that the data showed homoscedasticity. Essentially, an analysis of variances along the line of best fit was executed.
- ✓ **Assumption number six:** This involved ascertaining that the data did not show multicollinearity. Essentially, correlational analysis was used to check if the three predictor variables were highly correlated with each other in order to infer on the level of sophistication for the required statistical tool.

- ✓ **Assumption number seven:** This involved ensuring that there were no significant outliers, high leverage points, missing values or highly influential points.
- ✓ **Assumption number eight:** This involved checking that the residuals (errors) were approximately normally distributed.

Having satisfied the assumptions for the statistical tool, data analysis involved tracking labour drivers to determine whether their individual effects varied over the course of the planning horizon. This was achieved by use of scatter plots and graphs with trend lines superimposed on them (Schneider, 2011). The objective for this part of the study was to identify any well defined cyclical changes over time as well as random variations superimposed on them (SPSS, 2010; Agnolucci, 2009; Cheong, 2009; Cortazar & Schwartz, 2005; Costello *et al.,* 2008; Mentzer & Moon, 2004; Brocklebank & Dickey, 2003; Chatfield, 2000; Makridakis & Wheelwright, 1989). Drawing from this literature, the criterion was that any such variations were characteristic of time-variant labour drivers. This being the defining criterion for time-variant labour drivers, graphs for time-invariant labour drivers remained relatively constant with superimposed random variations over the planning time horizon (Schneider, 2011).

To derive statistical conclusions about variability of the many identified labour drivers, lagged correlation analyses were applied (Rosennberg, 1997). The criterion was that the magnitude of correlation indicated the strength of time-invariant labour driver. Furthermore, application of pared correlational analysis between predictor variables allowed for the identification of those labour drivers that had reasonably strong associations (Decoursey 2003). This was crucial because any such relationship required more elaborate statistical analysis. Therefore, correlation analysis was used as a fundamental statistical tool to identify relationships and the strengths of relationships among labour drivers. The criteria were that any labour drivers with magnitude of correlations between 0.00, 0.10-0.39, 0.4-0.69, 0.7-0.99 and 1.00 were considered as having zero, weak, moderate, strong and perfect correlation respectively (SPSS, 2010; Decoursey, 2003; Cohen & Manion, 1991; Cohen & Cohen, 1975). A single summary number statistically known as the "Coefficient of Determination" was used to establish how much variation in one variable was directly related to variation in another variable (SPSS, 2010; Mentzer & Moon, 2004).

5.4 Results

There was no observed systematicity in missing values and therefore, entries were missing in a way that created a random sample of responses (They wre Missing Completely At Random (MCAR)) which satisfy the assumption of an ignorable response mechanism.

Coincidencies in dates for missing values and equipment breakdowns as well as dates for staff collective job actions observed in limited number of recorded cases allowed for a logical conclussion that the data set had values missing in a way that created a random sample of responses. There were 2 missing values in the appendicular skeleton results and 3 each for axial skeleton and chest results. There were however no missing values on the number of patients column due to the patient statistics document found at the research sites. In the statistic output, the variable summary table was not displayed because no variable had more than the 10 % confidence interval for missing values (SPSS, 2010; Pigott, 2001). The overall summary of missing values is illustrated in Figure 5.1.

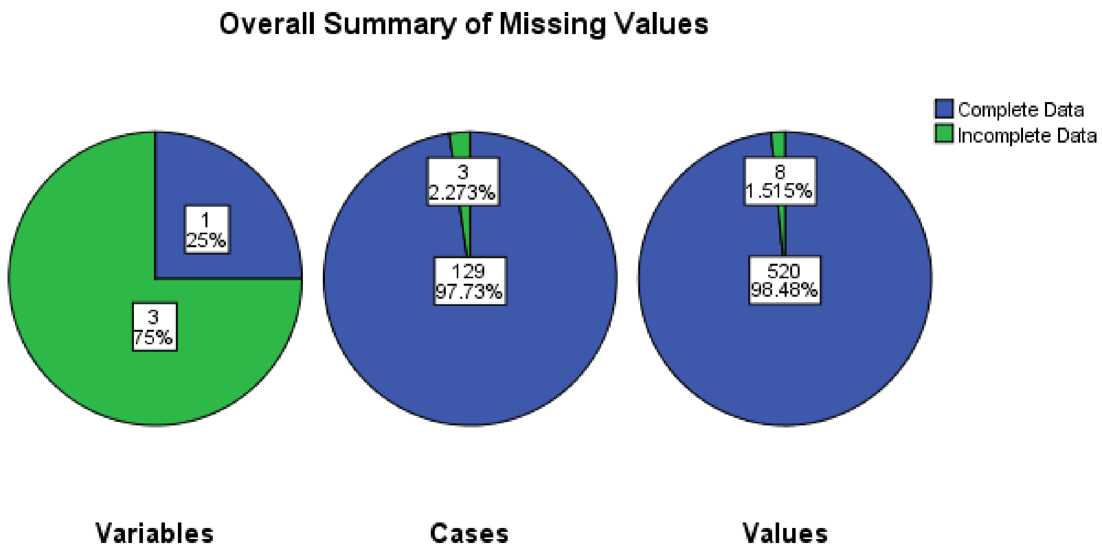

Figure 5.1: Overall summary of missing values analysis

There were four variables that were involved: appendicular skeleton, axial skeleton, chest and total number of patients. These formed the four quotas of the pie chart on variables. Out of these four variables, only the total number of patients had no missing values hence the 25% shown in the first pie chart. This can be understood by noting that, further to patient registers, departments also had documented statistical data regarding the total number of patients. These complemented the counts made from patient registers. However, in the statistical documents there were no breakdowns regarding how many were chest, axial or appendicular and these could only be obtained from patient registers. The second pie chart refers to cases (rows in spread sheet). There were only three cases that were incomplete out of 132 cases and hence the 2.27% shown. The third pie chart refers to values in the analysed columns. There were 8 missing values in total across all four columns of 132 values each with a total 528 values. This gave rise to the 1.52% missing values shown in the third pie chart.

The patterns chart (Figure 5.2) displays missing value patterns for the analysis variables. Each pattern corresponds to a group of cases that had the same pattern of incomplete and complete data. In this regard, pattern 1 represented cases that had no missing values. Pattern 2 represented cases that had missing values on “ChestTendency” (Number of chest examinations) and “AxialTendency” (Number of axial examinations), and Pattern 3 represented cases that had missing values on “ChestTendency” (Number of chest examinations), “AxialTendency” (Number of axial examinations) and “AppendicTendency” (Number of appendicular examinations).

The objective of producing Figure 5.2 was so that it orders analysis variables and patterns to reveal monotonicity where it existed. In the figure, all missing cells and nonmissing cells were contiguous. There were no “islands” of non-missing cells in the lower right portion of the chart and no “islands” of missing cells in the upper left portion of the chart. This revealed that the dataset was monotone (SPSS, 2010). Drawing from literature, missing values encountered in this study were so few that imputation could be avoided without significant statistical implications on the outcome of the study (SPSS, 2010; Pigott, 2001). Figure 5.2 and Figure 5.3 are illustrations of missing value patterns and a companion bar chart displays the percentage of observed missing cases for each pattern. From Figure 5.3, over half of the cases in the dataset had Pattern 1. The missing value patterns figure showed that this is the pattern for cases with no missing values. Pattern 2 represented cases with a missing value on AppendicTendency, ChestTendency and AxialTendency, while pattern 3 represents cases with a missing value on ChestTendency and AxialTendency. All cases were represented by these three patterns. Rounding up on the missing values, the analysis of missing patterns did not reveal any particular obstacles to multiple imputation (SPSS, 2010; Pigott, 2001). This implies that the use of the monotone method was feasible on this data set.

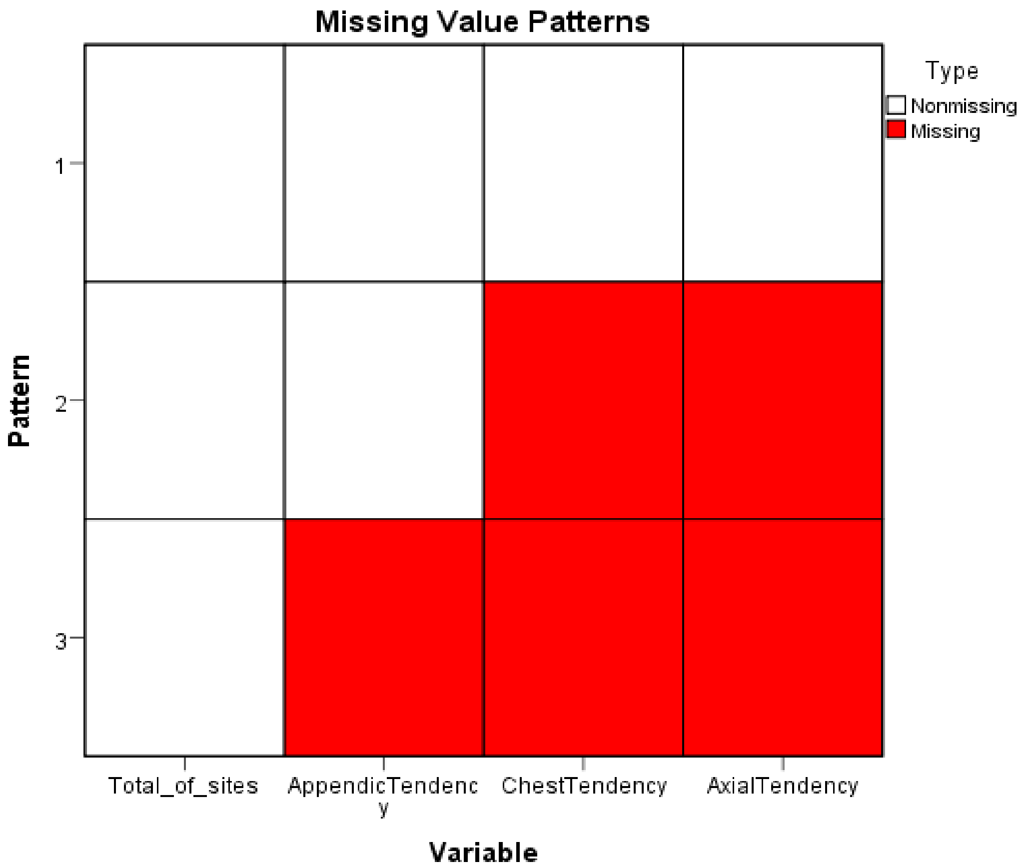

Figure 5.2: Missing value patterns for the analysis variable

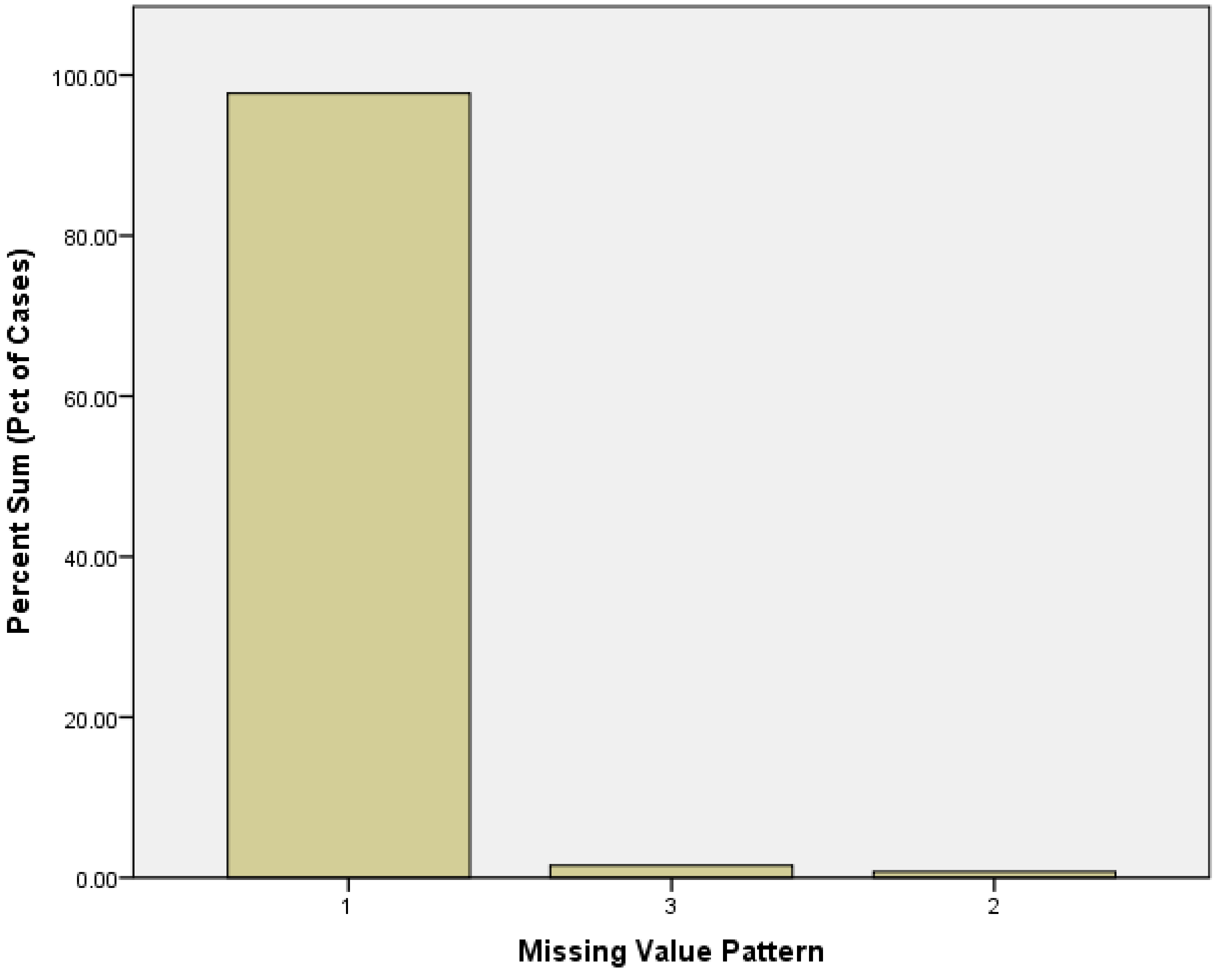

Figure 5.3: Percentage of observed missing cases for each pattern

The numbers of missing cases were within the 10% tolerance level above which the statistic displays variable summaries (SPSS, 2010; Pigott, 2001). Therefore, no variable summary was automatically displayed in this statistical output. Imputation specifications are displayed in Table 5.2.

Table 5.2: Imputation Specifications

Imputation Method	Automatic
Number of Imputations	4
Model for Scale Variables	Linear Regression
Interactions Included in Models	(none)
Maximum Percentage of Missing Values	100.0%
Maximum Number of Parameters in Imputation Model	100

The imputation results associated with imputation specification presented in Table 5.2 are presented in Table 5.3. Consistent with Figure 5.1-4, the observed number of axial examinations and the observed number of chest examinations had the most missing values (contributing 3 each to the list), while the observed number of appendicular examinations contributed the least (2 missing values). There were a total of 8 missing values out of 528 observations. This represented 1.5% observations. Importantly, the observed total number of patient's column had no missing values thanks to complementary patient statistics recorded separately by individual departments.

Table 5.3: Imputation Results

Imputation Method		Monotone
Fully Conditional Specification Method Iterations		n/a
Dependent Variables	Imputed	ChestTendency, AppendicTendency, AxialTendency
	Not Imputed(Too Many Missing Values)	n/a
	Not Imputed(No Missing Values)	Total_of_sites
Imputation Sequence		Total_of_sites, AppendicTendency, ChestTendency, AxialTendency

In Table 5.4, the imputation model for the predictor variables is displayed together with imputation model type, model effects, number of missing values and number of imputed values for each variable in the table.

Table 5.4: Imputation Models for the predictor variables

	Model		Missing Values	Imputed Values
	Type	Effects		
Working_ Number_ of_ App_Exams	Linear Regression	Total_of_sites	2	8
Working_ Number_ of_Chest_Exams	Linear Regression	Total_of_sites,AppendicTendency	3	12
Working_ Number_ of_Axial_Exams	Linear Regression	Total_of_sites,AppendicTendency,Chest Tendency	3	12

Multiple imputation descriptive statistics associated with the aforementioned imputation model is presented in appendix C such that the order of presentation is number of chest, appendicular and axial examinations. The three predictor (independent) variables involved in this study as well as the criterion (dependent) variable were on scale (continuous) measurement. The series for the three predictor variables exhibited a number of peaks that were not equally spaced. This was evidence that over and above the series having periodic components, they also had fluctuations that were not periodic. Consistent with literature, these were typical for real-time series data. Ignoring observed small-scale fluctuations, observed significant peaks were evidently separated by about three years. This was evidence of long term seasonality. Furthermore, the short term seasonal nature of radiology demand had typical highs during the holiday seasons (December holiday toping in the demand). This was evidence that the time series exhibited some form of an annual periodicity. There was no evidence of an upward growth alongside the upward series trend that was noticed on the seasonal variations. This was enough statistical evidence to rule out any suggestion that the seasonal variations were proportional to the level of the series. This implied that an additive model rather than a multiplicative model was at play. Detailed model description (Appendix 5.1) is annexed to this report while model output (Figure 5.5) illustrates the aforementioned assertions.

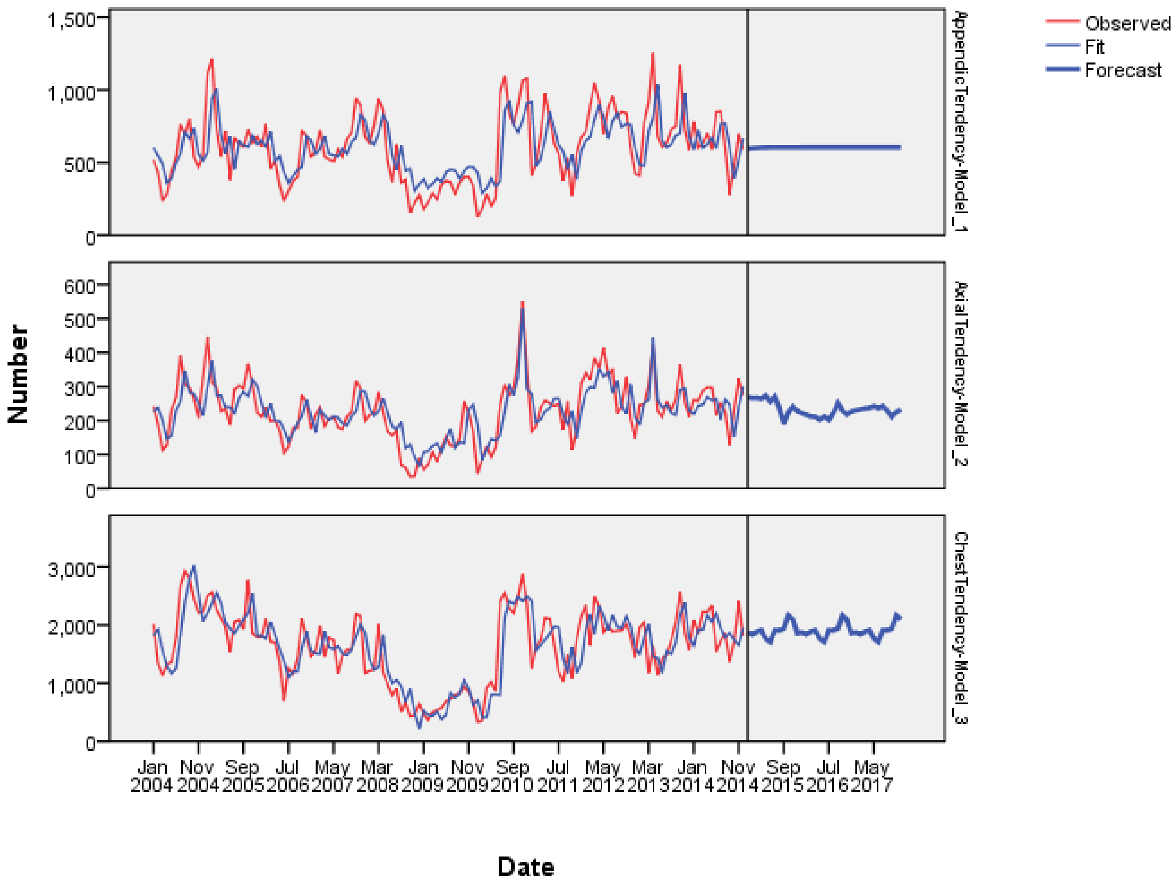

Figure 5.4: Predictor variables- observed, model fit and three year forecasts

Examining the autocorrelations and partial autocorrelations of the time series provided a more quantitative conclusion about the underlying periodicity. The plots shown in Figure 5.4 are those of the pragmatic ARIMA processes for this study. The plots for ACF (Figure 5.5) illustrate that, among the three predictor series, none of them had ACF that remained significant for more than six lags. All three rather quickly declined to zero thereby giving enough statistical evidence to conclude that the data represented stationary series. This was an important data characteristic for this study. Further analysis revealed that the three series had exponentially declining ACF and had spikes in the first one lag of the PACF thereby suggesting that autoregressive processes for this data were appropriate to describe the data and make predictions. This was because the observed spikes were consistent with the order of the autoregression model. In all the three predictor series, the observed exponentially declining ACF alternated between positive and negative values. This was consistent with literature for ACF and PACF plots from pragmatic data (SPSS, 2010; Mentzer & Moon, 2004)

In respect of chest examinations' plot, values of the PACF remained within the confidence interval while those for axial and appendicular skeletons exhibited some significant spikes in the tail region. Consistent with literature, for the purposes of making judgement about seasonality, those insignificant values were ignored (SPSS, 2010). Furthermore, there were no autocorrelation values that were suspected to be statistically significant by chance alone. Similarly, there were no statistically significant autocorrelations that were considered isolated at high lags, and that were also not occurring at seasonal lags.

The autocorrelation functions (Figure 5.5) showed significant peaks at a lag of 1 with long exponential tails which were typical patterns for time series data (SPSS, 2010). The significant peak at a lag of about 12 for axial examinations (Also barely touching the significant line for appendicular examinations) was suggestive of an annual seasonal component in the data. Importantly, this statistical event at a lag of about 12 was not visible enough for chest examinations. Further analysis of the partial autocorrelation function was therefore necessary to allow a more definitive conclusion. The significant peak at a lag of 12 in the partial autocorrelation function confirmed the presence of an annual seasonal component in the data. Results for the analysis in the frequency domain from Durbin-Watson test revealed that there was an independence of residuals ($p>0.05$ in all cases). There was therefore enough statistical evidence to conclude that there was independence of observations across the predictor variables.

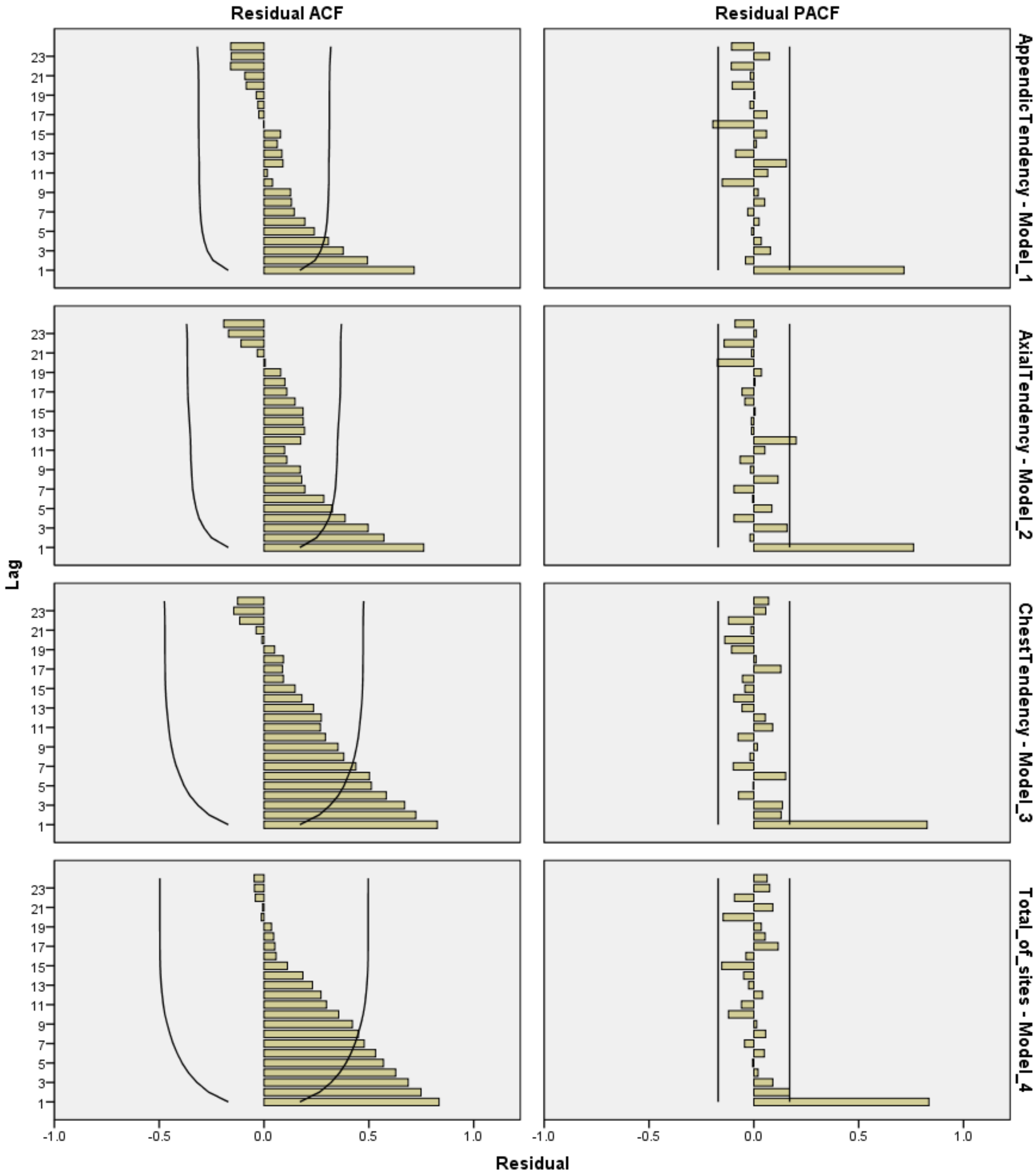

Figure 5.5: ACF and PACF plots for the observed time series data

To explore further the relationship between predictor variables, visual inspection was conducted on scatterplots (Figure 5.6, 5.7 & 5.8). This involved inspection of plots for each pair of scores obtained from the subjects in the sample. The trend was established by plotting scores on the first variable along the X (horizontal) axis and the corresponding scores on the second variable on the Y (vertical) axis. An inspection of these graphs provided information on both the direction of the relationship (positive or negative) and the strength of the relationship. The distribution of points for the predictor variables showed that for all three predictor variable plots, there was a general steady increase in the number of examinations from left to right. Furthermore, the shapes (width) of the clusters were generally even from one end to the other – a requirement for homoscedasticity. This means that generally, all points fell in a hypothetical pipe defined by blue parallel lines (shown in Figures 5.6, 7 & 8) across the time series horizon.

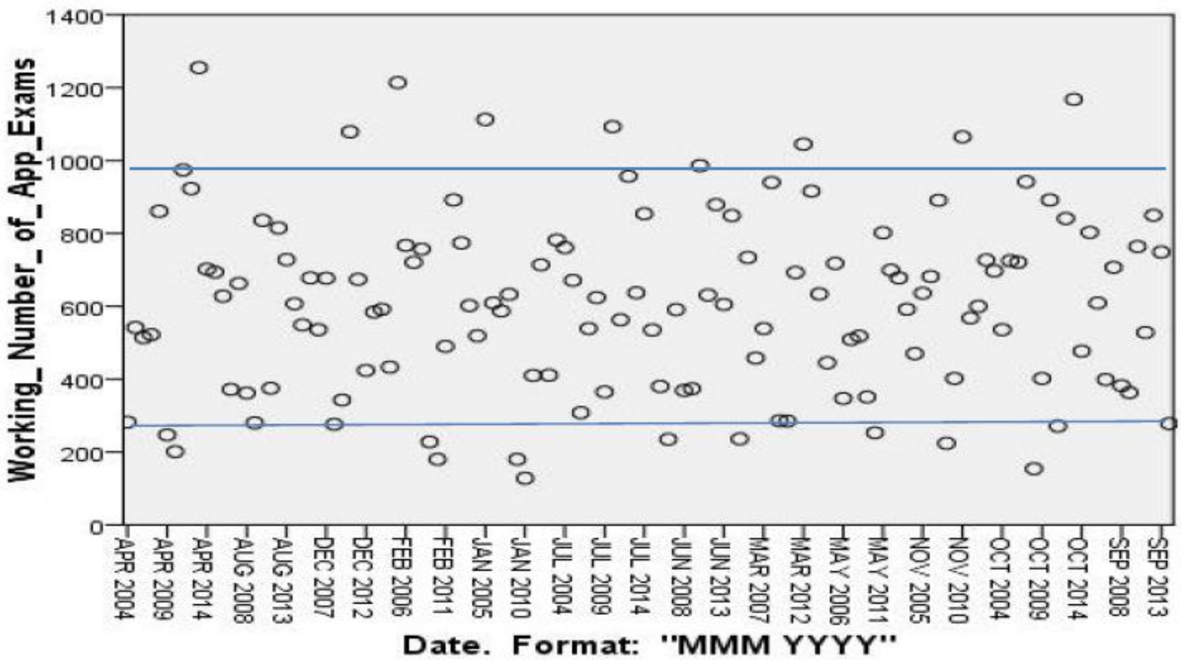

Figure 5.6: Scatter plot for appendicular skeleton predictor variable

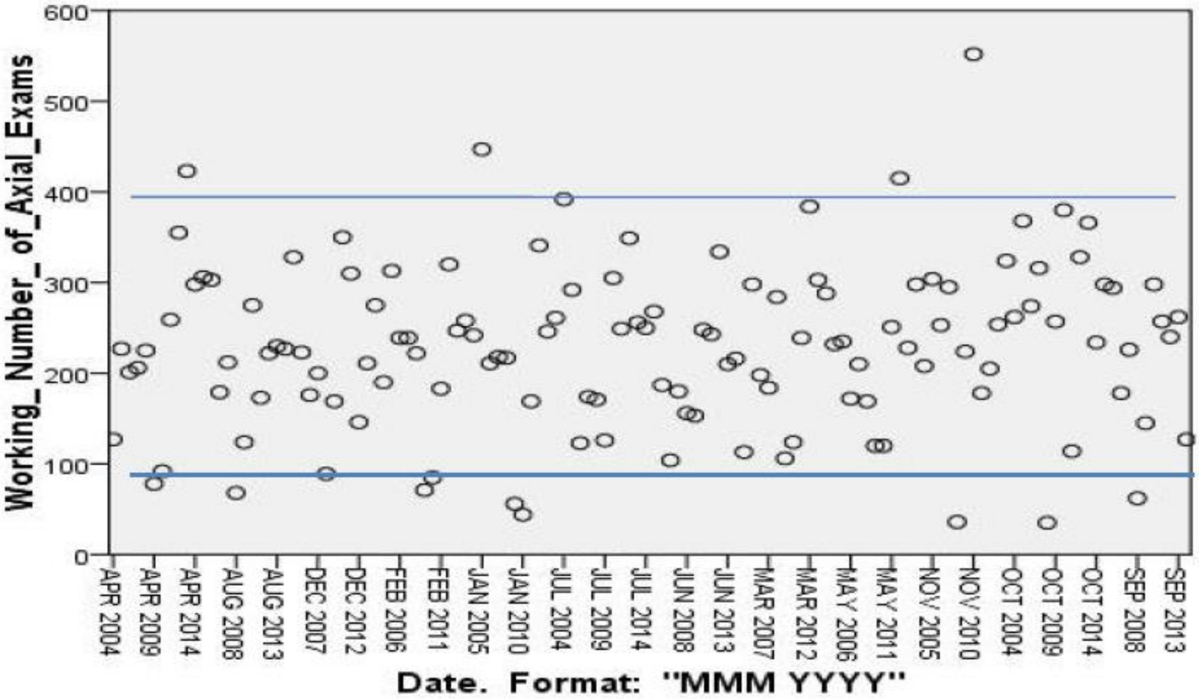

Figure 5.7: Scatter plot for axial skeleton predictor variable

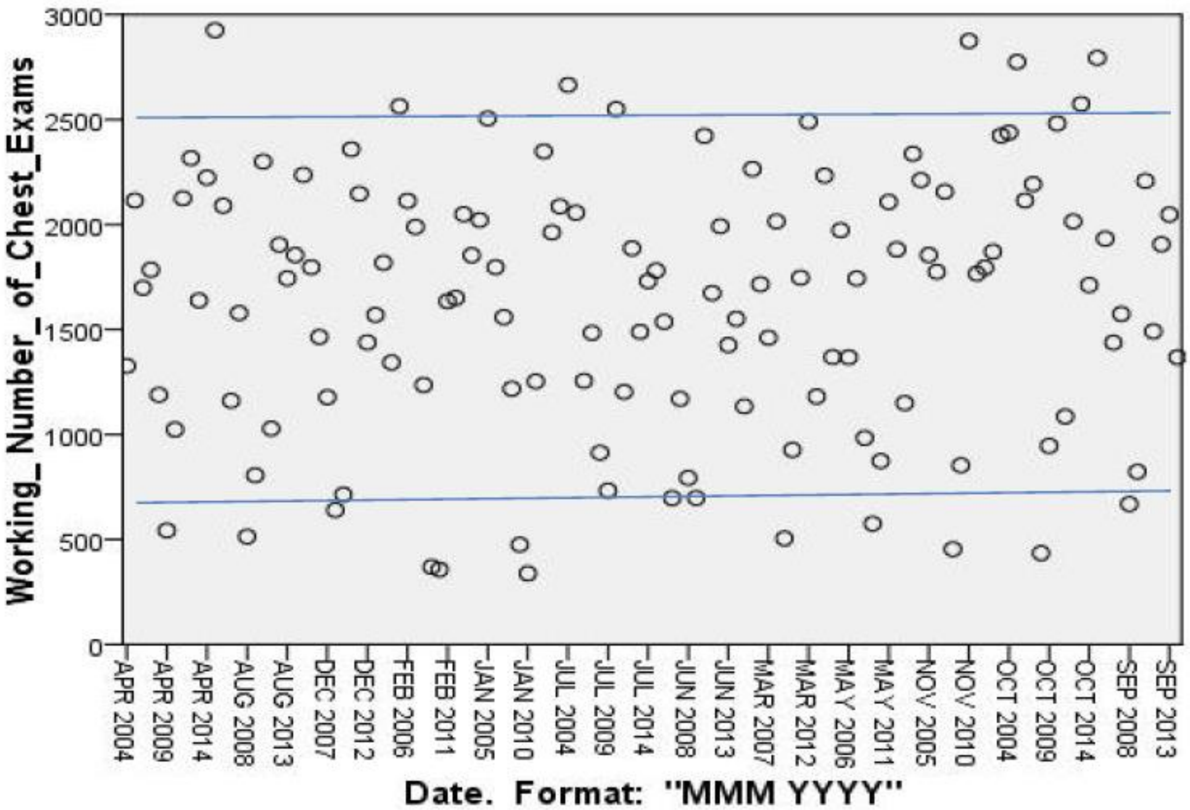

Figure 5.8: Scatter plot for chest radiography predictor variable

These observations were further supported by a model fit and predictive model (Figure 5.9) for the predictor variables.

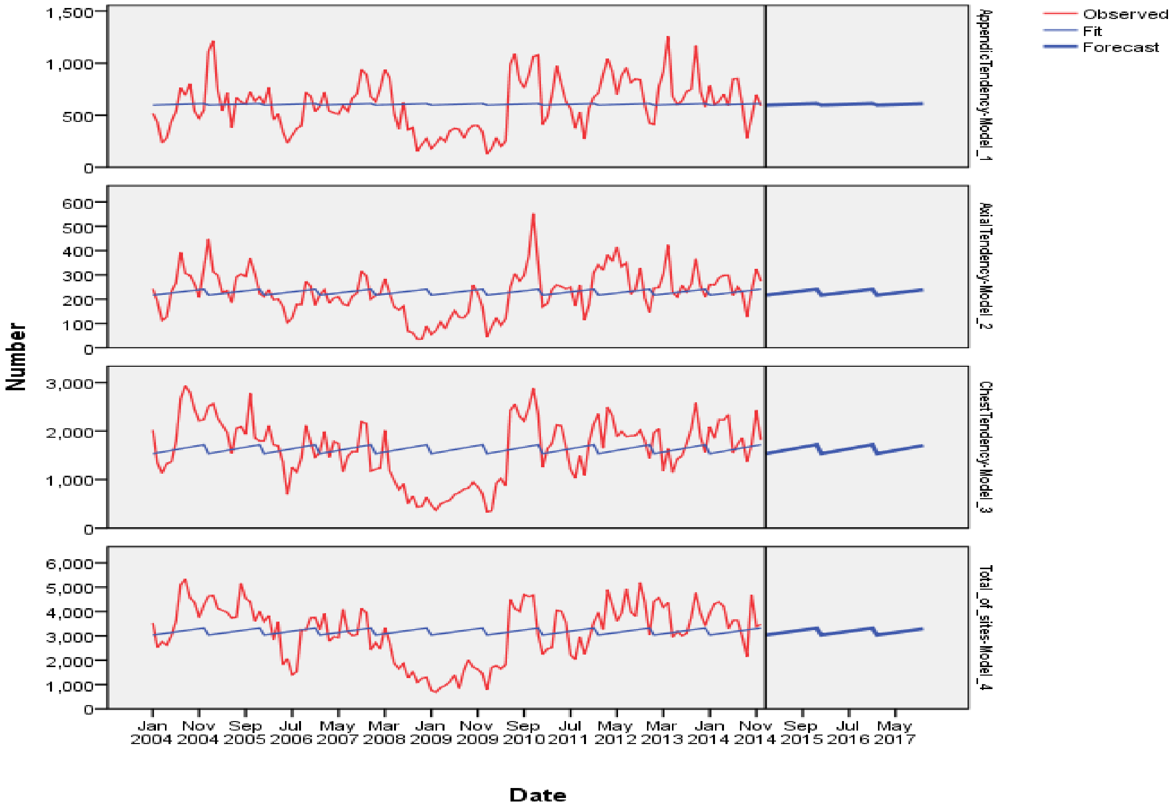

Figure 5.9: Model fit and predictions for predictor variables

In order to decide between parametric correlations and non parametric correlations, descriptive analysis of the three predictor series was conducted. Descriptive analysis of the frequency distribution patterns for the three predictor variables are shown in Table 5.5. There were 132 valid entries for each predictor series. From Table 5.5, the central tendencies with respect to the number of examinations for appendicular, axial and chest anatomical regions were 610+/-20, 230+/-8 and 1630+/-50 respectively. The median for appendicular (606) and that for axial (229) examinations were equal to their respective mean values while that for chest examinations was outside the error margins of the mean. Chest and appendicular examinations exhibited multi-modal distributions. However, in all three cases skewness and kurtosis values were insignificant adding to the fact that corelational approaches are fairly ‘robust’ so much so that they would tolerate minor violations of normality of data.

Table 5.5: Frequency distribution statistics for predictor variables

		Working_ Number_ of_ App_Exams	Working_ Number_ of_Axial_Exams	Working_ Number_ of_Chest_Exams
Number	Valid	132	132	132
	Missing	0	0	0
Mean		606	229	1627
Std. Error of Mean		21	8	54
Median		606	229	1724
Mode		892[a]	298	2115[a]
Skewness		.266	.236	-.232
Std. Error of Skewness		.211	.211	.211
Kurtosis		-.344	.599	-.683
Std. Error of Kurtosis		.419	.419	.419

[a] Multiple modes existed and the smallest value is shown

The relationship between the observed number of appendicular examinations and the number of axial examinations was investigated using Pearson product-moment correlation coefficient. Preliminary analyses were performed to rule out any significant violations of the assumptions of normality, linearity and homoscedasticity. Correlational results are displayed in Table 5.6, from which, to establish how much variance each pair of predictor variables shared, the coefficient of determination was calculated by squaring the r values. To convert these "r^2"values to 'percentage of variance', these were multiplied by 100 and this shifted the decimal place two columns to the right.

Table 5.6: Paired correlations for predictor variables and criterion variable

		Working_ Number_ of_ App_Exams	Working_ Number_ of_Axial_Exams	Working_ Number_ of_Chest_Exams	Working number of patients 1_5
Working_ Number_ of_ App_Exams	Pearson Correlation	1	.836**	.754**	.751**
	Sig. (2-tailed)		.000	.000	.000
	N	132	132	132	132
Working_ Number_ of_Axial_Exams	Pearson Correlation	.836**	1	.839**	.802**
	Sig. (2-tailed)	.000		.000	.000
	N	132	132	132	132
Working_ Number_ of_Chest_Exams	Pearson Correlation	.754**	.839**	1	.887**
	Sig. (2-tailed)	.000	.000		.000
	N	132	132	132	132
Working number of patients 1_5	Pearson Correlation	.751**	.802**	.887**	1
	Sig. (2-tailed)	.000	.000	.000	
	N	132	132	132	132

**. Correlation was significant at the 0.01 level (2-tailed).

There was a strong, positive correlation between the two variables [r=.836, n=132, p<.0005], with high numbers of appendicular examinations associated with high numbers of axial examinations. The associated coefficient of determination between these two variables was 0.699 which gave 69.9 per cent shared variance. This meant that the number of appendicular examinations helped to explain 69.9 per cent of the variance in the number of axial examinations. This is quite a respectable amount of variance explained. The relationship between the observed number of appendicular examinations and the number of chest examinations revealed a strong, positive correlation between the two predictor variables [r=.754, n=132, p<.0005], with high numbers of appendicular examinations associated with high numbers of chest examinations. The associated coefficient of determination between the two predictor variables was 0.569 which gave 56.9 per cent shared variance. This meant that the observed number of appendicular examinations helped to explain 56.9 per cent of the variance in the number of observed chest examinations. This was quite a respectable amount of variance explained. Similarly, the relationship between the observed number of axial examinations and the observed number of chest examinations revealed a strong, positive correlation between the two variables [$r=.839$, $n=132$, $p<.0005$], with high numbers of axial examinations associated with high numbers of chest examinations. The associated coefficient of determination between these two variables was 0.704 which gave 70.4 per cent shared variance. This means that the number of axial examinations helps to explain 70.4 per cent of the variance in the number of chest examinations. This is also quite a respectable amount of variance explained. The relationship between these predictor variables and the criterion variable (total number of patients who visited the research sites) was also investigated using Pearson product-moment correlation coefficient. There was a strong positive correlation between the number of appendicular examinations (predictor variable) and the observed total number of patients (criterion variable) visiting the research sites [$r=.751$, $n=132$, $p<.0005$], with high numbers of appendicular examinations associated with high numbers of patients visiting the research sites. The associated coefficient of determination between this predictor variable and the criterion variable was 0.564 which gave 56.4 per cent shared variance. This meant that the observed number of appendicular examinations helped to explain 56.4 per cent of the variance in the total number of patients visiting the research sites.

There was a strong positive correlation between the observed number of axial examinations (predictor variable) and the observed total number of patients (criterion variable) visiting the research sites [$r=.802$, $n=132$, $p<.0005$], with high numbers of axial examinations associated with high numbers of patients visiting the research sites. The associated coefficient of determination between this predictor variable and the criterion variable was 0.643 which gave 64.3 per cent shared variance. This meant that the observed number of axial examinations helped to explain 64.3 per cent of the variance in the total number of patients visiting the research sites. Similarly, there was a strong positive correlation between the number of chest examinations (predictor variable) and the observed total number of patients (criterion variable) visiting the research sites [$r=.887$, $n=132$, $p<.0005$], with high numbers of chest examinations associated with high numbers of patients visiting the research sites. The associated coefficient of determination between this predictor variable and the criterion variable was 0.787 which gave 78.7 per cent shared variance. This means that the observed number of chest examinations helped to explain 78.7 per cent of the variance in the total number of patients visiting the research sites. This was quite a respectable amount of variance explained.

In order to understand the variance in the predictor variables as they varied with time, correlational analysis was conducted with respect to month number in time series data. There were 132 months considered between January 2004 and December 2015 i.e. there were no missing values in the time series after the imputation exercise. These results are shown in Table 5.7.

Table 5.7: Variance in the predictor variables with month number in series data

Descriptor	Statistic	Month number in time series
Working_ Number_ of_ App_Exams	Pearson Correlation	.203**
	Sig. (2-tailed)	.000
	N	132
Working_ Number_ of_Axial_Exams	Pearson Correlation	.126
	Sig. (2-tailed)	.001
	N	132
Working_ Number_ of_Chest_Exams	Pearson Correlation	.001**
	Sig. (2-tailed)	.989
	N	132
Working number of patients 1_5	Pearson Correlation	.050**
	Sig. (2-tailed)	.200
	N	132

The relationship between the predictor variables (observed number of axial, appendicular and chest examinations) and month number in time series data was investigated using Pearson product-moment correlation coefficient. Preliminary analyses were performed to rule out any significant violations of the assumptions of normality, linearity and homoscedasticity. For all the three predictor variables as well as the criterion variable, there was a weak, positive correlation between the variables and the month number in time series data [r=.203, n=132, p<.0005 (appendicular); r=.126, n=132, p<.0005 (Axial); r=.0.001, n=132, p<.0005 (Chest); & r=0.05, n=132, p<.0005 (total number of examinations)], with high numbers of predictor variables associated with high month numbers in the time series data. The associated coefficients of determination between these respective cases were 0.041, 0.016, 0.000 and 0.0025 respectively. This gave 4.1, 1.6, 0.0 and 0.3 per cent shared variance. This means that month number in time series data helped to explain 4.1, 1.6, 0.0 and 0.3 per cent of the variance in the number of appendicular examinations, axial examinations, chest examinations and total number of patients examined respectively.

5.5 Discussions

The use of the document review method exposed this study to the problem of missing quantitative data. The problem of missing quantitative data especially when dealing with secondary data is not a new problem as many researchers have reported on this from as far back as the 1970s (Bowling, 2009; Haralambos & Holborn, 2000; Pigott, 2001; Schafer, 1997; Fay, 1996; Heitjan & Basu, 1996; Rubin, 1996; Little, 1988; Rubin, 1987; Little & Rubin, 1987; Cohen & Manion, 1991; Cohen & Cohen, 1975). Pigott (2001) explains that prominent among the researchers in this area is Rubin and Little. When it comes to missing value analysis, common problems that were cited relate to research informants refusing or forgetting to answer a survey question, files being lost, or data not being recorded properly (Haralambos & Holborn, 2000; Bowling, 2009; Pigott, 2001).

Consistent with reviewed literature, missingness of quantitative data encountered in this study was due to data that was not recorded in archived documents. Some recorded data that could help explain causal factors to these problems were incidents of discontinuities in dates recorded in patient registers which were presumably due to equipment breakdowns. Pigott (2001), reports that such a problem imposes expenses of collecting and recollecting data. In this regard, he says, many researchers use ad hoc methods such as complete case analysis, available case analysis (pair wise deletion), or single-value imputation. This researcher goes on to explain that while these methods are easily implemented, they require assumptions about the data that rarely hold in practice. However, when it comes to modern day analysis, it is fortunate that the development of computerised statistical methods has reached an advanced stage with model-based methods, such as maximum likelihood using the EM algorithm and multiple imputation, having been used by other researchers with great success in dealing with difficulties caused by missing data (SPSS, 2010; Pigott, 2001). With this background information in mind and in the interest of validity, this evidence based missing value analysis method was considered the best for this study. It was therefore befitting to apply multiple imputation model-based (computer based) method in dealing with missingness of data in this study. Literature explains that this computerised method is relatively more robust and is appropriate for a wider range of situations when compared to the more commonly used ad hoc methods (SPSS, 2010; Pigott, 2001).

Drawing a clear distinction between these ad hoc methods and model based methods was crucial in order to appreciate the approach chosen in this study. Ad hoc methods have been described by Pigott (2001) as easy to apply as well as that they are commonly applied in published work. Consequently, often too many a times when researchers are reviewing literature they would invariably come across work in which these most common and easy to apply methods are applied. As a result, researchers would sometimes choose to use "complete case analysis" in which only those cases with complete information are analysed (Pigott, 2001). On the same notion, sometimes researchers would decide to fill in a plausible value for the missing observations, such as the use of central tendency values (mean, median or mode) of the observed cases on that variable. On the contrary, computerised model based methods (multiple imputation (used in this study) as well as maximum likelihood method) were based on distributional models for the data. The motivation to use multiple imputation method was that the application of this method in missing value statistics has stood the test of time having been tried and tested since the nineteen eighties (SPSS, 2010; Pigott, 2001; Schafer, 1997; Little, 1988; Little & Rubin, 1987).

Consistent with previous research, the application of missing value statistics was a taxing and challenging procedure in the study of "diagnostic radiology capacity and demand: rends and forecasts" (Pigott, 2001; Schafer, 1997; Fay, 1996; Heitjan & Basu, 1996; Rubin, 1996; Little, 1988; Rubin, 1987; Little & Rubin, 1987). To other researchers, the advice is that, because of the difficulties associated with such computations, whenever possible, avoiding missing data is the optimal means for handling incomplete observations (SPSS, 2010). However, while great care was undertaken in the research procedures, selection of source documents and in recruiting participants, missing values were unavoidable and missing information occurred for reasons that were not anticipated. This problem was aggravated by the geographical distribution of data collection sites across the country which made collection and recollection of data an undesirable option. The decision of how to analyze data when there were missing data entries was the only viable option at this stage.

It was befitting, to use the data collection phase to make decisions about what data to collect and how to monitor data collection. The emphasis applied to the procedures associated with the data collection phase were particularly important because the scale and the distribution of the variables as well as the reasons for missing data formed two critical issues that were required in order to choose an appropriate missing data analysis technique. In this regard, the observed and recorded possible explanations for missing data were used as evidence to guide the decision about what missing data method was appropriate for the analysis at hand. The idea was to embrace the philosophy introduced by Little and Rubin (1987), echored by Schafer (1997) and Pigott (2001) which spells out methods that can be used for "non-ignorable" missing data. These researchers explain that where there is missing data, ruling out a non-ignorable response mechanism can simplify the analysis considerably.

In this regard, the aforementioned researchers introduced an analysis that categorises missingness. Drawing from literature, the first set of missing data was according to those entries that were missing in a way that creates a random sample of responses and code named Missing Completely At Random (MCAR). Rubin (1996), Heitjan and Basu (1996) as well as Pigott (2001) further talk about data that are missing for reasons related to completely observed variables in the data set. They call this latter category data Missing At Random (MAR). An important lesson drawn from this literature regarding MCAR and MAR is that these kinds of response mechanisms are termed ignorable and that both maximum likelihood and multiple imputation methods required the assumption of an ignorable response mechanism.

It is emphasised in the same literature that for ignorable response mechanisms the researchers can ignore the reasons for missing data when executing analysis of the data thereby simplifying the model-based methods. Consistent with this literature, it was difficult in this study to obtain empirical evidence about whether or not the observed data were MCAR or MAR. However, a careful analysis of recorded reasons for missing data allowed for a logical conclussion that the data set had values missing in a way that created a random sample of responses. Again, in order to increase the probability of an ignorable response mechanism and consistent with this literature, interviews were used simultaneously with direct observation and survey methods. This was enough justification for the multiple imputation missing data method used.

With imputation having been successfully implemented, the next step in the analysis of the data was to establish any relationship among the measured variables. A correlation analysis was used to achieve this goal. In this part the it was established whether the pairs of measured variables co varied, and in so doing, quantified the strength of the relationship. This analysis protocol was a standard procedure in statistical analysis to answer relational questions among variables (Decoursey, 2003).

A correlation coefficient was defined as a summary number that told whether a relationship existed between two variables, how strong that relationship was and whether the relationship was positive or negative (Decoursey, 2003). Associated with this summary number was the coefficient of determination which was defined as a summary number that told how much variation in one variable was directly related to variation in another variable (SPSS, 2010). With these aforementioned summary numbers, linear regression was used to make predictions about a criterion variable based on relational knowledge about predictor variables. The accuracy of these predictions were measured using a summary number called the Standard Error of Estimate (SPSS, 2010). It was therefore justified to use correlation analysis to establish the relations among the observed variables. However, important in this analysis is that, no causal effect was implied, since the situation in which inferences were made was limited to identifying associations and statistically- correlation does not imply causation (SPSS, 2010).

As outlined in missing data analysis, preliminary analyses were performed to rule out any significant violations of the assumptions of normality, linearity and homoscedasticity (SPSS. 2010). These preliminary analyses were important in ensuring validity of the statistical analyses. Significant correlations were considered to be those with magnitude above 0.4. In this study, all computed correlation coefficients fell in the acceptable range from -1 to +1. Statistical tests were further used to determine whether observed correlation were statistically significant or not. The magnitude of the sample correlation coefficients quantified thestrength of the linear associationbetween variables while the sign of the correlation established the direction of the relationship (Decoursey, 2003).

The observed strength of the association between pairs of variables was rated strong and positive except in the case of their association with month number in time series data where the association was rated weak and positive. In the former case, these values were consistent with pragmatic situations that have strong associations. The latter case statistically implied that there was an insignificant (weak) growth in so far as number of examined patients and number of examinations was concerned during the time series data horizon. This was consistent with economic and political crisis exhibited by the host country during the planning horizon. This means that as far as plain radiology utilisation was concerned there was an insignificant growth in the radiology sector during the planning horizon. There was enough statistical evidence to conclude that any constraints leading to observed queues were not due to an increase in utilisation patterns. Confounding or intermediate variables may be at play.

However, the existence of a weak linear correlation in the latter case did not mean that there was no non-linear association between the two continuous variables. It was then possible to make this inference because fundamentally, the computation of linear correlation coefficients does not detect non linear associations. Therefore, consistent with literature inclusion of scatter plots was an important step that was undertaken because it offered visual evaluation of the associations thereby complementing correlation analysis. These scatter plots showed positive (direct) association between all pairs of variables. This means that in the observed population, lower numbers of chest, appendicular and lumbar spine examinations were more likely to be associated with lower numbers of patients and also that higher numbers of patients were more likely to be experienced with increase in the number of months across the time series data horizon.

Further analytical tests on labour drivers were used to determine whether their individual effects varied over the course of the planning horizon or remained constant. The Attention was drawn (from literature) to the fact that over sufficiently long time, every labour driver becomes time variant but how long a time depended on time horizon for individual drivers (Schneider, 2011). With this information in mind, labour drivers were graphically tracked over time by use of trend lines in order to distinguish between time-variant and time-invariant labour drivers. Essentially, this was to identify well defined cyclical changes over time as well as any random variations superimposed on them. This was a unique feature that defined graphs for time-variant labour drivers. On the contrary, time-invariant labour drivers would remain relatively constant with superimposed random variations over the time horizon. The time taken to perform chest radiography per patient exhibited a relatively constant relationship over a period of months suggesting a time-invariant labour driver. However, an important time-variant labour driver for chest radiography was essentially the number of patients examined across the time series data horizon. Application of a lagged correlation analysis was also befitting because it enabled drawing up statistical conclusions about variability of the many identified labour drivers.

5.6 Conclusions

Many variables were identified as potential predictor variables for the number of patients received by radiology departments. Justification of exposures alone had a potential to reduce inappropriate radiology demand by as much as 78 percent but this variable was time invariant within the planning horison and therefore was not suitable to be used as the predictor variable for this study. Cases of overutilisation of radiology services, repeating examinations whose results are already known or have untenable results add to the problem of inappropriate radiology exposures but this could not be used for similar reasons as the previous. While some researchers have shown that the dynamic nature of radiology technology, dynamics of technological diffusion as well as the dynamic nature of the radiography curricula all have the potential to decrease radiology service transaction time and therefore increase the number of radiology patients that could be examined in any given time period, these variables required a much longer planning horison to be able to draw conclusions on them. These were not further explored. However, there was enough statistical evidence to conclude that the number of examinations performed per anatomical region were time variant within the planning horison and therefore, could be used to predict the number of patients seen.

5.7 Recommendations

The number of people that are exposed to ionising radiation is a safety issue raised by IAEA and ICRP. However, accurate prediction of the number of exposed people during radiological examinations has remained untenable and hence the extrapolations from the number of physicians per thousand population that have been used (UNSCEAR, 2008). Because these extrapolations have been associated with limitations regarding applicability to developing countries, it is recommended that the predictive power of linear regression based on the number of examinations per anatomical region, be explored. This has the potential to simplify the counting of individuals exposed to radiation and therefore, make it possible to compute accurately the associated man-sieverts. Further analysis may also explore the applicability of time series estimates and the number of films or exposures used.

CHAPTER SIX
FORECASTING DEMAND FOR RADIOLOGY SERVICES

Abstract

Forecasting demand for radiology services has come a long way to reach the type of forecasting presented in this chapter. First, it was logical and realistic to establish radiology patient care pathways and its associated labour drivers (Chapter 4). Second, there was need to characterise the aforementioned labour drivers to ensure that forecasting assumptions were not violated as it was important to understand real world paradigms (Chapter 5). Chapter 6 comes in upon the realisation that the world consists of a large number of alternatives and forecasting evolved as a way of examining the alternative futures and establishing their stochastic chances of occurring. In this study, forecasting patient numbers was paramount in modelling decisions for future radiology practice. In essence, the aim of this forecasting study was to ready policy makers for the future by offering evidence to modify variables now so as to improve the future. This philosophical approach was intriguing in that forecasts invariably invite policy shift which logically have a bearing on the future.

Drawing from literature, forecasts are associated with error so much that, regardless of amount of refinement in research methods used; forecasts always have an element of uncertainty until the forecast horison comes to pass. Consistent with logic, there is overwhelming evidence from literature that forecasting always has blind spots. Despite these limitations, providing forecasts is pivotal in formulating new policy. Most captivating is the fact that new policy inevitably affects the future thus impacting on forecast accuracy.

The purpose of this chapter was to provide forecast for the total number of radiology patients expected for the research sites based on historical data. The historical data was divided into model estimation and model evaluation periods. Two approaches were used to answer the question: endogenous and exogenous techniques. An overview of the techniques is presented to provide the reader with an understanding of how each technique works. Endogenous time series techniques were used to explore patterns in the historical data to come up with forecasts. Consistent with the definitive terminology, this endogenous technique looked inside (endo) the actual number of patients through time to define the underlying patterns. On the contrary, regression analysis (an exogenous technique) explored factors that were external (exo) to the actual number of patients to establish a relationship

among the external factors (predictor variable changes) and number of patients (criterion variable).

Endogenous technique revealed the level, trend, seasonality and noise in the data set. Exogenous technique revealed the strength and direction of the impact presented by predictor variables. An exogenous technique (multiple regression) was run to predict Total number of patients examined (PAT) from Total number of chest examinations (CHE), Total number of axial skeleton examinations (AXI) and Total number of appendicular skeleton examinations (APP). These variables statistically significantly predicted (PAT), $F(3, 128) = 175.422$, $p < .0005$, $R^2 = .804$. All three variables added statistically significantly to the prediction, $p < .05$. Both models had predictive errors falling within four percent and therefore there was enough statistical evidence to conclude that the models did a good job in predicting the variances in the observed patient numbers. .

6.1 Introduction

The specific objective of this chapter is to present the part of the study conducted to predict the future total number of radiology patients for the research sites by inductively reasoning from trends observed in historical data. This was accomplished through forecasting work generated by time-variant radiology labour drivers. Forecasting is an important scientific approach to the future that acknowledges that the world consists of a large number of alternatives. Forecasting evolved as a way of examining the alternative futures and establishing their stochastic chances of occurring. Forecasting of patient numbers was paramount in modelling decisions for future radiology utilisation. In essence, the aim of this forecasting study was to ready policy makers for the future by offering evidence to modify variables now to better the future of radiology utilisation. Philosophically, forecasts invariably invite policy shift thereby impacting on the future and altering forecast accuracy. This forecasting stage represented the final step towards fulfilling the objectives of this dissertation.

6.2 Method

There were two approaches that were considered feasible for the observed data: forecasting individual labour drivers in each period independently and forecasting labour drivers using aggregation-disaggregation approaches (SPSS, 2010; Rosenberg, 1997). The key labour driver was considered to be the number of patients served by a radiographer and that the workload due to each patient was time-invariant (Schneider, 2011; Rosenberg, 1997). It was considered logical to expect that the number of examinations per patient (which were by default not recorded) as well as competencies of radiographers (which were not the subject of this study) introduced randomness in the observed service transaction times for patients.

The historical data was divided into model estimation and model evaluation periods (SPSS, 2010). Consistent with this literature, two approaches were used to answer the question: endogenous and exogenous techniques. Endogenous time series technique was used to explore patterns in the historical data to come up with forecasts. Consistent with the definitive terminology (SPSS, 2010), this endogenous technique looked inside (endo) the actual number of patients through time to define the underlying patterns. Using the same conceptual literature, this was followed by the application of a regression analysis (an exogenous technique) to explored factors that were external (exo) to the actual number of patients. This was in order to establish the relationship among these external factors (predictor variable changes) and the number of patients (criterion variable).

The independent external factors approach required considerable calculations and generated a large number of forecasts across individual labour drivers over the entire planning periods. The disaggregation approach assumed that each period was independent of every other period, yet it was logical to expect that demand left unattended to in the previous period would inevitably spill over to the next period (SPSS, 2010; Rosenberg, 1997). Therefore, in this study, independent labour driver forecasting was limited to the preliminary stages of forecasting where particular interest was in qualifying consistencies of labour drivers. This analysis left the aggregation-disaggregation approach as the better option for the forecasting of demand for radiology services.

6.3 Data analysis

The selection of how to analyse and present the data involved ascertaining that the data met the data quality objectives as detected by the statistical test (SPSS, 2010). The time series patterns for this study were described in terms of two basic classes of components: trend and seasonality (SPSS, 2010; Mentzer & Moon, 2004; Brocklebank & Dickey, 2003; Chatfield, 2000; Rosenberg, 1997; Makridakis & Wheelwright, 1989). This literature formed the impetus of the data analysis for this dissertation such that trend represented a general systematic linear or nonlinear component that changed smoothly over time and did not at least systematically repeat within the time range (year 2004- 2015) captured in the study. On the other hand, seasonality patterns represented those that repeated themselves in systematic intervals over time during the aforementioned time range (SPSS, 2010; Mentzer & Moon, 2004). Naturally, these two general classes of time series patterns coexist and therefore, to satisfy the objectives of this study, the chosen statistic was in order to describe the trend as well as identify and quantify the variable effects on the observed demand for radiology services. For this reason, the chosen statistical approach was nonparametric (SPSS, 2010). Consistent with SPSS (2010), a preliminary review of the selected statistical tests requirements were conducted to satisfaction before applying the tool.

6.3.1 Statistical analysis: aggregation-disaggregation labour driver forecasting

An important requisite for the application of aggregation-disaggregation forecasting model was that the behaviour of the observed labour drivers be consistent (SPSS, 2010; Mentzer & Moon, 2004; Rosenberg, 1997). This requirement was achieved by visual (graphical) displays as well as correlation tests. In this forecasting model, demand data was combined across all planning periods. The observed data were collected over an eleven year period, and each month's total demand for radiology services was then expressed as a proportion of the total radiology demand for the year. The object was to establish whether the data clearly exhibited consistency necessary for an aggregation- disaggregation approach to forecasting: say month one in a year being consistently the busiest followed by month 2, 3 and so on (Schneider, 2011; Mentzer & Moon, 2004).

A correlation test was run on the data to add statistical evidence to qualify the consistency status of the data. The criteria for significance was that high correlation values (greater than 0.4) indicated that monthly demand for radiology services were significantly consistent as a proportion of yearly demand. The object of this analysis was to establish whether the data showed similar same-month demand patterns year after year so that an aggregation-disaggregation forecasting approach could be used within yearly demand (Schneider, 2011). Charts were further used to strengthen the validity of the conclusions with regard to consistency and trends in the data.

6.3.2 Statistical analysis: smoothing of graphs

The main outcome measure of this study was to establish demand trend for radiology services in the period of the study and then predict future demand. In order to establish a trend, a smooth curve representing the observed data had to be established (SPSS, 2010;

Mentzer & Moon, 2004; Brocklebank & Dickey, 2003; Chatfield, 2000; Rosenberg, 1997; Makridakis & Wheelwright, 1989). The objective of the smoothing process was to enable the explaination of why the demand peaks and lags at the times and volumes they did while at the same time ensuring that the explanation was not shrouded by unpredictable (random or noise component) variations.

Therefore, the first step in the statistical process of trend identification was smoothing the data using moving average technique together with the negative exponentially weighted smoothing technique (SPSS, 2010). This process retained the general shape of the original forecast while at the same time eliminating the randomness (the teeth) of that forecast by making up for erratic data. In moving averages approach, each element of the series (month) was replaced by a weighted average of 2 surrounding months making 2 the width of the smoothing window (SPSS, 2010; Rosenberg, 1997).

6.3.3 Statistical analysis: The Forecast Equation

The main outcome measure of this study was a forecast for radiology demand. Inferential analysis to test for the presence of a consistent trend and to measure the magnitude of trend by inferring from the slope was used (Rosenberg, 1997). The Wilcoxon-Mann-Whitney step trend analysis was used to determine variable effects while Hodges-Lehmann estimator (SPSS, 2010) was used to determine the magnitude of the step due to a variable (variable effect). These steps were pivotal in the identification of a function associated with the smoothed monotonous time series data.

Identification of the period for seasonal variations in the demand for radiology was fundamental to forecasting. Seasonality was analysed by measuring correlation between two measurements separated by a lag k in the time series radiology demand data (Rosenberg, 1997). In statistical format, this essentially means correlation dependency of order k between each i'th element of the radiology time series data and the $(i\text{-}k)^{th}$ element (where i=2 to 120). This correlation dependency was measured by autocorrelation (i.e., a correlation between these two terms). The criterion was that if the measurement error was not too large, seasonality could be visually identified in the series as a pattern that repeats every k^{th} element (Rosenberg, 1997).

In order to give visual perception of the seasonal patterns, autocorrelation correlograms to display graphically and numerically the autocorrelation function (*ACF*), that is, serial correlation coefficients (and their standard errors) for consecutive lags in specified range of lags were used. In these correlograms, the size of auto correlation was the desired outcome because the criterion specified from the onset was that of very strong and therefore highly significant autocorrelations (Refer to statistical assumptions page 18). The rationale for examining these correlograms was that since autocorrelation for consecutive lags were formally dependent; this therefore implied that the pattern of serial dependencies would change considerably after removing the first order auto correlation which statistically means after differencing the series with a lag of 1 (SPSS, 2010; Rosenberg, 1997). This logic of statistical treatment was vital for this study in removing serial dependency and therefore further transformed the time series data.

The serial dependency for a lag of *k* was removed by differencing the series, that is converting each *i*'th element of the series into its difference from the $(i\text{-}k)^{th}$ element in the time series data (Rosenberg, 1997). The reason for engaging such transformations were that by so doing the hidden nature of seasonal dependencies in the series could be identified (SPSS, 2010). This was an important consideration because if autocorrelations for consecutive lags were interdependent, removing some of the autocorrelations, all too often eliminates them or may make some other seasonalities more apparent. This was also an important consideration because removal of seasonal dependencies also made the time series data stationary which was an important requirement for the subsequent statistical analysis (SPSS, 2010; Rosenberg, 1997).

6.3.4 Statistical analysis: Tracking Forecast Accuracy

Particularly important was knowledge that forecasts are rarely perfect and as such measurement and tracking of forecast accuracy for this study was fundamental to ensure that the forecasting method was appropriate and valid (SPSS, 2010; Mentzer & Moon, 2004; Brocklebank & Dickey, 2003; Chatfield, 2000; Rosenberg, 1997; Makridakis & Wheelwright, 1989). Drawing from literature, two common yardsticks for measuring forecast accuracy which are the Mean Absolute Percentage Error (MAPE) and the Coefficient of Variation (COV) of the forecast error were engaged (Agnolucci, 2009; Cheong, 2009; Cortazar & Schwartz, 2005; Costello *et al.,* 2008; Mentzer & Moon, 2004; Brocklebank & Dickey, 2003; Chatfield, 2000; Makridakis & Wheelwright, 1989).

Calculation of MAPE and COV was explicitly explained in the SPSS (2010) users' guide- the statistical software that was used in this dissertation. Adapting these formulae to the *diagnostic radiology capacity and demand: trends and forecasts*, this meant that "actual demand" formed the denominator of both measures. This meant that, both MAPE and COV measured relative error (Agnolucci, 2009; Cheong, 2009; Costello *et al.,* 2008; Cortazar & Schwartz, 2005). In the analysis, MAPE was found by calculating the mean of the absolute value of the error, dividing by the actual demand and then multiplying the outcome by 100 percent. On the other hand, COV was found by calculating the standard deviation of the error and dividing it by the average demand (SPSS, 2010).

6.4 Results

The relationship between the predictor variables and the criterion variable (total number of patients who visited the research sites) was investigated using "Time Series" modelling and "Multiple Regression" modelling of the total number of patients for the research sites. Preliminary analyses were performed to rule out any significant violations of the assumptions of normality, linearity and homoscedasticity.

Linear regression Model Summary statistics extracted from SPSS (version 21) comprise parameters: R, R^2, adjusted R^2, and the standard error of the estimate. These parameters were used to determine how well the regression model fit the data. All predictor variables as well as the criterion variable were entered in the analysis. There were no missing values after multiple imputation. The value of R represents the observed multiple correlation coefficient for the data set. The criterion was that R represents one measure of the quality (SPSS, 2010) for the prediction of the dependent variable (Total number of patients). The statistical analysis gave an R value of 0.897 which indicated a good level of prediction. The associated "R Square" represents the R^2 value (previously defined in chapter 5 as the coefficient of determination). This coefficient of determination represents the proportion of variance in the criterion variable that was explained by the predictor variables. This is been defined in literature as technically representing the proportion of variation accounted for by the regression model above and beyond the mean model (SPSS, 2010; Agnolucci, 2009; Cheong, 2009; Cortazar & Schwartz, 2005; Costello *et al.,* 2008; Mentzer & Moon, 2004; Brocklebank & Dickey, 2003; Chatfield, 2000). The value for the coefficient of determination for this model was 0.804 which meant that the predictor variables explained 80.4% variability of the criterion variable which was consistent with the observed "Adjusted R Square" (*adj.* R^2) value for the model (0.800). The significance test of the model involved the F-ratio. The F-

ratio in the Analysis of Variances (ANOVA) tested whether the overall regression model was a good fit for the data. The test showed that the independent variables statistically significantly predicted the dependent variable, $F(3, 128) = 175.422$, $p < .0005$. This meant that the regression model was a good fit of the data.

Estimated model coefficients from the statistic were used to draw up Equation 6.1. The constant, Appendicular, Axial and Appendicular examinations coefficients were respectively equal to 356.26, 0.69, 1.25 and 1.30. From this statistical output, the general form of the equation to predict Total number of patients examined (PAT) from Total number of chest examinations (CHE), Total number of axial skeleton examinations (AXI)and Total number of appendicular skeleton examinations (APP), is therefore:

Predicted PAT = 356.26 + (1.30 x CHE) + (1.25 x AXI) + (0.69 x APP) ..... **Equation 6.1**

The “unstandardised coefficients” obtained from the the statistic indicate how much the predictor variable varied with the criterion variable when all other predictor variables were held constant. Symbolised as B_0, B_1, B_2 and B_3 for the Constant, Appendicular, Axial and Chest examinations respectively, these were numerically equal to 356.26, 0.69, 1.25 and 1.30 respectively. This meant that for each one 100 examination increase in Appendicular, axial and Chest examinations, there was an increase in number of patients examined of 69, 125 and 130 respectively. The statistical significance test of each of the predictor variables was also conducted. This procedural step was undertaken to test whether the unstandardised (or standardised) coefficients were equal to 0 (zero) in the population. The criterion was that for $p < .05$, there was enough statistical evidence to conclude that the coefficients were statistically significantly different to 0 (zero). The *t*-value and their corresponding *p*-value that were used to draw statistical conclusions were located in the "**t**" and"**Sig.**" columns of the SPSS output table.

The results of the significant test showed that, from the "Sig.**"** column, number of appendicular examinations and number of chest examinations predictor variable coefficients were statistically significantly different from zero (both p-values less than 0.05). However, the number of axial examinations predictor variable coefficient was statistically not significantly different from zero (p-values greater than 0.05). In all cases the t-value was positive meaning that the mean coefficient was greater than zero. Importantly, although the intercept, B_0, was by default displayed in the statistical significance column, this was not considered an important or interesting finding because in practice it is generally ignored and was therefore not pursued in this study.

In conclusion, a multiple regression was run to predict Total number of patients examined (PAT) from Total number of chest examinations (CHE), Total number of axial skeleton examinations (AXI)and Total number of appendicular skeleton examinations (APP). These variables statistically significantly predicted (PAT), $F(3, 128) = 175.422$, $p< .0005$, $R^2 = .804$. All three variables added statistically significantly to the prediction, $p< .05$.

Predicted PAT = 356.26 + (1.30 x CHE) + (1.25 x AXI) + (0.69 x APP) ..... **Equation 6.1**

6.4.1 Analysis in the time series domain

The relationship between working number of patients with month number in time series data was investigated using Pearson product-moment correlation coefficient. There was a weak, positive correlation between the criterion variable and month number in time series data [r=0.05, n=132, p<.0005], with high numbers of patients associated with high month numbers. The associated coefficient of determination was 0.0025. This gave 0.3 per cent shared variance. This means that month number in time series data helped to explain 0.3 per cent of the variance in the number of patients examined. This is evidence that there was a weak synchrony between the number of patients and time so much so that the radiology patient numbers had no meaningful net growth in the time horizon. These modeling results in the time series domain emanated from models that were applied to variables in the active dataset with the same names as the variables specified in the models. All these variables represented a time point and were therefore treated as time series data. Successive cases were separated by a constant time interval –one calendar month. The data set was divided into three parts: model estimation (January 2004 to December 2013), model validation (January 2014 to December 2014) and forecasting (January 2015 to December 2025) periods. Results for two best fitting time series models are described forthwith. The model description contains an entry for the estimated model plus both a model identifier and the model type. The model identifier consists of the name (label) of the dependent variable and a system-assigned name. The dependent variable was Working number of patients 1_5 while the system-assigned name was Model_1 and the model type is ARIMA(0,0,3)(0,0,0).

Consistent with correlational test results, the Expert Modeler used for this data determined that working number of patients 1_5 was best described by seasonal ARIMA model with zero order of differencing and third order of moving averages. This conclusion was derived from the fact that ARIMA model types are listed using the standard notation of ARIMA (p,d,q)(P,D,Q), where p is the order of autoregression, d is the order of differencing (or integration), q the order of moving-average, and (P,D,Q) their seasonal counterparts (SPSS, 2010). The seasonal nature of the model was testimony of the seasonal peaks that were visible in the series plot (Figure 6.1) and the zero order of differencing was evident in the observed flatness of the trend. The observed seasonal counterparts (0, 0, 0) explain the observed seasonal effect that was constant over the time horizon.

The second model has was consistent with the ARIMA model and reflects that the data could be described by a simple seasonal model. Also consistent with the description of the aforementioned ARIMA model, are the observed seasonality and trend characteristics. The model statistics provides summary information and goodness-of-fit statistics for the best fitting model as determined by the EXPERT MODELER. The model was labeled with the model identifier.

While the Models offered quite a number of different goodness-of-fit statistics, only the stationary R-squared value was used in this study. This statistic was chosen because it provided an estimate of the proportion of the total variation in the series that was explained by the models. Furthermore, stationary R-squared value was preferred over ordinary R-squared because the time series data had shown convincing evidence that a trend and seasonal pattern were imbedded in the data. The criteria were that larger values of stationary R-squared (up to a maximum value of 1) indicated better fit. A value of 0.01-0.29, 0.30-0.49 & 0.50- 0.95 meant a weak, moderate and a very good account of variance in the series by the model. Stationary R-squared value for the chosen ARIMA model for this study was 0.848 while that for the Simple Seasonal Model was 0.566. The ARIMA model was able to account for 84.8 percent variance while the Simple Seasonal model was able to account for 56.6 percent variance. This meant that; while the two models gave a good account of the variances in the observed data, the ARIMA model was better between the two.

Ljung-Box statistic, (modified Box-Pierce statistic) was used to check whether the models were correctly specified. The significance value obtained for the ARIMA model (p=0.028) was less than 0.05 and therefore significant. However, the significance value for the Simple Seasonal model (p=0.705) was greater than 0.05 and therefore was considered to be not significant. This implied that there was structure in the observed series that was not accounted for by the ARIMA model. However, there was enough statistical evidence to conclude that any structure in the observed series that was not accounted for by the Simple Seasonal model was only due to chance. Both the ARIMA and the Simple Seasonal models did not detect any points that were considered to be outliers in the observed series. Therefore, there was enough statistical evidence to conclude that there was no need for any points to be removed from the series for both models.

In the models' parameters' Table 6.7, values for all of the parameters in the model together with an entry for each estimated model, labeled by the model identifier are displayed. To add clarity to the analysis, a choice was made to list all of the variables in the models, including the dependent variable and independent variables that the Expert Modeler had determined as significant. There were two significant predictors (Working_Number_of_Chest_Exams and the Working_Number_of_App_Exams) identified by the model. Model evaluation data involved data for the period January 2014 to December 2014. Models were applied to predict the number of patients in this range after which the parameters were compared between the two models as well as to the observed data. The model fit and forecast across model evaluation time period is shown in Figure 6.1.

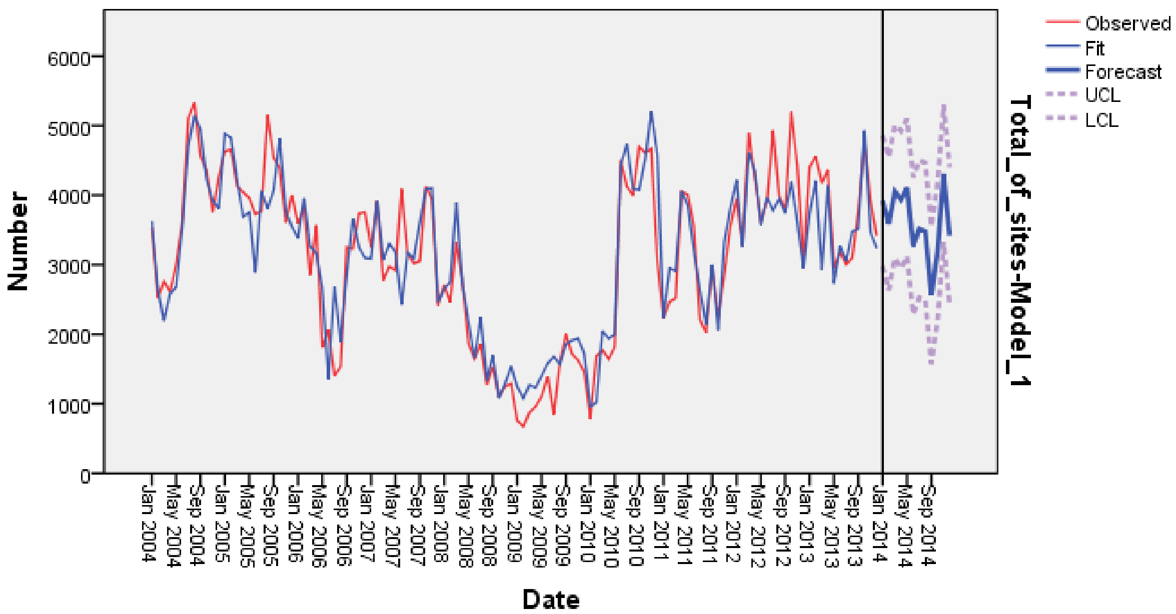

Figure 6.1: ARIMA model evaluation: Model fit and forecast across evaluation time horison

The central tendencies for the three categories were: Observed number of patients, 3700+/-200 patients; Predicted number of patients by ARIMA, 3600+/- 100 patients and Predicted number of patients by Multiple regression, 3600+/-200 patients. The two predictions and the observed number of patients fell within error margins of each other. The time series plot exhibited numerous peaks, many of which appeared to be equally spaced, as well as a weakly defined upward trend. The somehow equally spaced peaks confirmed the presence of a periodic component to the time series. Sharp, random and ill-defined peaks confirmed the existence of random (white) noise to the series.

The autocorrelation functions (Figure 5.6: Total_of_sites1_5) had significant peaks at a lag of 1 with long exponential tails which were typical patterns for time series data (SPSS, 2010). The significant peak at a lag of about 12 was suggestive of an annual seasonal component in the data. Analysis of the partial autocorrelation function allowed a more definitive conclusion. The significant peak at a lag of 12 in the partial autocorrelation function confirmed the presence of an annual seasonal component in the data. Results for the analysis in the frequency domain from Durbin-Watson test revealed that there was an independence of residuals ($p>0.05$ in all cases). The aforementioned evidence for a seasonal pattern paved the way for Seasonal Decomposition procedure of the series (SPSS, 2010). The procedure decomposed the series into a seasonal component, a combined trend and cycle component, and an “error” component. Results of this procedure are summarized in Figure 6.2. The applied Seasonal Decomposition procedure created four new variables (series) whose three-letter prefixes are subsequently defined drawing from Figure 6.2.

The results plotted in Figure 6.2 demonstrate variations in SAF, STC, ERR and SAF (SPSS, 2010). In Figure 6.2, the abbreviation SAF stood for the seasonal adjustment factors. These values were particularly important in providing pointers regarding the effect of each period on the level of the series. STC stood for the smoothed trend-cycle components. These values provided evidence with regard to the trend and cyclical behaviour present in the series. ERR represented the residual or “error” values. These were values that remained after the seasonal, trend, and cycle components had been removed from the time series. Also plotted in Figure 6.2 is the seasonal adjusted series for Total_of_sites (SAS).

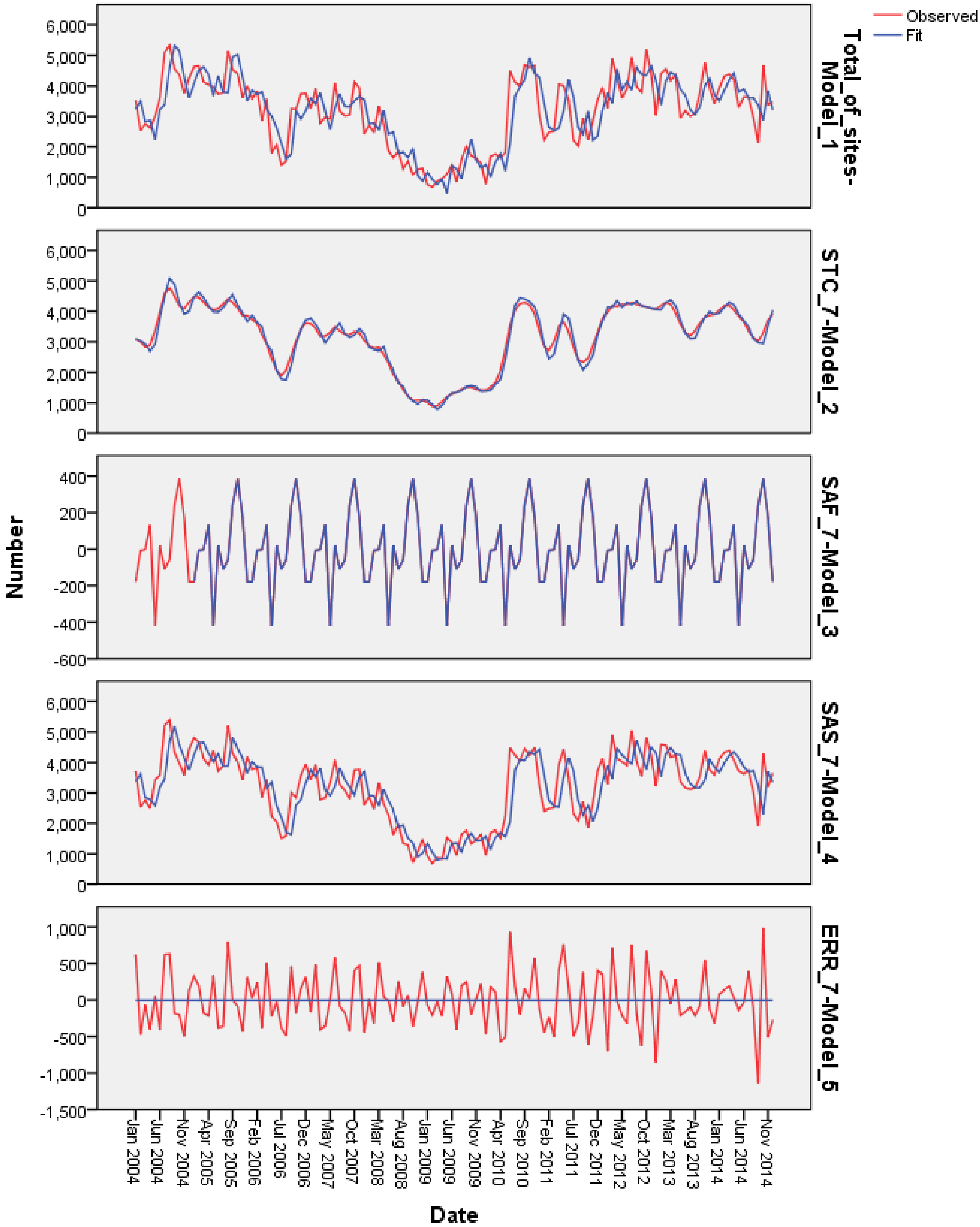

Figure 6.2: Seasonal decomposition of the time series

Figure 6.3 is a magnified smoothed trend cycle component. The graph shows a trend that goes downwards and then upwards, this might be a cycle. In the procedure to obtain a trend cycle, seasonal adjustments were added to the seasonally adjusted series to obtain the observed values. The objective of this adjustment was to remove the seasonal effect from the series in order to visualise other characteristics of interest that could have been "masked" by the seasonal component.

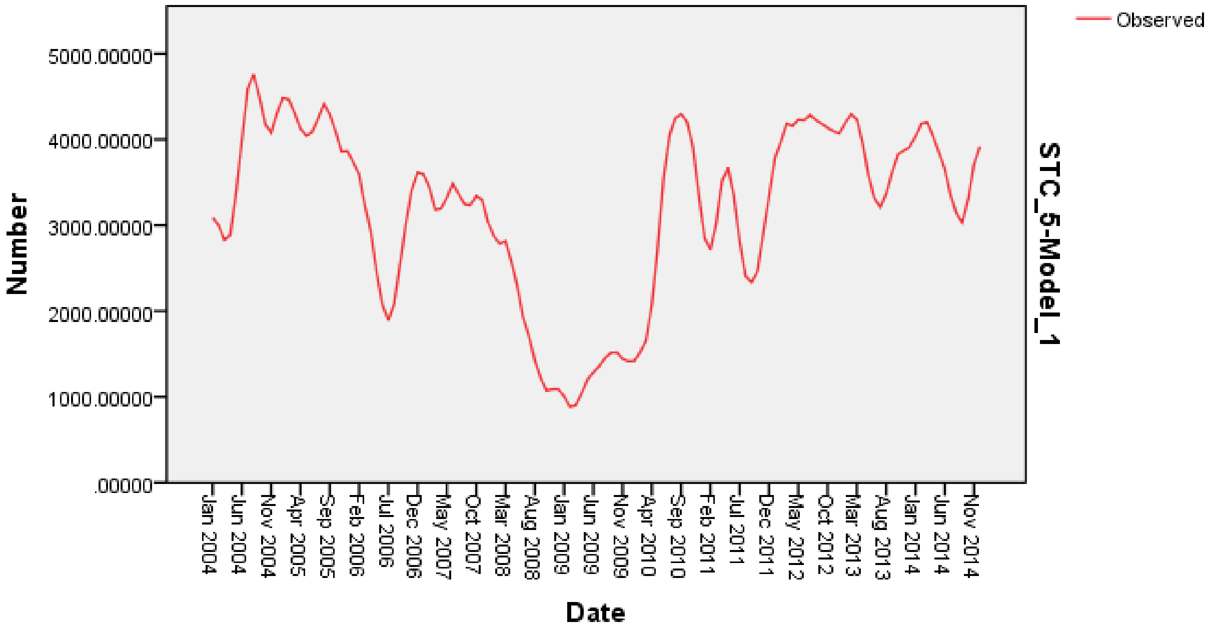

Figure 6.3: Seasonal adjusted series for Total_of_sites

The seasonal nature of the number of patients seeking radiology services had highs lasting about two years and typically occurring after every two years. Spikes that were systematic with holidays were also observed. This confirmed the existence of an annual seasonal component to the data. There were also peaks that did not appear to be part of the seasonal pattern and which appeared to represent significant deviations from the neighbouring data points. These points were however considered insignificant deviation because no statistical evidence emerged to support the assertion that other significant factors existed (The Expert Modeler had not identified them as outliers).

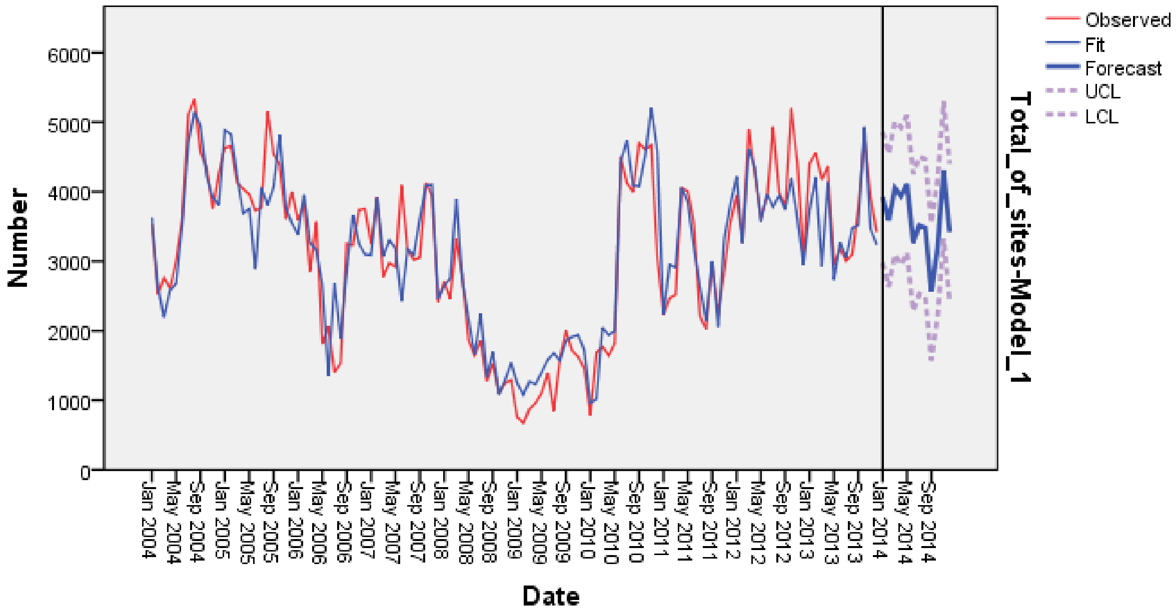

Figure 6.4[a]: Predicted values for the model evaluation period (Jan. 2014-Dec 2014)

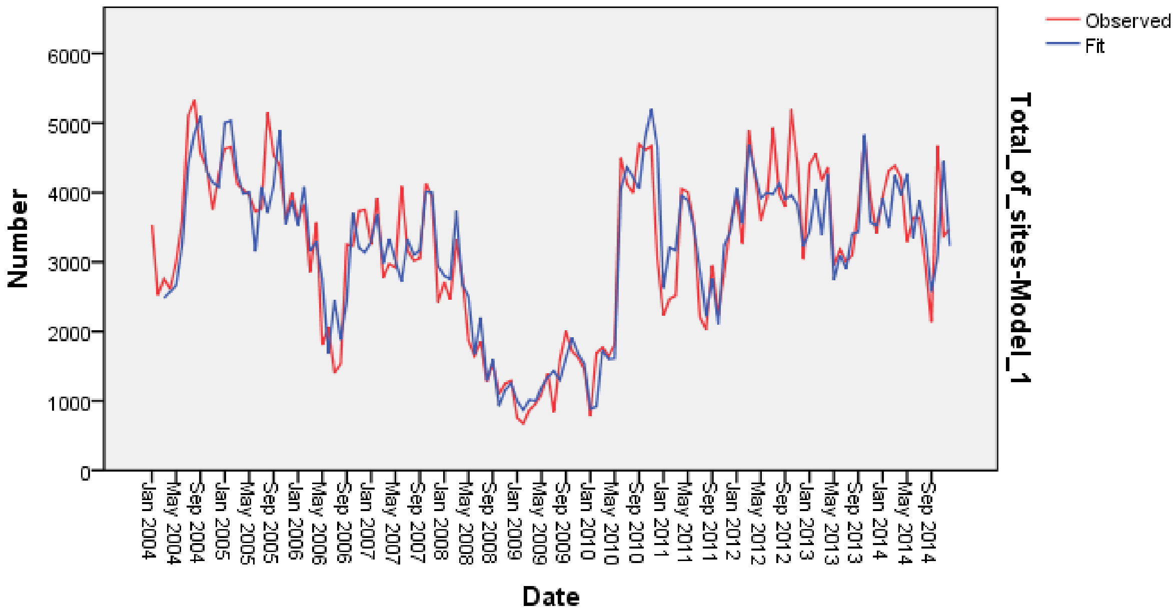

Figure 6.4[b]: Model fit to observed data for the evaluation period

The predicted values showed a good agreement with the observed values, indicating that the model had satisfactory predictive ability. This was evident in the way the model predicted the seasonal peaks of the series data as well as capturing the trend of the data. Furthermore, the observed values all fell within the upper and lower correlation limits of the predictions.

Table 6.1: Model fit and observed values

Model		Jan 2014	Feb 2014	Mar 2014	Apr 2014	May 2014
Working number of patients 1_5-Model_1	Forecast	3922	3590	4053	3935	4110
	UCL	4860	4547	5010	4922	5097
	LCL	2983	2633	3096	2948	3122
	Observed	3938	4316	4389	4206	3294

Table 6.2: Model fit and observed values (continued)

Model		Jun 2014	Jul 2014	Aug 2014	Sep 2014	Oct 2014
Working number of patients 1_5-Model_1	Forecast	3271	3515	3479	2562	3182
	UCL	4258	4502	4466	3549	4170
	LCL	2283	2527	2492	1574	2195
	Observed	3637	3635	2967	2140	4676

Table 6.3: Model fit and observed values (continued)

Model		Nov 2014	Dec 2014
Working number of patients 1_5-Model_1	Forecast	4311	3417
	UCL	5298	4405
	LCL	3324	2430
	Observed	3380	3468

Drawing from Tables 6.1-3, there was enough statistical evidence to conclude that the model was in good agreement with the observed values. The observed values fell within the upper and lower correlation limits predicted by the model and therefore its predictive ability was was considered very good for the analysis at hand. Results from the application of the simple seasonal model in forecasting the number of patients for the research site for the next ten years are shown in Figure 6.5 in which a plot of the Adjusted Predicted Value and the Standard Error of Predicted Value are also provided.

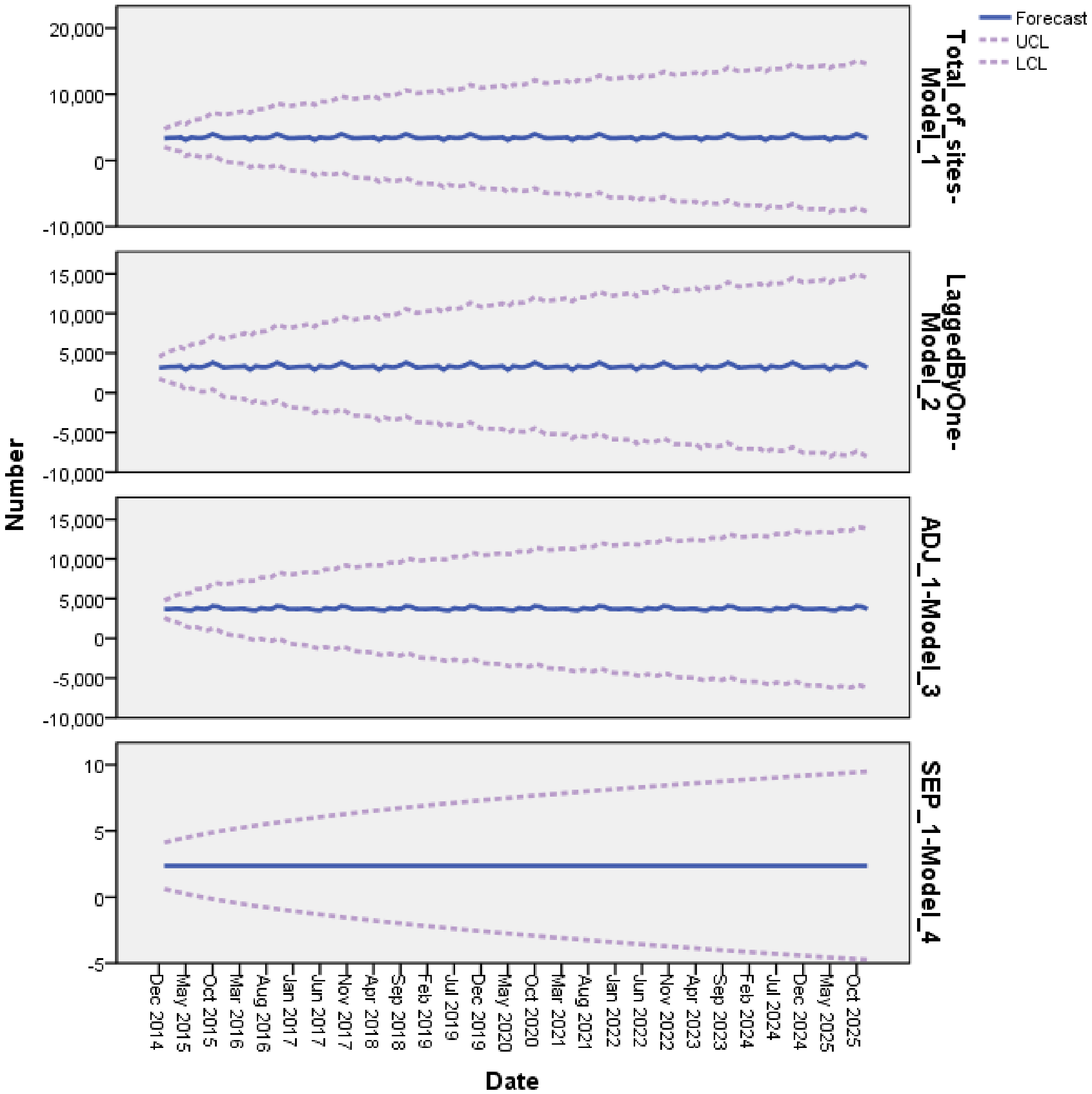

Figure 6.5: Ten year forecast for the number of radiology patients

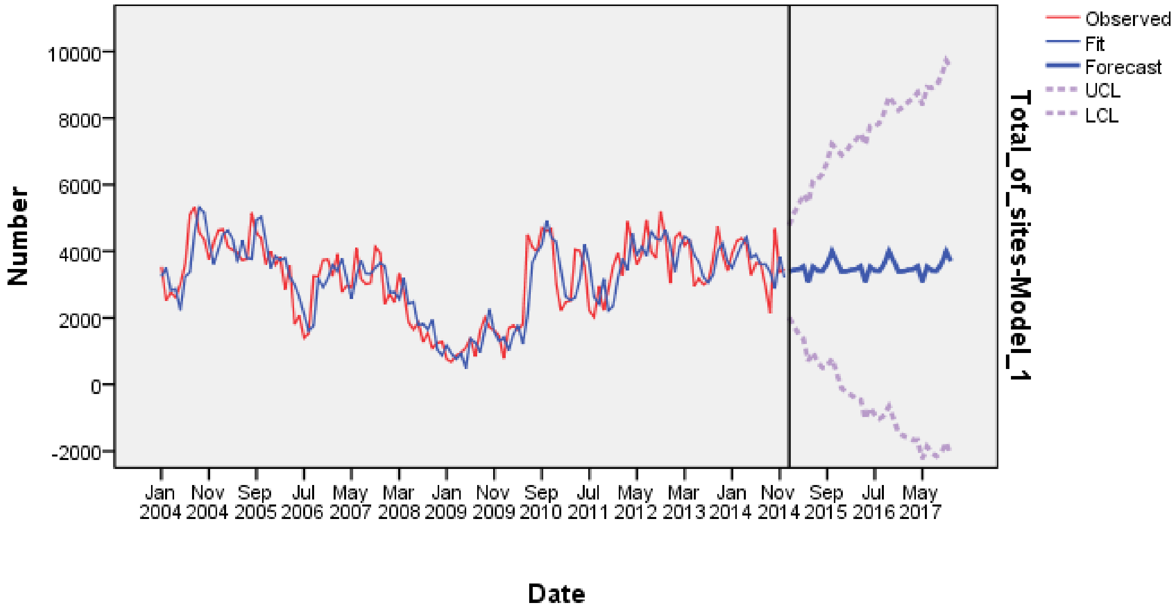

Figure 6.6 Magnified version of the forecast plot (Jan 2015-Dec 2017)

Actual figures used to come up with these forecast graphs are in Appendix F. Drawing from these forecasts, generally the number of radiology patients for the next ten years is projected to remain within current monthly figures with no significant net growth. These should remain within 5% of the predicted values.

6.5 Discussions

The objective of chapter six was to predict future numbers of patients seeking radiology services (future demand for radiology services) in order to aid policy formulation regarding future demand for radiology resources. Drawing from previous research, a predictor variable was an observable that was correlated to the variance in the criterion variable (SPSS, 2010; Mentzer & Moon, 2004; Brocklebank & Dickey, 2003; Chatfield, 2000; Rosenberg, 1997; Makridakis & Wheelwright, 1989). In this study, the criterion variable (monthly number of radiology patients) was time variant. In the aforementioned literature, time series datais definedas a set of observations obtained by measuring a single variable regularly over a period of time. Consistent with this literature definition, a series of frequency data representing the monthly number of patients visiting radiology departments and the number of examinations thereof that were observed in this study, were time series observations.

What these variables had in common was that variables were observed at regular (monthly) intervals over an 11 year length of time- defined in literature as the time horizon for the study (Schneider, 2011). An important lesson drawn from the definition of time series data was that, a typical time series is a single sequence of observations representing measurements taken at regular intervals. Further to the definition of time series data, many researchers have successfully used time series data to predict future observables (SPSS, 2010; Agnolucci, 2009; Cheong, 2009; Cortazar & Schwartz, 2005; Costello *et al.,* 2008; Mentzer & Moon, 2004; Brocklebank & Dickey, 2003; Chatfield, 2000; Makridakis & Wheelwright, 1989). The main outcome measure with regard to the time series analysis performed in this study was the forecast for the future numbers of radiology patients based on a model of the series that explained the past values. The ability to make successful predictions was important to policy makers especially in optimisation of resource utilisation as well as epidemiology studies; particularly cancer prevalence studies.

The importance of the research outcomes directed the writing of this thesis be critical about validity issues which included the criteria used to select a method to analyse and present the data. It was therefore befitting to ascertain that the data met the data quality objectives as detected by the statistical tests that were applied (SPSS, 2010). Specifically, and consistent with literature, preliminary analyses were performed to rule out any significant violations of the assumptions of normality, linearity and homoscedasticity. According to literature from the proprietor of the software package used (SPSS, 2010), these preliminary steps undertaken were enough evidence that the statistic produced valid output. In order to further safe guard validity of the study, three approaches were explored to model the criterion variable: linear regression, Simple Seasonal Modeling and Auto Regressive Integration of Moving Averages (ARIMA). All three models statistically significantly predicted the criterion variable. This triangulation of results was an important consideration as it added to the validity of the models. Many researchers have used this validation approach in which model output is compared with known data to aid in the validation process (SPSS, 2010; Agnolucci, 2009; Cheong, 2009; Costello *et al.,* 2008; Cortazar & Schwartz, 2005; Mentzer & Moon, 2004; Brocklebank & Dickey, 2003; Chatfield, 2000; Makridakis & Wheelwright, 1989).

Turning to the observed data itself, consistent with many researchers, the time series patterns for this study were described in terms of two basic classes of components: trend and seasonality (SPSS, 2010; Mentzer & Moon, 2004; Makridakis & Wheelwright, 1989). By literature definition, trend represented a general systematic linear or nonlinear component that changed smoothly over time and did not at least systematically repeat within the time range (year 2004- 2015) captured in this study. On the other hand, seasonality patterns represented those that repeated themselves in systematic intervals over time during the aforementioned time range. Many researchers have presented such examples of data coming from a pragmatic situation, albeit from different professions (SPSS, 2010; Agnolucci, 2009; Cheong, 2009; Cortazar & Schwartz, 2005; Costello *et al.,* 2008; Mentzer & Moon, 2004; Brocklebank & Dickey, 2003; Chatfield, 2000; Makridakis & Wheelwright, 1989). It emerged in this study that these two general classes of time series patterns coexisted in the observed data. To satisfy the objectives of this study, a statistic that described the trend as well as identified and quantified the variable effects on the observed demand for radiology services was chosen. The chosen statistical approach was nonparametric because of its robust applicability (SPSS, 2010). Because the selected statistical tests requirements were reviewed to satisfy all the statistical assumptions, this was a plus towards ensuring validity of the study (SPSS, 2010; Mentzer & Moon, 2009).

The observed consistency in the periodicity among the predictor variables as well as the criterion variable was a clear indication that the data exhibited consistency necessary for an aggregation- disaggregation approach to forecasting (Schneider, 2011; Rosenberg, 1997). This consistency evidence was observed in all periods. A correlation test on the data added statistical evidence to qualify the consistency status of the data (SPSS, 2010; Decoursey, 2003; Rosenberg, 1997). With all these correlation values greater than 0.75, this was enough statistical evidence to conclude that the monthly number of examinations were significantly consistent as a proportion of the annual number of radiology patients attended to. This analysis established that the data showed similar same-month demand patterns year after year. The validity of this conclusion was further strengthened by use of charts in which the observed month on month frequencies among the variables varied in synchrony.

The variance in the number of patients was accounted for by chest examinations followed by axial and then appendicular examinations. This raises questions whether the patient numbers were pathologically driven or trauma driven. Solutions to this question were not explored in this study although interview results showed that some radiographers believed that chest trends are a reflection of pathological trends while appendicular trends reflect trauma trends. However, strong correlation among these variables suggests that there was an exogenous factor that modelled the three variables somehow in the same manner.

An accepted definition of a trend is a smooth curve representing the observed data (SPSS, 2010; Mentzer & Moon, 2004; Rosenberg, 1997). It was therefore, appropriate that the data be smoothed before any attempt to explain the variances. The smoothed data made it easier to visualise and explain sustained peaks and troughs in demand by ensuring that the graphs were not shrouded by unpredictable variations (random or noise component). The observed effect was that the smoothing process retained the general shape of the original plots while at the same time eliminating the randomness (the teeth) of the plots by making up for erratic data. In this way a trend was established. With respect to trend analysis, the null hypothesis: H_0 was that there was no trend. However, as has been established, the aforementioned statistical tests brought with them precise mathematical definition of what was meant by "no trend", including a set of background assumptions related to the type of distribution and serial correlation data (SPSS, 2010; Mentzer & Moon, 2004; Rosenberg, 1997). Therefore, the outcome of the test for a trend was a "decision" to the effect that either H_0 was rejected or not rejected. In this aforementioned literature, it was clear that failing to reject H_0 did not mean that it was "proven" that there was no trend but rather a statement that the available statistical evidence was not sufficient to conclude that there was a trend. In this study, the test that was employed was directly analogous to regression, where the test for significance of the correlation coefficient “r” was also the significance test for a simple linear regression coefficient “R” data (SPSS, 2010; Mentzer & Moon, 2004; Rosenberg, 1997). The choice for a nonparametric test statistic ensured that no assumption of normality was mandatory, although “no serial correlation” remained a must for the resulting p-values to be correct. The test was applied to establish whether the central value or median changed over time.

In this study, the nonparametric output was triangulated with a parametric regression of Y (criterion variable) on T (predictor variables) namely simple linear regression of Y on T as a test for trend (SPSS, 2010; Mentzer & Moon, 2004; Decoursey, 2003; Rosenberg, 1997):

$Y = b_0 + b_1 \cdot T + e$ ……………………………………………………….Eqn 6.1

In this case the null hypothesis was that the slope coefficient $b_1 = 0$. Consistent with literature, the parametric test made stronger assumptions about the distribution of Y over time than did the nonparametric test. This was evidenced by the magnitude of the correlation values. Data had to be checked for normality of residuals, constant variance and linearity of the relationship using residuals plots. The observed t-statistic on b_1 was significantly different from 0 and therefore the null hypothesis of zero slope over time was rejected. This was enough statistical evidence to conclude that there was a linear trend in Y (criterion variable) over time.

Analysis of the observed trend established that from 2004 there was a general gradual decline in the demand for radiology services at the research sites. An all time low was reached and maintained between 2007 and 2010. This low coincided well with the peak of the host country's economic and political meltdown. Thereafter, the demand started to peak gradually towards the original cyclic equilibrium level (pre 2004 levels). This period was also important in that it was the time when the host country introduced multicurrency regime. Observed highs that were associated with cyclic variations (periodic) had their length generally limited to three year duration and separated by a low lasting about one year. Reasons for this behaviour were not investigated although this appeared to be in synchrony with the country's political 5 year calendar.

Evidence from Ljung-Box statistic, (modified Box-Pierce statistic) confirmed that there was structure in the data that was not accounted for. Evidence of variations that were not accounted for in this study (Exogenous Variations) suggests that there remains room to improve on this study. It appears these aforementioned variables inevitably had considerable influence on the criterion variable (response variable Y). However, data treatment revealed that these "exogenous" variables accounted for natural and random phenomena on the behaviour of the criterion variable data (Mentzer & Moon, 2004). It was therefore appropriate to remove these variations in the criterion variable that were caused by exogenous variables. This action saw the background variability (sometimes referred to as "noise") reduced so that the existing trend "signal" was easily seen (SPSS, 2010; Mentzer & Moon, 2004; Rosenberg, 1997). In turn, this increased the ability (power) of the trend test to discern changes in the criterion variable with the changes in the predictor variables.

The use of autocorrelation correlograms to display serial correlation coefficients (and their standard errors) for consecutive lags gave a visual perception of the seasonal patterns. This way serial dependency was removed and the time series data was transformed making it possible to identify the hidden nature of seasonal dependencies in the series (SPSS, 2010; Agnolucci, 2009; Cheong, 2009; Cortazar & Schwartz, 2005; Costello *et al.,* 2008; Mentzer & Moon, 2004; Brocklebank & Dickey, 2003; Chatfield, 2000; Makridakis & Wheelwright, 1989). This was an important consideration because removal of seasonal dependencies also made the time series data stationary which was an important requirement for tracking forecast accuracy. The aforementioned researchers explain that forecasts are only an estimate of the future and therefore, it is vital to explore forecast accuracy to establish the worth of the prediction. In this study, measurement and tracking of forecast accuracy was engaged as a fundamental step to ensure that the forecasting method was appropriate and valid (SPSS, 2010; Mentzer & Moon, 2004; Rosenberg, 1997). In this regard, two common yardsticks for measuring forecast accuracy were used as applied in this literature. These were the Mean Absolute Percentage Error (MAPE) and the Coefficient Of Variation of the forecast error (COV). These were inherent in the calculation of correlation coefficients.

Computation of correlation coefficients between pairs of variables generally denoted as X and Y was based on a fundamental statistical notation:

$$r = \frac{\mathrm{Cov}(x, y)}{\sqrt{s_x^2 * s_y^2}}$$ .... Eqn 6.2 (Decoursey, 2003).

where in Cov(x,y) was the covariance of X and Y, while the sample variances of X and Y, were defined as

$$s_x^2 = \frac{\Sigma(X - \overline{X})^2}{n - 1} \quad \text{and} \quad s_y^2 = \frac{\Sigma(Y - \overline{Y})^2}{n - 1}$$ ....Eqn 6.3

In essence, these variances of X and Y measured the variability of X and Y observations around their respective sample means considered separately. Accordingly, the observed covariances represented a measure of the variability of the variable pairs around their means that were considered simultaneously. The covariance itself was also computed using a fundamental equation:

$$\mathrm{Cov}(x, y) = \frac{\Sigma(X - \overline{X})(Y - \overline{Y})}{n - 1}$$ ....Eqn 6.4

Both MAPE and COV measured relative error. Literature explains that because of the error associated with forecasting, “Bias” refers to persistent forecast error which may be consistent under-forecasting or over-forecasting (SPSS, 2010). Generally, forecast accuracy is measured using Mean Absolute Percent Error. An interpretation of MAPE that best suits operations research was chosen. This was an important consideration because the thrust of this study was on demand and capacity utilisation. In this regard Forecast Error was defined as the deviation of the forecasted quantity from the actual quantity. As a percentage of actual quantity, this was represented as:

Absolute Error (%) value of {(Actual – Forecast/A) = % |(A - F)/A| ……….Equation 6.5

Logically, the criteria were errors close to 0% meant increasing forecast accuracy and because forecast accuracy was the converse of Error:

Forecast accuracy (%) = 1 – Error (%)……………………………………..Equation 6.6

Forecast Accuracy as used in this study was a measure of how close the actual values were to the forecasted value (SPSS, 2010; Mentzer & Moon, 2004; Rosenberg, 1997). According to guiding literature (SPSS, 2010; Mentzer & Moon, 2004; Rosenberg, 1997), the time series was divided into an *estimation* (2004-2013) and *validation* period (2014). The models, developed on the basis of the observations that were listed in the estimation period, were then tested to see how well they fit the data in the validation period. The statistics from this validation period were that (Table 6.8,) the central tendencies for the three categories were: Observed number of patients, 3700+/- 200 (before rounding 3671) patients; Predicted number of patients by ARIMA, 3600+/- 100 (before rounding 3612) patients and Predicted number of patients by Multiple regression, 3600+/-200 (before rounding 3630) patients. This meant that the forecast error was 2% for ARIMA and 1% for Linear Regression. This represented a high accuracy (98% and 99% respectively). This was an important consideration because making predictions for points that were already known (i.e. points in the validation period), it was possible to quantify how well the model succeeded at forecasting. This was enough evidence to conclude that the models did a good job of forecasting. The estimation period was then redefined to include the holdout cases. The final model was built using the complete set of observed data (SPSS, 2010; Mentzer & Moon, 2004; Rosenberg, 1997).

Using the chosen statistical analysis package (SPSS version 21), it s possible to estimate exponential smoothing, univariate Auto Regressive Integrated Moving Average (ARIMA), multivariate ARIMA models for time series, and produced forecasts for the observed data. Because the adopted procedure involved an Expert Modeler, the statistic automatically identified and estimated the best- fitting ARIMA or exponential smoothing model for the dependent variable series. This essentially, ensured that identification of appropriate models was not through trial and error.

6.6 Conclusions

In conclusion, three models were established and evaluated: Linear Regression, ARIMA and Simple Seasonal. A multiple regression was run to predict Total number of patients examined (PAT) from Total number of chest examinations (CHE), Total number of axial skeleton examinations (AXI) and Total number of appendicular skeleton examinations (APP). These variables statistically significantly predicted (PAT), $F(3, 128) = 175.422$, $p < .0005$, $R^2 = .804$. All three variables added statistically significantly to the prediction, $p < .05$. The coefficient of determination was 0.804 which meant that the model accounted for 80.4% of the observed variances in the number of radiology patients. This was enough statistical evidence to conclude that the Linear Regression model was able to predict the number of patients at the research sites.

Predicted PAT = 356.26 + (1.30 x CHE) + (1.25 x AXI) + (0.69 x APP) ..... **Equation 6.1**

Turning to the ARIMA and Simple Seasonal models, the R-squared value for the chosen ARIMA model for predicting PAT was 0.848 (Table 6.6) while that for the Simple Seasonal Model was 0.566. The ARIMA model was able to account for 84.8 percent variance while the Simple Seasonal model was able to account for 56.6 percent variance. This meant that both models did an excellent job of explaining the variances in the observed PAT data, with the ARIMA model being the better performing model between the two. However, among the three models that were tried, the ARIMA model performed exceptionally well followed by the Linear Regression model and then the Simple seasonal model.

Evaluation of the models (Table 6.8) using the evaluation data (hold out data) revealed that the central tendencies for the three categories were: Observed number of patients, 3700+/-200 patients; Predicted number of patients by ARIMA, 3600+/- 100 patients and Predicted number of patients by Multiple regression, 3600+/-200 patients. The three central tendencies fell within error margins of each other meaning that they could be used interchangeably. The error margins gave enough statistical evidence to conclude that the ARIMA model was more precise compared to the Linear Regression model. Consistent with the observation that the central tendencies fell within error margins of each other, there was no significant difference ($p < .05$) among the three aforementioned data sets. The forecast error was 2% for ARIMA and 1% for Linear Regression. This represented a high accuracy (98% and 99% respectively).There was enough statistical evidence to conclude that the two selected models statistically significantly predicted PAT. This means that the two models Linear Regression and ARIMA could be used interchangeably to predict PAT, with no significant difference in the accuracy of the predictions. However, because PAT as used in equation 6.1 refers to the total number of patients at a research site, transforming this to the total number of plain radiology patients for Zimbabwe required incorporation of proportional representation at different referral levels. Zimbabwe had 202 referral hospitals offering, among other services, radiology services. The 202 health facilities were distributed among secondary (181), tertiary (7) and central (14) referral levels (ZMOHCC, 2009). Consistent with the stratification (referral) levels in Zimbabwe's healthcare delivery system, the observed utilisation of x-rays for diagnostic purposes varied among these referral levels. This was also consistent with UNSCEAR (2008) report in which the variation was observed among strata of countries. Logically, therefore, these ratios in respect of the number of facilities at each referral level would proportionately model the total number of patients for Zimbabwe. Drawing from the stratification of health care in Zimbabwe, an equation derived from this study to estimate the total number of plain radiology patients for Zimbabwe can be written as:

$$PAT_{Zimbabwe} = 181 x PAT_{secondary} + 14 x PAT_{central} + 7 x PAT_{tertiary} \quad \text{Equation 6.7}$$

Where $PAT_{Zimbabwe}$ is the total predicted number of patients for Zimbabwe and $PAT_{secondary}$, $PAT_{central}$, and $PAT_{tertiary}$ are central tendency values for the number of patients at the respective referral levels.

Utilisation trends reported by UNSCEAR (2008) were from a sample of countries which was then extrapolated to a global perspective and the committee itself acknowledges that there were significant uncertainties in many of the calculated utilisation results. Findings made in this study strongly support this asserting that the UNSCEAR (2008) findings were compromised by these uncertainties. This study revealed evidence of continued blurring of scope of practice boundaries among healthcare professionals in Zimbabwe. This resulted in more healthcare personnel being able to refer patients for radiology and therefore, the use of the number of physicians by UNSCEAR (2008) to estimate utilisation of radiology is increasing becoming inaccurate.

Regarding the trend, time series plot exhibited numerous peaks, many of which appeared to be equally spaced, as well as a weakly defined upward trend towards the end of the data collection window. The somehow equally spaced peaks confirmed the presence of a periodic component to the time series. Sharp, random and ill-defined peaks confirmed the existence of random (white) noise to the series. Significant peaks on autocorrelation functions (Figure 5.6) seen at a lag of 1 with long exponential tails were typical patterns for time series data (SPSS, 2010). The significant peak at a lag of about 12 was suggestive of an annual seasonal component in the data. This assertion was consistent with results for an analysis of the partial autocorrelation function in which the significant peak at a lag of 12 was enough statistical information to conclude that there was the presence of an annual seasonal component in the data. Further analysis in the frequency domain using Durbin-Watson test (SPSS, 2010) revealed that there was an independence of residuals ($p>0.05$ in all cases) which was enough statistical evidence for a seasonal pattern in the data. Subsequent seasonal decomposition procedure decomposed the series into a seasonal component, a combined trend and cycle component, and an “error” component (Figure 6.2.).

The seasonal adjustment factors (SAF) showed that periods remained marginally at the same level of the series during the time horizon for the study. This was enough statistical evidence to conclude that there was no meaningful growth in the utilisation of plain radiology during the time horizon for the study. This was consistent with smoothed trend-cycle (STC) also shown in Figure 6.2. These values provided evidence regards the trend and cyclical behaviour present in the series. From the beginning to the end of the plot, a trend that goes downwards and then upwards thereby representing a cycle was observed for the data set (Figure 6.3b.). In the results set, consistent with notations used in the statistical tool used for the analysis, ERR represented the residual or “error” values. These were values that remained after the seasonal, trend, and cycle components had been removed from the time series data. Also plotted in Figure 6.2 is the seasonal adjusted series for Total_of_sites (SAS).

Figure 6.7: Radiology utilisation trend for the 11 year period

The seasonal nature of the number of patients seeking radiology services had highs lasting about two years and typically occurring after every two years. Spikes that were systematic with holidays were also observed. This confirmed the existence of an annual seasonal component to the data. There were also peaks that did not appear to be part of the seasonal pattern and which appeared to represent significant deviations from the neighbouring data points. These points were however considered insignificant deviation because no statistical evidence emerged to support another assertion (The Expert Modeler had not identified them as outliers). In conclusion, there was enough statistical evidence to conclude that the models were in good agreement with the observed values so much that their individual predictive abilities were considered satisfactory for the analysis at hand.

Forecasts for the number of patients for the next ten years are shown in Figure 6.6 in which a plot of the Adjusted Predicted Value and the Standard Error of Predicted Value are also provided. Inclusion of these parameters was an important consideration for the validity of forecasts. In conclusion with regard to the predicted number of plain radiology patients for the next ten years ending 2025, the radiology utilisation will remain subdued with marginal growth. Equipment and human resources, levels that are adequate today, should remain adequate for the next ten years with only marginal expected increases which have no consequence on staffing levels.

6.8 Recommendations

Equity and optimisation of resource utilisation should remain the priority of the ministry. Population statistics posted by the World Bank (Worldometers, 2016) show that the average annual percent change in Zimbabwean population, resulting from a surplus (or deficit) of births over deaths and the balance of migrants entering and leaving a country had a consistent positive steady growth from 2004 (0.7% growth rate) to 2015 (2.31% growth rate). This population growth rate should inform further research regarding how great a burden would be imposed on Zimbabwe by the changing needs of its population for radiology infrastructure, associated resources and human recapital (Worldometers, 2016). The outcome of this recommendation can then feed into the improvement of the model. This is important because a growth of nearly 25% in the population (15 million in 2014 to 19 million in 2025) is represents a significant change. A distortion in the demand trends is also expected to be stimulated by the nationwide introduction of digital x-ray machines initiated at the time of going to press for this thesis. This is because digital technology should open a new era by widening indications, cross sectional imaging and improved service transaction times. The ministry should prioritise efficiency in redeployment, redistribution and utilisation of existing resources. There remains great potential to improve service transaction time and quality of service for diagnostic radiology patients by accelerating radiography programme review as well as role extension (skill mix). Recommended deployment/redeployment of resources should be accompanied by relevant training. Further research should explore continuous professional development needs for radiographers as well as existing radiography curricula deficiencies. The research should spell out possible solutions and their impact on the practice of radiography.

CHAPTER SEVEN

THE RESEARCH PROCESS

7.1 Introduction

The research process for this dissertation was evidence based. It involved evidence based methods for identifying, developing, evaluating and expressing philosophical ideas on primary, secondary and original sources of data. These sources of data formed the basis of recommendations as well as formulated plans. In this chapter, a summary of procedures used to develop this study is given.

The process of writing this dissertation required continuous, extensive, re-evaluation and revision of the topic and the way it was presented in order to align with the procedures that were finally used to answer the research question. In line with the available information on the ground, the process involved revision of the initial research plan, adding new material and deleting extraneous material as new insights emerged during the research.

The main outcome measure in this dissertation was to produce and disseminate new knowledge created through the scientific research process. The study was based on secondary sources of data together with original primary data collected via research instruments designed and validated during the research process. Secondary data sources were pivotal in the provision of an overview of existing published knowledge on the topic as well as current debates on the topic. The aforementioned published knowledge provided the dissertation with a contextual background necessary to establish how the new knowledge described in this study differed from what was already known. The methodological philosophy used in this study may best be described as house style in that it blended basic and applied research approaches. It was basic research because it explained causes, effects, and the nature of radiology capacity and demand. It was applied research because it found solutions to the specific pragmatic problem by establishing trends and predicting patient numbers. Putting the two together, this study addressed the problem of a gap in information on “diagnostic radiology capacity and demand: trends and forecasts”.

7.2 Validity of the research methodologies

Evaluation of the quality of measures for this study was guided by the realisation that reliability and validity of the measures were key indicators of research quality. Furthermore, because the main outcome measure of this study was a model to predict patient numbers, the model’s error, accuracy and responsiveness to change were of utmost importance

(SPSS, 2010; Brown *et al.,* 2013; Rosenberg, 1997). Generally, a measurement process involves assigning numbers to observations in order to quantify phenomena. Phenomena that formed the impetus of this study were radiology demand, capacity, trends and forecasts. These were centered on quantification of monthly patient and examination numbers and were therefore pragmatic constructs as opposed to abstract concepts or theoretical constructs. Consistent with literature, the underlying advantage gained by the use of pragmatic constructs for this study was that measurement of pragmatic constructs involved relatively less complex validation processes compared to theoretical constructs (Kimberlin and Winterstein, 2008). Drawing from the aforementioned literature, when it comes to theoretical constructs, operationalisation of theoretical constructs in defined variables as well as the development and application of instruments or tests to quantify these variables is prerequisite. Measurement processes used for the main outcome measure in this study were primarily focused on pragmatic issues derived from the measurement of monthly frequencies of examinations and patient numbers. This approach was a plus for this study. This is not to say theoretical constructs were not part of this dissertation. These were limited to secondary outcomes to support primary outcomes.

Data sources for measures in this study involved document review that was conducted with radiographer research assistants, patient and staff interviews that were both administered by the researcher. The main research question was answered using measures developed from patient information available in medical records, radiology examinations and request forms. This was a plus for the study in that whenever verification issues arose the , it was possible to refer back to the source documents for verification. This was an important property for the data because it allowed repeatability of the study. Literature explains that measures from these data sources are generally, “considered objective because the reliability and validity of the measures are known, with the error margins and reporting of results meeting general rigorous standards” (Kimberlin & Winterstein, 2008).

Consideration of the reliability required invoking inferences from the classical test theory which says that observed measurements comprise both the “true” score and the associated “error” in the measurement process (Crocker & Algina, 1986). The error being the unwanted part of a measurement, rigorous validating process was conducted essentially to minimise error in the model. Both the accuracy and the associated error of the models were calculated. These were both within expected levels for accurate predictions. Possible sources of measurement error were identified through piloting and every effort was made to minimize their effects.

Reliability estimates were used to evaluate predicted patient numbers from three different models scoring the event rates using the same instrument (inter-rater (model) reliability). The observed strong positive pair wise correlation (r>0.9) among model outputs was enough statistical evidence to conclude that the models were highly reliable. To ensure stability of measurements, test–retest reliability was conducted with the data set split into model development and model evaluation sets (Brown *et al.,* 2013; SPSS, 2010; Rosenberg, 1997). This meant that each of the three models were administered to the time series data at two different points in time and the same correlation analysis further determined. Pair wise correlation revealed enough statistical evidence to conclude that there was a strong positive association among the three sets of scores. On its own this was evidence enough to conclude that the models were highly reliable in the prediction of patient numbers. Internal consistency for each of the models was used to establish an estimate of the equivalence of predictive strength of each of the models between the estimation and the hold out data sets. There was enough statistical evidence that each model estimate was consistent when it came to the hold out values.

The document review process reviewed data that was originally gathered for clinical records. Data sources were in the form of patient registries and examination request forms. These secondary data sources were used because they appropriately measured the variables required to answer the research questions: number of examinations and patients as well as reasons for the requested examinations. Because these data elements were present in the aforementioned data sets, there was no initial motivation to consider whether any proxy measures for the variables of interest were necessary. However, it emerged during the research process that there were incidences where documentation at research sites was inadequate (SPSS, 2010; Brown *et al.,* 2013). This prompted an exploration of evidence based methods to cater for missing values. The first option was consideration of proxy measures which essentially required rigorous “conceptual analysis of how closely the variables of interest and proxy measures were associated” (Kimberlin & Winterstein, 2008).

Medical aid claims database and number of films purchased were initially identified as an option to estimate missing entries which were in the form of number of patients who visited the radiology departments for plain radiology. However, it became clear that some patients were sent back for lack of funds and some patients had multiple examinations which were also affected by repeat examinations. This meant that regarding the medical aid claims data base, many patients were simply not on medical aid or simply could not afford the charged service fees. It also emerged that even for medical aid patients; some radiology services may not have been covered by medical aid and thus did not appear in the database. These short comings were enough evidence that these proxy estimates would otherwise distort the measurements and hence this was compelling towards application of multiple imputation method (SPSS, 2010, Pigott, 2001; Fay, 1996). This literature explains that measures from this statistical approach are objective because the reliability and validity of the measures are known.

A review of how previous researchers have used multiple imputation was pivotal in establishing what is known about the reliability and validity of document review data sets. This was particularly important because the reviewed documents were not compiled specifically for the purposes of this research. Fortunately, while it was envisaged that this documentation would be guided by institutional policy, provider training and provider preferences, there was no significant variance in documentation format across sites. All sites used the same format that only varied slightly on the amount of documented detail. This is not to say the document review had no short comings other than missing data. There is evidence in literature that retrospective document review is "often used as the gold standard for validation of other measures" although it has an element of unreliability specifically regarding interrater reliability (Kimberlin & Winterstein, 2008). Kimberlin and Winterstein (2008) explain that in a literature survey of 244 document review articles, only 5% mentioned interrater reliability while 0.4% did a statistical test for this reliability.

In this study, the researcher administered the instrument and acknowledges that while every effort was made to ensure the reliability and validity of the document review process there were pockets of missing data that could not be avoided. Of particular note is that out of the three disadvantages of retrospective document review processes emphasised by Kimberlin and Winterstein (2008), a standardized abstraction instrument was applied across all research sites and the instrument was rigorously piloted. This is consistent with notions of some researchers (Yawn & Wollan, 2005; Reisch *et al.,* 2003). However, because the researcher was involved in the development of the proposal as well as in the abstraction process, blinding of the abstractor (researcher) to study hypotheses was impossible. While the importance of this blinding is acknowledged, it is noted that in cited literature, Kimberlin and Winterstein (2008) claim that blinding to study hypotheses was mentioned in only 3% of their citations. This may be a reflection of the impractical nature of this requirement in most situations. A documented consequence of failure to adhere to the blinding is bias (Yawn &

Wollan, 2005; Reisch *et al.,* 2003). Considering challenges associated with the implementation of this requirement especially when a researcher is involved in the data collection process, logically, it is rather impractical to expect all researchers to adhere to this requirement.

7.3 Comprehensiveness and relevance of the literature review

The advent of the internet has seen the amount of health care research that is accessible to researchers grow enormously over the past two decades. There is no doubt that there has been an increase in health care staff undertaking research as part of academic studies and that evidence based practice is fast becoming established in health care practice. It is not surprising then that searching the literature for information on the research keywords (patient care pathway, for example) revealed a large number of research reports from an array of sources. The reports varied in terms of quality, comprehensiveness and relevance to the research question at hand. Drawing from literature, this forced the division of the literature review process for this study into two (Hewitt, 2007; Hart, 1999). There was searching and then critical evaluation of research literature. Because of the aforementioned wide variances in the quality of published work, searching the literature was a complex process and therefore a research method in its own right. In this regard, the approach adopted for the literature review process was evidence research (Hewitt, 2007; Hart, 1999). In this process, specific technical terms and guidelines were drawn from literature to identify relevant literature. The process was systematically conducted.

Critical evaluation of identified literature enabled reading the research articles objectively which was a plus for this dissertation. The main outcome measure of this objectivity was the identification of good points and bad points, the strengths and weaknesses, the usefulness and limitations of reviewed articles (Hewitt, 2007; Hart, 1999). Logically, because of the aforementioned variances in the quality of available literature, not all published research was considered good quality for this study. Critical evaluation of reviewed literature revealed that many of these studies, had limitations which resulted in the article in question being excluded from the list. This was an important consideration for this study as the process saw the an increase in the understanding of the research process.

Consistent with Hewitt (2007), the preliminary literature review helped to further identify and clarify the research problem as well as provide theoretical input to the research idea. A detailed literature review then provided an up-to-date picture of the research area of interest particularly with respect to which areas had been investigated and the results obtained. For each of the aforementioned areas, methods of investigation that had been used successfully and therefore could be used in this dissertation were identified. Careful analysis of these methods gave indications of eminent problems and possible solutions, common findings among studies and inconsistencies between and among studies. In so doing, this analysis was able to reveal gaps in the knowledge base which then gave pointers for further research in this dissertation.

Guided by Hewitt (2007), comprehensiveness of the reviewed literature was achieved by ensuring that the subject area was divided into a list of focus areas each represented by a keyword. The process of formulating keywords for the study was aimed at increasing chances of retrieving relevant information from a literature search. These keywords formed a description of the research subject by essentially ensuring that each keyword identified a part of the subject area and provided a focus for the search in the associated area. The process of creating keywords involved identifying key concepts in the research area. A careful analysis of these concepts in terms of their scope allowed identification of broader terms that defined the scope of the dissertation. These were then defined with increasing precision to produce narrower terms, a list of synonyms and a list of related terms (Hewitt, 2007; Hart, 1999). The critical step was then the grouping of terms to the subject headings to be used in the search as keywords.

The output of a search produced a large number of references that was rather impractical to manage. Therefore, the first level of the analysis was to go over the list of references in order to remove any duplicates and be satisfied about the relevance and quality of the material produced by the search. This approach was consistent with that recommended by Hewitt (2007). However, the challenging part of this approach was that the aforementioned assessment on the strength of reviewed abstracts was difficult such that the full paper had to be reviewed instead. This assessment process was time consuming but was a necessary process to ensure that quality literature was used to guide this dissertation. It was necessary primarily because literature has it on record that contents of an article may not necessarily represent facts but may instead represent the views or opinions that are not evidence based (Hewitt, 2007). Ensuring that included literature was peer reviewed was a requirement for this dissertation because this acted as a primary filtering stage giving assurance that only works of sufficient quality were referred to. Further evaluation then involved a decision that before a detailed analysis of each article, a preview of the associated abstract with respect to the introduction, headings and subheadings, tables and figures, discussion and conclusions would be conducted, and then the reference list. This was important in that it gave an impression of the detail and errors in the article. The list of references was particularly important in that inclusion of a range of articles spanning over many years, with books, articles and other reputable formats included, gave assurance that a comprehensive search of the literature was done by the author.

Having gone through the aforementioned process of literature review, this gave confidence that the literature review presented in this study put the present research problem into context. Evident in the outcome of the review is a summary of the current state of knowledge about “radiology capacity and demand: trends and forecast”. The literature review also identified gaps in the cited literature thereby making a strong case for carrying out research in this area of radiology. There was enough evidence in literature that the topic has not been extensively researched previously and that therefore, the proposed research would make a contribution to the existing knowledge base. Furthermore, because previous research findings recommend further research in the subject (ECRP, 2008), this gave more evidence to support the execution of this study. The literature review was up to date with older literature used to put the subject into context. Every effort was made to avoid overlooking key pieces of literature by the use of a systematic process of evaluating reviewed literature. When it came to synthesis of the reviewed literature, focus was put in pulling sources with similar arguments together in order to give a balanced review of differing viewpoints encountered in the literature. In this regard, all references listed by the thesis were appraised in the dissertation thereby ensuring that citations had relevant contents to the study of “radiology capacity and demand: trends and forecast”.

7.4 Adequacy of the findings

The adequacy of the research findings for this study was considered with respect to the data collection process and then with respects to the results that followed (Hewitt, 2007). Identification of factors that could have affected the outcome of the data collection process formed the impetus of the first part. The data collection instruments were administered by the researcher and in part by two radiographer research assistants. With respect to interviews, the importance was drawn to the fact that involvement of three people in collecting the data could affect the reliability and validity of the data. In order to minimise any such effects, the use of an unstructured schedule was reserved for the researcher while the research assistants were involved in the recruitment of participants for the interview process. This was because there was a possibility that each interviewer was likely to use the unstructured schedule in a different way thereby affecting consistency of the data. However, when it came to the frequency of examinations and patients, research assistants collected the data together with the researcher because a highly structured schedule was involved and the possibility of the data collection process affecting consistency was highly unlikely.

Literature explains that when a researcher personally collects interview data, there is a high chance of interviewer bias (Yawn & Wollan, 2005; Reisch *et al.,* 2003). This means that some respondents become reluctant to say their honest opinions. While many researchers advocate that "time of day, day of the week, time of the year or total period of time taken for data collection" impact on outcomes, the data collection times for this study was spread over a year with the data collection team engaging with participants throughout the day thereby allaying the aforementioned fears. However, in the absence of documented retrospective data with respect to staff establishments, it was observed that participants could hardly recall past events from far in the past. Similarly, because the data exhibited some seasonality patterns, it was therefore possible that when it came to interview data, participants gave varied opinions depending on the season.

The second part in the analysis of the adequacy of the results was focused on the results themselves. One of the most important considerations in this regard was the description of the respondents. The five departments that were enrolled for the study represented all radiology referral levels prescribed in the ZMOHCC (2009) which are secondary, tertiary and central levels. In addition there was representation for the private practice.

When it came to human participants, eighty seven were recruited to give their views on the practice of radiology. These were from various departments across the country including departments that were not participating and this gave information from those departments. The list comprised thirty two radiographers and fifty three patients. Out of these radiographers, six were academics. The inclusion of academic radiographers was appropriate in that it allowed the presentation of ideas regarding the dynamics of radiography curricula against practice dynamics. All these participants responded positively and their views were captured in this report. The high response rates encountered in this study suggests that the research design was well matched to the task at hand and that the method of data collection encouraged potential respondents to subscribe to the study. While the data collection tool looked long and difficult to complete the encouraging aspect was that it did not cause offence to the participants. In this regard, importance is drawn to the characteristics of the sample.

The analysis of the sample characteristics is important because it provides further information about key characteristics of those who took part in the study. The radiology departments that took part in the study comprised one private and four public institutions. The departments were from three provinces. Three departments were from a metropolitan province of Bulawayo. These departments were key in drawing conclusions as to whether demand that fell out of one centre was absorbed by another department in the same catchment area. Out of these three one was private while the remaining two were public institutions. The two public institutions charged the same fees that were stipulated by government. This aspect was important in eliminating the impact of fees variations when explaining demand trends among the centres. One department was from district level and one was from the capital city, Harare. Radiology departments that were from Harare and Bulawayo provinces were in referral hospitals. These departments accounted for the bulk of radiology requests referred from within the hospital, outside and beyond the provinces. On the other hand, district radiology departments accounted for the bulk of less complicated cases which excluded specialised imaging techniques- a preserve of referral centres. This was an important characteristic of the sample which explained examination trends where more powerful diagnostic technologies were not available.

The use of a sample comprising both elective and interventional radiology patients was appropriate in that it gave practice insights from the two perspectives. The use of a random sample of patients as well as all recruited practicing radiographers in the measurement of service transaction times was an important consideration because it allowed generalisability of the service transaction time across all patients, radiographers and departments. This characteristic of the sample gives conditions that guide readers of this dissertation who may consider implementing the research findings in their practices as knowledge of how the research sample compares with the population proposed by the reader is an important consideration.

The scope of this study was enormous as evidenced by the length of the data collection instrument. All results of the study were systematically and comprehensively presented in Chapters 4. 5 and 6 to cover the complete list of data captured using the data collection instrument. In selecting this presentation approach, priority was to make the results easy to understand. The chosen approach was befitting in that conclusions from chapter 4 were prerequisite to the work in Chapter 5 whose conclusions were also prerequisite to the work in chapter six. This presentation made the results easy to follow thus enhancing the potential value of the research. Every effort was made to ensure that where tables and figures were used, they were clearly captioned to match with information contained in text. This was in order to make them easy to follow.

Important in data presentation was that presentation of results using words, numbers or percentages may be misleading where small samples are concerned. In this regard, where small samples were involved such as in the sample of research sites, numbers were preferred while for large samples such as in the numbers of patients (thousands) percentages were used without loss of practicality in the results. The results section covered all the objectives. There was a comprehensive descriptive and inferential statistical analysis in the results chapters. Where hypotheses were involved, there was enough statistical evidence to reject or uphold the hypotheses. The presentation approach added clarity to the study making it easy to follow. There was enough evidence to conclude that every effort was made to ensure that the research findings were adequate and in line with the set objectives.

7.5 Personal insights in the field of the study

Radiology departments are pivotal in patient care pathways. They provide diagnostic information for most patients. Diagnostic information is vital in directing the course of a patient management process such that physicians can make informed, logical and deliberate treatment decisions. However, this very important service comes at a significant cost due to when it comes to investments in these sophisticated modalities. A direct result of this is that any economy would manage low numbers of radiology departments and hence it is important to identify and efficiently manage bottlenecks in radiology patient care pathways.

The current practice of radiology care appears rather segregated in that important planning functions such as capacity and demand are clearly evident in policy planning processes. There is widespread evidence that capacity planning organs exemplified by equipment and personnel deployment are not integrated. Because of this fragmentation, the physically separated planning functions lead to poor coordination in the management of scarce resources. While the deployment of both human and equipment resources are supply driven, personnel on the ground have enough capacity to advise policy makers on the best way forward. The existing problem is that the current supply driven resource management process leads to variation mismatches in service delivery. Application of modern evidence in the deployment of resources is not visible on the ground. In this scenario, suboptimal alignment of the stochastic demand and resource capacity compromise the departments' bid to fulfil their mission with regard to equity. The problem is aggravated by a mismatch among the three key pillars of radiography: the dynamic nature of radiology technology, dynamic nature of radiography (scope) practice and dynamic nature of radiography curricula.

7.6 Conclusions

The scope of the study was delimited to the field that was investigated as evidenced by the use of a complete set of data in the data collection instruments. The chosen presentation style was aimed at producing a logical and scientific document. This essentially, made it easy to follow the study in that solutions to one question lead to the other in synchrony. In the report itself, background information leads directly to the investigated problem thereby making it easy to appreciate the conceptualisation of the problem. The research question, the problem and specific objectives were consistent with the instrument as well as the analysis protocol used in the report. There was enough evidence that the presented background information and the literature review were in synchrony.

Gaps in the knowledge base that the study intended to answer were spelt out in the literature review in synchrony with the identified problem. The instrument, method and analysis protocols correlated well with the research question identified in the reviewed literature and were based on recommendations by previous researchers. It can be said that the data collection instrument was appropriate as evidenced by the response rate and the adequacy of findings. Documented findings in the dissertation report have adequate evidence (findings) that was in turn used to answer the research question. The use of statistical analysis documented in the dissertation report as a basis for arguments in comparing study findings with existing knowledge base was a plus for this study. This was an important consideration particularly in the evaluation of the study findings against existing opinions in order to substantiate conclusions drawn from the dissertation as well as link these to personal insights in the field of study. Regarding ethical issues, every effort was made to ensure that ethical issues were adequately attended to as evidenced by the fact that the study was approved by two ethics review boards and there were no incidents associated with the study. Furthermore, undertaking to adhere to standards of anonymity and confidentiality was upheld throughout the study.

CHAPTER EIGHT

THE RESEARCH OUTCOMES

8.1 Introduction

The aim of this study was to provide evidence basedforecast for radiology demand that would support policies aimed at optimising radiology resource allocation and utilisation as required in ensuring equitable, accessible and acceptable quality health services prescribed in the National Health Strategy (2009-2015) as well as in Section 29 and 76 of the Zimbabwean constitution.

A review of previous research set the parameters and assumptions under which the theory development took place. These parameters were established through the evaluation of previous research processes in respect of their limitations, gaps, achievements and further research recommendations. Particularly captivating was that when it came to non health disciplines, like economics for example, modelled relationships among labour drivers formed the impetus of conveying the connections between labour drivers and output. A realisation was made that production, as seen in economics or operations research, is a process in as much as radiology patient care is a process. Furthermore, improvement methodologies used in non health situations have stood the test of time. However, to apply these improvement methodologies in health systems, there was a need to apply evidence based modification to the non health improvement methodologies to suit clinical processes. Essentially, when it came to making statistical predictions, this involved using models to predict future clinical statistics. Theorising or model building, as it is sometimes called, was conceptually captivating in that it involved visualising connections between ideas and defining those ideas in the context of the dissertation. Further to theorising, the practicality of measuring variables in synchrony with the data collection instrument design was fraught with validation issues.

There was need for the data collection instrument to reflect the relationships and constructs predicted by the developed model. The systematic method of validating the research process followed in this dissertation made a contribution to the study and will be of use to researchers who employ retrospective document review (secondary data sources) research methods. The research outcomes of this dissertation provide a significant contribution to resource management policy formulation in line with the mission of the parent ministry: “To provide, administer, coordinate, promote and advocate for the provision of equitable, appropriate, accessible, affordable and acceptable quality health services and care to Zimbabweans while maximizing the use of available resources, in line with the Primary Health Care Approach”.

Compelling evidence to conduct this research can be summarised as:

(a) According to global statistics, diagnostic radiology exposures contribute the most towards artificial exposure to ionising radiation (a teratogen),

(b) Technology and practices in diagnostic radiology are changing rapidly thereby impacting on justification requirements and the frequency of exposures,

(c) Because ionising radiation is a teratogen, frequency of diagnostic radiology exposures was a thematic priority of the United Nations Scientific Committee's strategic plan (2009-2013),

(d) The scientific committee of the United Nations had particularly requested the secretariat to prepare a detailed plan for a report on the frequency of exposures thereby making the scope of this study globally relevant and

(e) The aforementioned Committee had also requested for a Global Survey of Medical Radiation Usage and Exposures and has called for close cooperation with international researchers in this regard.

8.2 Research outcomes for the study of diagnostic radiology capacity and demand: trends and forecast

The radiology patient care partway for the research sites consisted basically of three parts: the registration process for an examination, activities in the examination room and evaluation and interpretation of images. For all plain radiography examinations, radiographers performed the imaging process as well as the associated image evaluation. The radiology patient care pathway started at the point of registering a walk in patient for an examination. These patients joined the waiting queue. The radiographer prepared the room and the patient before each examination. Justification of examinations was limited by the completeness and accuracy of radiological requests. In all cases, at the end of the examination, the radiographer would evaluate the images and also make himself or herself available to assist the referrer in interpreting the images if the need arose. In one centre, where a radiologist facility was available, the radiographs were interpreted by the radiologist. There was evidence that in some cases services of a radiologist were solicited due to the complexity of the examinations. In all five departments, accident and emergency patients were prioritised to go in front of the queue. The activities that were observed are summarised in Table 4.1 (Chapter 4). Calculated demand to capacity ratios for the research site revealed that all but one observed activity stages were significantly over capacitated and there was significant under utilisation of personnel resources. However, the results showed that for most of the years, there was under-capacity in respect of X-ray equipment. Activities performed by radiographers are evidence of a trend towards less and less direct supervision by a radiologist during radiological procedures. There was an acute shortage of radiologists and radiographers had gradually, unofficially and by default moved to extending their roles towards full evaluation and interpretation of plain radiology images.

Three predictor variables were found to be strongly correlated to the number of patients and were thus selected for this study. These were examination numbers for chest, axial and appendicular regions taken collectively. The time series data for the three predictor variables exhibited a number of peaks that were not equally spaced. This was evidence that over and above the series having periodic components, they also had fluctuations that were not periodic. Ignoring observed small-scale fluctuations, observed significant peaks were evidently separated by about three years. Furthermore, the short term seasonal nature of radiology demand had typical highs during the holiday seasons (December holiday toping in the demand). There was no evidence of an upward growth alongside the upward series trend that was noticed on the seasonal variations.

None of the plots for ACF (Figure 5.6) among the three predictor series remained significant for more than six lags. All three ACF rather quickly declined to zero. All three predictor variable series had exponentially declining ACF that had spikes in the first lag of the PACF. In all the three predictor series, the observed exponentially declining ACF alternated between positive and negative values. In respect of chest examinations' plot, values of the PACF remained within the confidence interval while those for axial and appendicular skeleton exhibited some significant spikes in the tail region. The autocorrelation functions (Figure 5.6) showed significant peaks at a lag of 1 with long exponential tails. There was a significant peak at a lag of about 12. Importantly, this statistical event at a lag of about 12 was not visible for chest examinations. Results for the analysis in the frequency domain from Durbin-Watson test revealed that there was an independence of residuals ($p>0.05$ in all cases).

In conclusion, three models were established and evaluated: Linear Regression, ARIMA and Simple Seasonal. A multiple regression was run to predict Total number of patients examined (PAT) from Total number of chest examinations (CHE), Total number of axial skeleton examinations (AXI)and Total number of appendicular skeleton examinations (APP).

These variables statistically significantly predicted (PAT), $F(3, 128) = 175.422$, $p < .0005$, $R^2 = .804$. All three variables added statistically significantly to the prediction, $p < .05$. The coefficient of determination was 0.804 which meant that the model accounted for 80.4% of the variance in the number of radiology patients that were observed. This was enough statistical evidence to conclude that the Linear Regression model did a good job in predicting the number of patients at the research sites.

Predicted PAT = 356.26 + (1.30 x CHE) + (1.25 x AXI) + (0.69 x APP) ..... **Equation 6.1**

Using the model evaluation data, the observed number of patients was 3700+/- 200 patients. Predicted number of patients by ARIMA, 3600+/- 100 patients and Predicted number of patients by Multiple regression was 3600+/-200 patients. The two models' predictions and the actual value were within the error margins of each other and there was no significant difference ($p < .05$)among the three aforementioned data sets. The trend, time series plot exhibited numerous peaks, many of which appeared to be equally spaced, as well as a weakly defined upward trend towards the end of the data collection window. The significant peak at a lag of about 12 was suggestive of an annual seasonal component in the data. This assertion was consistent with results for an analysis of the partial autocorrelation function in which the significant peak at a lag of 12 was enough statistical information to conclude that there was the presence of an annual seasonal component in the data. Further analysis in the frequency domain using Durbin-Watson test revealed that there was an independence of residuals (p>0.05 in all cases) which was enough statistical evidence for a seasonal pattern in the data. Subsequent seasonal decomposition procedure decomposed the series into a seasonal component, a combined trend and cycle component, and an "error" component.

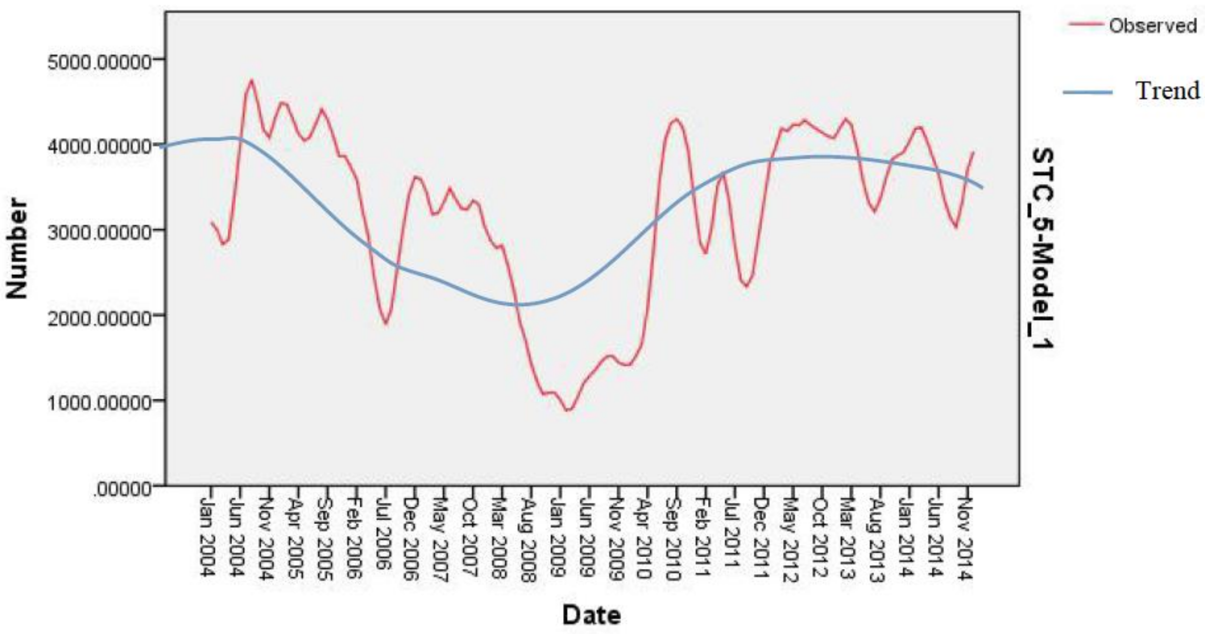

Figure 8.1: The observed trend

The seasonal adjustment factors (SAF) showed that periods remained marginally at the same level of the series during the time horison for the study. This was further evidence that plain radiology demand showed marginal growth during the data collection time horizon. A trend that goes downwards and then upwards thereby representing a cycle was observed for the data set (Figure 8.1).

8.3 Summary of discussions

There are many variables that are listed in literature as having an impact on the demand for radiology services. These include radiological technique, justification of requests, awareness of exposure guidelines, cost of examinations, health level stratification, case mix adjusted ratio, service transaction time and technology diffusion. Out of these variables only the justification of requests has been explored by previous researchers for Zimbabwe (Sibanda, 2012). With respect to poor justification of requests, these can be classified into repeating investigations which have already been done, doing an investigation when the results are unlikely to affect patient management, doing the wrong procedure, failing to provide appropriate clinical information and questions that the imaging investigation should answer and over investigating. These variables are associated with each other. While linear regression is undoubtedly a method of choice in multiple relational analysis, Sibanda (2012) did not take the research a step further to derive a demand equation for radiology services and also engage in predictive modelling to forecast radiological demand using these variables.

Therefore, this discussion may best be summarised by noting that, although labour drivers for radiology services have been suggested in a global perspective, few studies have explored and quantified their interactions and therefore, their relative impact on the number of patients (diagnostic radiology demand) attended to in radiology departments. This analysis would essentially require time variant labour drivers. Most of these labour drivers identified in cited literature were time invariant in the short to medium term time period. The use of examination numbers in this dissertation was consistent with time variant labour drivers suggested in the improvement methodologies (UKNHS, 2006; UKNHS, 2005). Reviewed literature also explains that there is limited research in respect of the subject from radiographers' perspective in their capacity as radiology service providers. As radiology service providers, radiographers hold key information as their perceptions are continuously refined through experiences with a multitude of referrals, interaction with a variety of clinicians and patients, and they have vast knowledge of indications for radiology examinations. Radiographers' as well as patients' perceptions of the mechanisms behind observed usage of radiological investigations are invaluable in policy formulation aimed at optimally managing radiology resources. Therefore, this literature review formed the impetus of this study by informing about how the diversity of these factors could be categorised, ranked and interrelated when the patients' and radiographers' perspective alongside document review information were considered with the intention to forecast radiology demand.

8.4 Conclusions

The trend was towards less and less direct supervision of radiologist during radiological procedures. Because of the acute shortage of radiologists, radiographers have gradually, unofficially and by default extended their roles towards full evaluation and interpretation of plain radiology images. This was however without the much needed formalisation, training and regularization. Emerging from this research outcome are opportunities for an enternet based health system (e-Health) for Zimbabwe to promote paperless online operations and teleaccess to specialist services especially for remote communities. Radiographers (NUST) are trained in e-Health from undergraduate level. The established radiology patient care pathways can be summarised into two models: a standard process which represents patients who followed the most common process among the observed participants (Figure 8.2) and a direct interpretation process which represented those patients who followed the least popular examination process (Figure 8.3). These observed pathways are similar to what was reported by Schneider (2011).

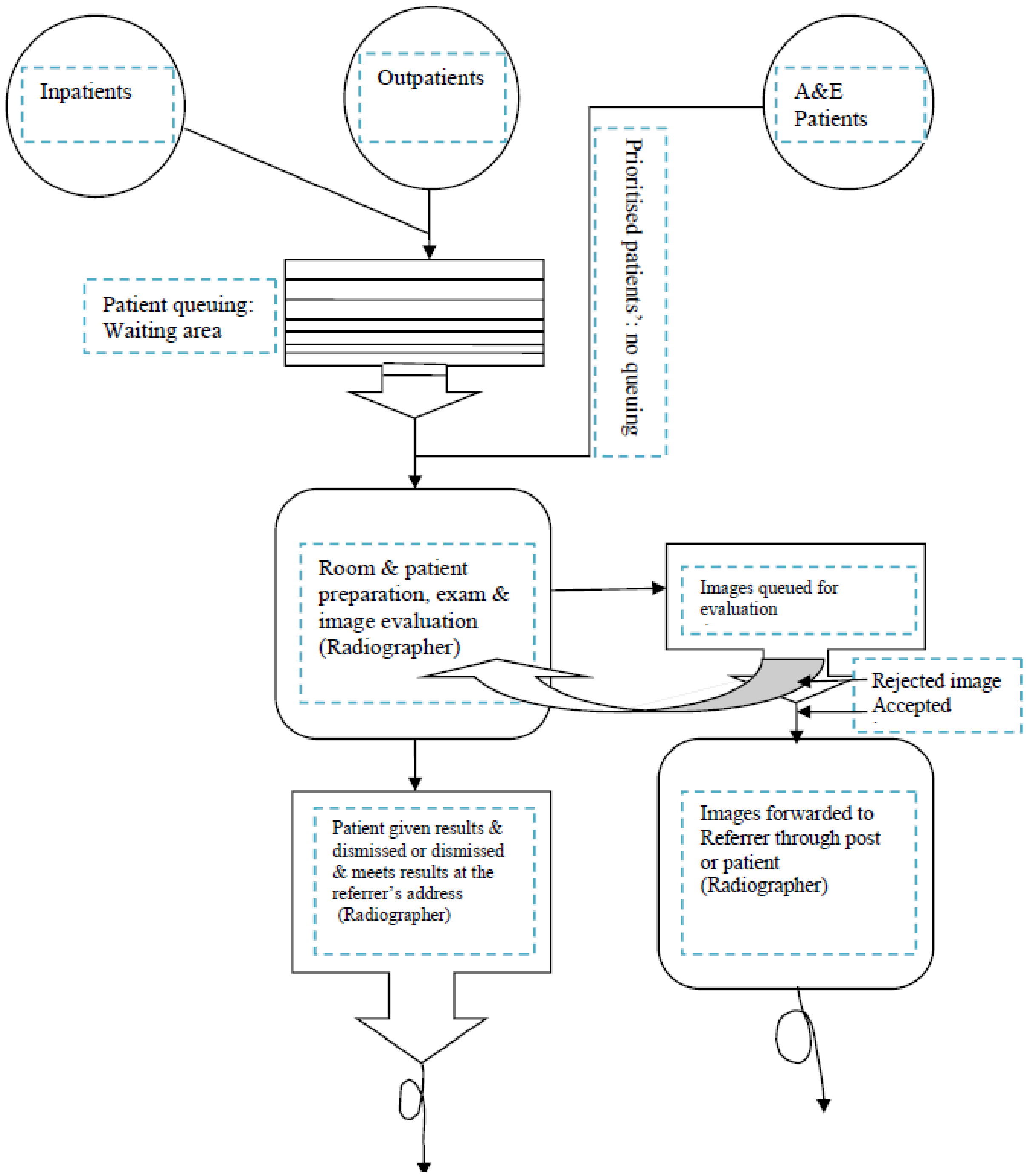

Figure 8.2: Common radiological patient care pathway

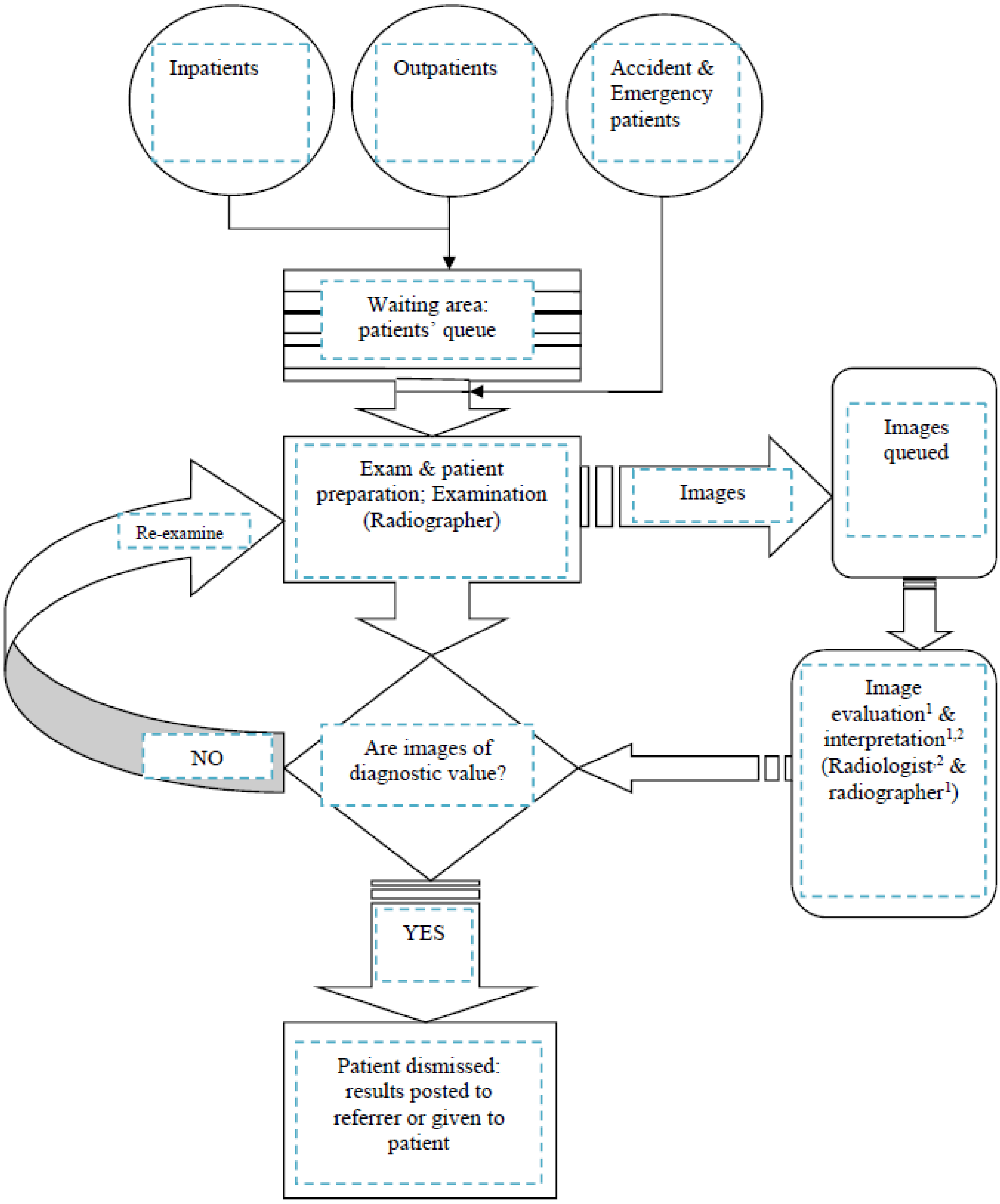

Figure 8.3: Patient care pathway with image reporting

Turning to the time series data, the observed small scale fluctuations were typical for real-time series data. This was evidence of long term seasonality. The observed short term seasonal nature of radiology demand was evidence that the time series exhibited some form of an annual periodicity. Lack of evidence of an upward growth alongside the lack of an upward series trend on the seasonal variations, was enough statistical evidence to rule out any suggestion that the seasonal variations were proportional to the level of the series. This implied that an additive model rather than a multiplicative model was at play. Detailed model output (Figure 5.5) illustrates the aforementioned assertions.

The fact that none of the three plots for ACF (Figure 5.6), among the three predictor series, remained significant for more than six lags means that all three rather quickly declined to zero thereby giving enough statistical evidence to conclude that the data represented stationary series. The observed exponentially declining ACF and spikes in the first one lag of the PACF were suggestive that autoregressive processes for this data were appropriate to describe the data and make predictions because the observed spikes were consistent with the order of the autoregression model. The fact that ACF alternated between positive and negative values was consistent with literature for ACF and PACF plots from pragmatic data. For the purposes of making judgement about seasonality, insignificant values were ignored.

There were no autocorrelation values that were suspected to be statistically significant by chance alone. Similarly, there were no statistically significant autocorrelations that were considered isolated at high lags, and that were also not occurring at seasonal lags. The significant peak at a lag of about 12 for axial examinations (Also barely touching the significant line for appendicular examinations) was suggestive of an annual seasonal component in the data. The lack of this peak for chest examinations suggested that there was a hidden force in the variation for the number of chest examinations. The significant peak at a lag of 12 in the partial autocorrelation function confirmed the presence of an annual seasonal component in the data. Results for the analysis in the frequency domain from Durbin-Watson test revealed that there was an independence of residuals ($p>0.05$ in all cases) and there was therefore enough statistical evidence to conclude that there was independence of observations across the predictor variables.

Model evaluation established that the observed number of patients, the number predicted by ARIMA and the number predicted by Multiple Regression were within error margins of each other, and there was no significant difference ($p< .05$) among the three aforementioned data sets. This was statistical evidence to conclude that the two selected models statistically significantly predicted (PAT). This means that the two models (Multiple Regression and ARIMA) could be used interchangeable to predict (PAT), with no significant loss or gain in the accuracy of the predictions.

In the trend plot, the somehow equally spaced peaks confirmed the presence of a periodic component to the time series. The location of small periodic peaks on the time domain was evidence that holidays played a great part in modelling the number of patients at the research sites. Evidence of Sharp, random and ill-defined peaks confirmed the existence of random (white) noise to the series. This noise component accounts for fluctuations in patient numbers due to accidents, equipment breakdowns and lack of consumables for example. Independence of residuals ($p>0.05$ in all cases) revealed by Durbin-Watson test was enough statistical evidence to confirm a seasonal pattern in the data. The fact that seasonal adjustment factors (SAF) showed that periods remained marginally at the same level of the series during the time horison for the study was enough statistical evidence to conclude that there was no meaningful growth in the utilisation of plain radiology during the time horison for the study. A trend that goes downwards and then upwards thereby representing a cycle was observed for the data set (Figure 6.3b.).

The seasonal nature of the number of patients seeking radiology services had highs lasting about two years and typically occurring after every two years. Spikes that were systematic with holidays were also observed. This confirmed the existence of an annual seasonal component to the data. There were also peaks that did not appear to be part of the seasonal pattern and which appeared to represent significant deviations from the neighbouring data points. These points were however considered insignificantly deviating because no statistical evidence emerged to support this assertion (The Expert Modeler had not identified them as outliers). In conclusion, there was enough statistical evidence to conclude that the models were in good agreement with the observed values so much that their individual predictive abilities were considered satisfactory for the analysis at hand.

Forecasting the number of patients for the research site for the next ten years are shown in Figure 6.6 in which a plot of the Adjusted Predicted Value and the Standard Error of Predicted Value are also provided. In conclusion with regard to the predicted number of plain radiology patients for the next ten years ending 2025, the radiology utilisation will remain subdued with marginal growth. Equipment and human resource levels that are adequate today should remain adequate for the next ten years with only marginal expected increases which have no consequence on staffing levels.

8.5 Limitations of the research process

While the developed theory did a good job of predicting the number of radiology patients and provide pertinent information in support of policy change regarding resource management, the study fell short of quantifying redeployment of human resources. Reviewing the scope of practice and curricula of radiographers was not the focus of this research. Inclusion of these components would have exposed specific needs for the existing radiography curricula against the dynamic nature of radiography practice to facilitate the implementation of the research findings.

8.6 Recommendations for further research

Overall recommendations can best be presented in the context of the Zimbabwe National Health Strategy (ZMOHCC, 2013). The foreword in the Zimbabwe Ministry of Health and Childcare's National Health Strategy (NHS 2009-2015) reads:

> *"Uncertainties over <u>resources</u> have made it difficult to set concrete targets to attain over the life of this strategy; however, a comprehensive Monitoring and Evaluation plan will be developed as an immediate first step to enable integrated monitoring of strategy implementation and impact"* (ZMOHCC, 2013).

Evidence from this dissertation may not have come at a better time than this. Drawing from the research outcomes, recommendations for the radiology patient care pathways are basically three fold: educate, capacitate and use informed management policies.

With respect to radiology departments, the ministry should at least for a ten year period, focus its investment on radiology equipment and, instead of increasing radiographic staff capacity, focus on evidence based redeployment to solve observed variation mismatches in demand and capacity. Investment should focus on reinstating existing x-ray examination rooms and fostering resource management skills. Further research must focus on what is causing the peaks and troughs in the demand and capacity in order to redeploy radiology staff to match the variations. Evidence based selection of Continuous Professional Development (CPD) activities is strongly recommended in order to foster immediate academic and technical competence of staff in radiology towards an understanding of time management and reflective practice. There is a need for the staff to appreciate what they can do internally to solve the problems before looking for external solutions. The Radiation Protection Authority of Zimbabwe should be engaged to assume more regulatory roles in stimulating improved completeness, accuracy and justification of exposures. Visibility of RPAZ regulatory activities should be enhanced.

It is not enough to have the scope of practice for radiographers being a topical issue among key stake holders in Zimbabwe (NUST, UZ, ZIMCHE and AHPC for example). Urgent action is recommended to blur role boundaries and promote synergy throughout radiology patient care pathways. This should be coupled with radiography education that is responsive to the dynamic nature of radiology practice trends (demands) in order to meet changing priorities such as e-Health. Strongly recommended is the adoption of e-Health which will ensure that the right health information is securely and electronically provided to clients at the right time thereby optimising the quality and efficiency of health care delivery as prescribed by the Ministry (ZMOHCC, 2009). It is only through this responsive training that an effective formalisation and regularisation of extended roles can have positive impact on the delivery of radiology services. However, ways will have to be defined to cater for those radiographers already in practice possibly by developing their skills over and above those developed during pre-registration education and training. The AHPC should therefore, research and avail a new modernised scope of pre-registration education so that proactive educational institutions can support and enable the widening scope of practice in the training of radiographers.

It is recommended that consideration of this policy shift be considered in line with the projected impact of role extension on the work load for radiographers. This calls for the use of predicted numbers of radiology patients together with the service transaction time that is associated with extended roles to define new demand to capacity ratios and therefore any new bottlenecks in the system. The number of people that are exposed to ionising radiation is also an issue (IAEA, 2010; IAEA, 2008; ICRP, 2007). However, carrying out man count has remained untenable and hence the extrapolations that have been used based on the number of available physicians. Because these extrapolations have been associated with limitations regards applicability to developing countries, it is recommended that the predictive power of linear regression based on the number of examinations per anatomical region be explored. This has the potential to simplify the counting of individuals exposed to radiation and therefore, make it possible to accurately compute associated man-sievets. Further analysis may also explore the applicability of time series estimates and number of films or exposures used.

Accurate prediction of patient numbers is pivotal in optimized resource deployment. In order to achieve equity as enshrined in the vision, mission and national health strategy as well as the constitution of Zimbabwe, it is recommended that the ministry prioritise evidence based redeployment of resources with the intention to realise optimised resource utilisation. The redeployment must be informed by accurate projections of radiology service demand as detailed in this dissertation. With all things being equal and because growth in the patient numbers is projected to remain subdued for the next ten years, the ministry should prioritise efficiency in redeployment and redistribution of existing resources. Mechanisms to consider in this distribution were explored in this dissertation: demand to capacity ratios. There remains great potential to improve service transaction time and quality of service for diagnostic radiology patients. Synergy at ministry level can be pivotal in accelerating these very important radiography issues which are hinged on radiography education programme review, role extension (skill mix) and rationalisation of activities done by radiographers. Research into CPD needs for radiographers may help guide the implementation process by identifying possible solutions and their impact on workloads associated with the practice of radiography.

Lest we forget the Zimbabwe Ministry of Health and Child Care wrote, in its National Health Strategy (2009-2015) that, *"its vision will be attained through guaranteeing every Zimbabwean access to comprehensive and effective health services"* all in the interest of furthering the mission of the Ministry of Health and Child Care:

MISSION STATEMENT

To provide, administer, coordinate, promote and advocate for the provision of equitable, appropriate, accessible, affordable and acceptable quality health services and care to Zimbabweans while maximizing the use of available resources, in line with the Primary Health Care Approach. (ZMOHCC, 2009)

All being said, the study of "Diagnostic radiology capacity and demand in Zimbabwe: trends and forecast" was fascinating. Philosophical evidence presented in this dissertation is intriguing but even more captivating is that, "*there is nothing more difficult to take in hand, more perilous to conduct, or more uncertain in its success, than to take the lead in the introduction of a new order of things. Because the innovator has for enemies all those who have done well under the old conditions and lukewarm defenders in those who may do well under the new...*" (Machiavelli 1469-1527).

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APPENDICES

Appendix A: Informed consent forms

i. Informed consent form and certificate (English version)

Cape Peninsula
University of Technology

Project Title: Diagnostic radiology capacity and demand in Zimbabwe: trends and forecast

Principal Investigator: Lidion Sibanda, Mr.

Phone number : 00263 772345775

What you should know about this research study:

- I will give you this consent so that you may read about the purpose, risks, and benefits of this research study.
- Routine radiological care is based upon the best known radiology examination protocols and is provided with the main goal of obtaining a specialist opinion on the diagnosis of an individual patient. The main goal of research studies is to gain knowledge that may help future patients.
- I cannot promise that this research will benefit you. Just like regular care, this research can have effects that can be serious or minor.
- You have the right to refuse to take part, or agree to take part now and change your mind later.
- Whatever you decide, will not affect your regular care or employment.

- Please review this consent form carefully. Ask any questions before you make a decision.

- Your participation is voluntary.

This Informed Consent Form has two parts:

Part I. Information sheet (to share information about the study with you)

Part II. Certificate of consent (for signatures if you choose to participate)

You will be given a copy of the full Informed Consent Form.

INFORMATION SHEET

PURPOSE

You are being asked to participate in a nationwide research on the justification, capacity and demand for radiology services in Zimbabwe**.** The purpose of the study is to develop a model for forecasting future utilization of radiology services.You were selected as a possible participant in this nationwide study because we feel that your status in this radiology department can contribute much to my understanding and knowledge of radiological patient care.

PROCEDURES AND DURATION

If you decide to participate, you will take part in an interview and also complete a questionnaire in a comfortable place of your choice. If you do not wish to answer any of the questions, you may say so or leave them unanswered. The collected data will be confidential and no one else will access it except members of the research team. Further to this I will review radiology administrative data that includes request forms, registers and policy documents as a non participant observer. The interview and the questionnaire will be over and above the standard procedure for the radiology department and will be done solely for the purposes of the study. The nationwide data collection period will be three years but I will be at this particular radiology department for two weeks solely to collect data.

RISKS AND DISCOMFORTS

There is a risk that you may share some personal or confidential information by chance, or that you may feel uncomfortable responding to some topics. I will endeavor that this does not happen by ensuring that you do not have to respond to any questions that make you uncomfortable.

BENEFITS AND/OR COMPENSATION

You will not be provided any incentives to take part in this research. Furthermore, we cannot and do not guarantee or promise that you will receive any direct benefits as a result of participating in this project but that your participation will help us to find out more about service delivery in your department and how we can better the allocation of resources. This will be of great importance in the improvement of health delivery system in Zimbabwe.

CONFIDENTIALITY

If you indicate your willingness to participate in this study by signing this document, we plan to disclose non biographic information for verification purposes to the research team and MRCZ ethics review board. Any information that is obtained in connection with this study that can be identified with you will remain confidential and will be disclosed only with your permission. Under some circumstances, the MRCZ may need to review patient records for compliance audits. We will not share information from you with anyone outside the aforementioned research team. Information identifiable with regard to agency name may only be listed in the evaluation report, that is, the information will not be listed in the thesis or any other future publications. We will also ask each of you to keep what was recorded in the questionnaires confidential. You should know, however, that I cannot prevent participants from sharing things that should be confidential.

ADDITIONAL COSTS

Your participation in this study will not add costs to you**.**

CERTIFICATE OF CONSENT: SIGNATURE PAGE

PROJECT TITLE: Diagnostic radiology capacity and demand in Zimbabwe: trends and forecast

Before you sign this form, please ask any questions on any aspect of this study that is unclear to you. You may take as much time as necessary to think it over.

AUTHORIZATION

You are making a decision whether or not to participate in this study. Your signature indicates that you have read and understood the information provided above, have had all your questions answered, and have decided to participate.

____ ____________

Name of Research Participant (please print) Date

____ ____________

Signature of Participant or legally authorized representative Time

____

Relationship to the Participant

__________________________ ________________ ____________

Name of Staff Obtaining Consent Signature Date

__________________________ ________________ ____________

Name of Witness (*if required*) Signature Date

YOU WILL BE OFFERED A COPY OF THIS CONSENT FORM TO KEEP.

If you have any questions concerning this study or consent form beyond those answered by the investigator, including questions about the research, your rights as a research participant or research-related injuries; or if you feel that you have been treated unfairly and would like to talk to someone other than a member of the research team, please feel free to contact the Medical Research Council of Zimbabwe (MRCZ) on telephone (04)791792 or (04) 791193 and cell phone lines 0772 433 166 or 0779 439 564. The MRCZ Offices are located at the National Institute of Health Research premises at Corner Josiah Tongogara and Mazowe Avenue in Harare.

ii. Informed consent form and certificate (IsiNdebele version)

Cape Peninsula University of Technology

Isihloko socwayisiso: "Diagnostic radiology capacity and demand in Zimbabwe: trends and forecast"

Ibizo lalowo ocwayisisayo: Lidion Sibanda, Mr.

Inombolo yocingo : 00263 772345775

Okumele ukwazi mayelana lecwayisiso le:

- Ngikunika lencwadi yesivumelwano ukuze ubale mayelana lenhloso, ingozi kanye lokuqakatheka kwalecwayisiso.
- Izigulane ezithola uncedo lwe "radiology" ziluphiwa ngendlela ephakeme kuhloswe ukutholakala kombono wengcitshi zalolugatsha mayelana lalokho okucatshangelwa ukuthi yiyonankinga yesigulani. Isiqokoqela socwayisiso yikwengeza ulwazi lobungcitshi olunganceda izigulane zakusasa.
- Angingeke ngikuthembise ukuthi uzathola lutho kulecwayisiso. Yebona ye kungenzeka ingozi ecwayisisweni le, lalobanje lengozi ingenzakala lakulabo abangekho kucwayisiso le.
- Ulelungelo lokuvuma kumbe ukuyala ukungena kulecwayisiso, kumbe njalo ukuvuma ukungena manje kodwa njalo ubuye ujikise ingqondo yakho lalabo nini.
- Laloba yisiphi isinqumo sakho lokhu akusoze kuphawule ukwelatshwa kwakho kumbe umsebenzi wakho.

- Ngicela uzwisise kuhle isivumelwano lesi. Ubuze imibuzo ongaba layo andubana ulobe isinqumo sakho.
- Ukungena kwakho kule cwayisiso kungentando yakho.

Lolugwalo lwesivumelwano esilemfundiso lulezigaba ezimbili:

Isigaba sakuqala: Ugwalo lolwazi (Luhlose ukufundisa mayelana lecwayisiso le)

Isigaba sesibili: Isithupha sesivumelwano (Sihlose ukulobelana phansi lawe uma uvuma ukungena kucwayisiso le)

UGWALO LOLWAZI

INHLOSO YOCWAYISISO

Ucelwa ukuthi ungene kucwayisiso yeZimbabwe jikelele ekhangela ubuqotho bezizatho zokuhlaziya izigulane ngamagagasi, ubunengi bezigulane ezihlaziywa ngamagagasi kanye lenengi yezigulane ezande ukudinga uncedo lwe"radiology". Inhloso yocwayisiso lolu yikukhombisa okulobungcitshi ukuthi ngeminyaka ezayo lolugatsha lwezempilakahle luzabe luhlola izigulane ezinengi okungakanani. Ukhethwe njengomunye walabo abangangena kulecwayisiso ngoba ngilethemba lokuthi ulwazi lwakho lungaphathisa ekuzwisiseni kwami isiphatho sezigulane kugatsha lwe"radiology".

OKUZAYENZAKALA

Uma ungavuma ukungena kulecwayisiso ngizakubuza imibuzo elotshiweyo njalo ngixoxe lawe endaweni epholile ekhethwe nguwe. Uma ungafuni ukuphendula laloba yiwuphi umbuzo uzatsho kumbe uyekele ukuphendula. Impendulo ngizazigcina mfihlo okutsho ukuthi akula omunye ozazibona ngaphandle kwalabo abaphathelane lecwayisiso le. Phezu kwale imibuzo ngiza hlolisisa ingwalo zezigulani kanye lemithetho yezibhedlela (request forms, registers and policy documents). Imibuzo yami kanye lengxoxo yami lawe ingaphandle kwemibuzo ebuzwa abangekho ecwayisisweni le okutsho ukuthi iqondane lecwayisiso le kuphela. Icwayisiso yeZimbabwe jikelele iza thatha phose iminyaka emithathu kodwa ngizacwayisisa esibhedlela sinye ngasinye okwamaviki amabili kuphela.

INGOZI ENGABAKHONA ECWAYISISWENI

Kungenzekala ukuthi ulobise infihlo ungazimisele kumbe uzwe ungakhululekanga ukuphendula eminye imibuzo. Ngizayenza konke engikwenelisayo ukuze lokhu kungenzeki ngokunanzelela ukuthi awuphenduli imibuzo ekwenza ungakhululeki.

IMBHADALO LOKUQAKATHEKA KWECWAYISISO LE

Awusose uthole imbadalo ngokungena kucwayisiso le. Phezu kwalokhu, angingeke ngikuthembise ukuthi uzathola inzuzo yokungena kucwayisiso le kodwa ukungena kwakho kuzanginceda ukuzwisisa ngesiphatho sezigulani lokuthi lapha okuphambaniseka khona kungalungisiswa njani ikakhulu ngokwaba inotho yezibhedlela. Lokhu kuqakathekile kakhulu kugatsha lwezempilakahle

IMFIHLO

Uma ungatshengisa isifiso sakho sokungena kucwayisiso le ngokuloba uphawu lwakho (Signature) kusithupha sokuvumelana ngizakwabelana ulwazi onginike lona lalabo abancedisana lami kucwayisiso le. Ngikhangelele ukwabelana ulwazi olungeke lukhombise ibizo lakho labe “MRCZ ethics review board” inhloso kuyikubanika amandla okuhlolisisa ubuqotho becwayisiso le. Ulwazi olutholakale kulecwayisiso olungakhombisa ibizo lakho luzabayimfihlo kodwa luza bonakala uma uvumelane lalokho. Kwandile ukuthi ingcitshi ezihlola ubuqotho becwayisiso (umzekeliso i”MRCZ”) zicele ukuhlolisisa ubuqotho lobu. Angisoze ngembule infihlo kuloba ngubani ongaphandle kwalezingcitshi. Ulwazi olungakhombisa ibiso lesibhedlela luzalotshwa kuphela kusifinqo sogwalo locwayisiso oluqodane lesibhedlela. Lokhu kutsho ukuthi lolulwazi alusoze lulotshwe kungwalo zomphakathi. Ngizacela njalo ukuthi bonke abazangena kucwayisiso bangembuli infihlo yengxoxo kumphakathi. Kodwa ngicela uzwisise ukuthi angeke ngenelise ukuvikela bonke abangene kucwayisiso ukwambula infihlo.

UKWENGEZA IMBADALO

Ukungena kwakho kule cwayisiso akusoze kwengeze indleko kuwe**.**

ISITHUPHA SESIVUMELWANO: "SIGNATURE PAGE"

ISIHLOKO SOCWAYISISO: "Diagnostic radiology capacity and demand in Zimbabwe: trends and forecast"

Ungakalobi uphawu lwakho (signature), ngicela ubuze imibuzo ongaba ulayo mayelana lecwayisiso le. Ulelungelo lokuthatha isikhathi osifunayo ucabanga isibopho sakho ngaloludaba.

ISIVUMELWANO

Lapha wenza isivumelwano sokungena kumbe ukungangeni kucwayisiso le. Ukuloba uphawu lwakho (signature) kulolu ugwalo kukhombisa ukuthi ubalile wazwisisa ulwazi oluphiweyo mayelana lecwayisiso le njalo imibuzo yakho yonke iphenduliwe okugcweleyo kungakho ukhetha ukungena kucwayisiso le.

____ ____________

Ibizo lalowo ongena kucwayisiso (Bhala kucace) Date

____ ____________

Uphawu lwalowo ongena kucwayisiso Time

("Signature of Participant or legally authorized representative")

____

Ubuhlobo longene kucwayisiso

_________________________ ____________ ____________

Ibizo lalowo ocwayisisayo Signature Date

_________________________ ____________ ____________

Ufakazi Signature Date

UZAPHIWA INCWADI YOFAKAZI YALESISIVUMELWANO UKUZE UYIGCINE.

Uma ulemibuzo mayelana lecwayisiso le kumbe ugwalo lwesivumelwano lesi engaphezu kwaleyo ephendulwe ngocwayisisayo, okungagoqela eyesiphatho osiphiweyo kumbe ma ulombono wokuthi awuphathwanga kuhle kungakho ufisa ukukhuluma lomunye ongekho phakathi kocwayisiso, ngicela ukhululeke ukuxoxa le"Medical Research Council of Zimbabwe (MRCZ)" kucingo (04)791792 kumbe (04) 791193 kumbe 0772 433 166/0779 439 564. Amahofisi e"MRCZ" atholakala ku "National Institute of Health Research premises at Corner Josiah Tongogara and Mazowe Avenue" eHarare.

iii. Informed consent form and certificate (Shona version)

Cape Peninsula
University of Technology

Musoro wetsvakiridzo: "Diagnostic radiology capacity and demand in Zimbabwe: trends and forecast"

Arikuita tsvakiridzo iyi : Lidion Sibanda, Mr.

Runhare : 00263 772345775

Zvamunofanira kuziva pamusoro petsvakiridzo iyi:

- Ndirikukupa gwaro iri rinedzidziso kuitira kuti uwane ruzivo pamusoro pechinangwa, njodzi uyezwe nekukosha kwetsvakiridzo iyi.
- Wongororo yevarwere pachishandiswa "radiology" inoitwa navana mazvikokota pachishandiswa gwara repamusoro, dodzvo ririrokuti pabude zvinenge zvichifungidzirwa kuti ndiro dambudziko remurwere. Chinangwa chetsvakiridzo iyi ndechekuwana dzidzo yakawedzerwa inogona kuzobatsira varwere vemangwana.
- Handingavimbisi kuti uchawana zvingakubatsira mukuva mukati metsvakiridzo iyi. Hongu pane njodzi inogona kuitika mutsvakiridzo iyi kunyange njodzi iyi ichigona zve kuitika kune avo vasina kupinda mutsvakiridzo iyi.

- Isarudzo yenyu kuva mumwe wevachapinda mutsvakiridzo kana kuti kwete. Munotenderwa kubuda mutsvakiridzo chero zvazvo muchinge mambobvuma kupinda.
- Sarudzo yamuchaita haina zvaichashandura pabasa renyu kana nekuongororwa kwenyu.
- Ndapota, wongororai zvakanaka gwaro iri rekubvuma kupinda mutsvakiridzo. Kana muine mibvundzo bvunzai musati masarudza kupinda kana kusapinda mutsvakiridzo.
- Chido chenyu kusarudza kupinda mutsvakiridzo iyi.

Gwaro iri rekubvuma kupinda mutsvakiridzo rine zvikamu zviviri:

Chikamu chokutanga: Tsanangudzo (Chikamu ichi chinopa ruzivo kwamuri pamusoro peongororo netsvakiridzo yandiri kuita.)

Chikamu chechipiri: Kutaridza kuti mabvuma kuti munoda kuva mumwe wevachapinda mutsvakiridzo iyi (Munokumbirwa kuzoisa rupawo rwenyu kana kuti siginecha kuratidza kuti manzwisisa uye matenda kupinda mutsvakiridzo).

TSANANGURO PAMUSORO PETSVAKIRIDZO IYI

CHINANGWA CHETSVAKIRIDZO

Ndiri kukukumbirai kuti muve mumwe wevachapinda mutsvakiridzo yenyika yose yemuZimbabwe yekuongorora kodzero, kudiwa, kuwanikwa, uye kukosha kunoita “radiology” muZimbabwe. Donzvo rangu nderekuti tigokwanisa kubuda neurongwa hwunotaridza kuti munguva inotevera “Radiology” inenge ichidiwa zvakadii uye neuwandu hwakadii munyika yeZimbabwe. Masarudzwa kuti muve mumwe anogona kupinda mutsvakiridzo iyi nokuti ndinobvuma kuti ruzivo rwenyu nekunzwisisa kwenyu mubazi iri runogona kundibatsira zvikuru mukunzvisisa bazi re”radiology”.

MAITIRWO ETSVAKIRIDZO

Kana mukatenda kupinda mutsvakiridzo iyi, mucha pindura mibvunzo yakanyorwa papepa uye ndichazodawo kuita hurukuro nemi panzvimbo yamunozvisarudzira yamunonzwa makasununguka muri. Kana musingadi kupindura mimwe yemibvunzo munogona kutaura kana kuti munoyisiya isina kupindurwa. Zvose zvatichawana mutsvakiridzo hazviratidzwe vamwe vanhu kunze kwe avo varikuita tsvakiridzo neni kana kuti vanamazvikokota mukuwongorora kuti zvabuda mutsvakiridzo zvakanyorwa nemazvo. Hurukuro iyi uyezve nemibvunzo yakanyorwa papepa handiyo mibvunzo inobvunzva vasiri mutsvakiridzo. Pamusoro pazvo ndichatarisawo magwaro anoratidza mashandiro anoita bazi re"radiology" ndichitarisa mapepa anobva kunana chiremba, mabhuku anonyorerwa varwere (request forms and registers) nemagwaro ane mitemo yechipatara. Izvi ndichazviita nekutarisa koga pasina zvandinobvunza kana kuita. Ndirikutarisira kuti tsvakiridzo iyi ichatora makore matatu asi pachipatara chimwe nechimwe ndichatora mavhiki maviri ndichiita tsvakiridzo iyi.

NJODZI INGAVA MUTSVAKIRIDZO

Pane njodzi yokuti munogona kukanganisa motaura zvinhu zviri pedyo nemoyo wenyu kana kuti zvamusingadi kuti zvizikanwe, kana kuti munogona kusasununguka kupindura mimwe mibvunzo. Ndichaedza chose kuti izvi zvisaitika nekuona kuti hamuwanikwe muchipindura mibvunzo yamusina kusununguka kupindura.

MUBHADHARO NEKUKOSHA KWETSVAKIRIDZO IYI

Hamuna mubhadharo wamuchapiwa kuti muve mukati metsvakiridzo iyi. Zvichakadaro, handivimbisi kuti pane zvamuchawana mukuva mukati metsvakiridzo iyi asi umbowo hwamuchandipa hwuchandibatsira kuziva mashandiro ebazi re"radiology" uye kuti zvinhu zviripo zvingashandiswa sei zvakanaka. Izvi zvichabatsira mukuronga zviwanikwa zvakakosha zvinoshandiswa mubazi re"radiology".

KUSAFUMURA NEKUCHENGETEDZA RUZIVO RWABUDA MUTSVAKIRIDZO.

Kana maratidza kuda kupinda mutsvakiridzo iyi nekunyora rupawo kana kuti siginecha yenyu mugwaro iri, ndine hwurongwa hwekugova ruzivo runogona kushandiswa kuwongorora chokwadi chezvinenge zvabuda mutsvakiridzo iyi nevamwe varikubatsirana neni patsvakiridzo uyezve ne MRCZ. Ruzivo runogona kunongedza zita rako handizorufumuri kunze kwekuti wandisunungura kuita saizvozvo. Izvi zvinogona kuitika kana MRCZ yada kuwongorora chokwadi cheruzivo rwandinenge ndanyora. Zvisinei, ruzivo rwakadai handingorufumuri kuna ani zvake kunze kweivava vandataura. Ndinovimbisa zvakare kuti ruzivo runogona kunongedza chipatara ichi ruchanyorwa mugwaro runopa ruzivo muchipatara ichi chete. Munoziva kuti, handina masimba anogona kuita kuti ani zvake apinda mutsvakiridzo iyi asafumura zvaanenge anzva muhurukuro dzetsvakiridzo.

KUBHADHARA KUPINDA MUTSVAKIRIDZO

Kupinda mutsvakiridzo iyi hakuwendzeri mubhadaro wamunotarisirwa kubvisa.

CHITUPA CHEKUBVUMA KUPINDA MUTSVAKIRIDZO: GWARO RERUPAWO

MUSORO WETSVAKIRIDZO: "Diagnostic radiology capacity and demand in Zimbabwe: trends and forecast"

Musati maisa rupawo rwenyu mugwaro iri ndapota bvunzai mibvunzo yamungava nayo pamusoro petsvakiridzo iyi. Munogona kutora chero nguva yamunoda muchifunga nezvazvo.

KUBVUMA KUPINDA MUTSVAKIRIDZO

Murikuita fungwa yekuti muchipinda kana kuti kwete mutsvakiridzo iyi. Rupawo rwenyu mugwaro iri runoreva kuti maverenga zvizere mukanzvisisa, uyezve mibvunzo yenyu yese ikapindurwa zvizere mukagutsikana ndosaka masarudza kupinda mutsvakiridzo iyi.

____ ____________

Zita remupinduri arikubvuma kupinda mutsvakiridzo (Nyora Zvakanaka) Date

____ ____________

Rupawo remupinduri Time

____

Vukama Nemupinduri

______________________________ ________ ______________

Zita remushandi akumbira chibvumirano Rupawo Date

______________________________ ________ ______________

Zita reavo vange varipo Rupawo Date

KANA MADA TSAMBA YENYU YEKUBVUMA YAMUNOSARA NAYO MUCHAPIWA

Kana muine mibvunzo yakanangana netsvakiridzo iyi kana kuti negwaro iri rinedzidziso yekubvumirana isina kupindurwa zvizere ne avo varikuita tsvakiridzo zvichibatanidza nemibvunzo yakanangana netsvakiridzo, kodzero yenyu, njodzi ingangoitika, kana kuti mune mawonero ekuti hamuna kubatwa nehunhu izvo zvichiita kuti mushuvire kutaura nemumwe asiri weavo varikuita tsvakiridzo, ndapota munogona kutaura neve"Medical Research Council of Zimbabwe" (MRCZ) murunhare (04)791792, (04) 791193 kana kuti 0772433166 or 0779439564. Ve"MRCZ" vanowanikwa ku"National Institute of Health Research premises" pa-Corner Josiah Tongogara na Mazowe Avenue kuHarare.

Appendix B: Final data collection instruments

i. COVER PAGE QUESTIONNAIRE

Diagnostic radiology capacity and demand in Zimbabwe: trends and forecast.

This questionnaire has been designed to collect views of those knowledgeable in diagnostic radiology from selected hospitals across Zimbabwe. This is in order to identify variables introduced to the Zimbabwe healthcare system between July 2004 and July 2014 that might have had an impact on demand for radiology services.

This questionnaire component is part of a research project towards a Doctor of Technology in Radiography at the Cape Peninsula University of Technology in South Africa. The aim of the study is to develop a predictive model for forecasting the demand for diagnostic radiology services in Zimbabwe.

For your interest, further analysis is proposed to establish accuracy, justification, demand trends and the impact the identified variables might have had on data collected for the months July 2004 to July 2014.

Thank you for your input.

Lidion Sibanda

March 2014

The following information request is <u>optional</u> and respondents are free to withdraw at any stage of the research. The returned questionnaires will be treated according to ethical standards of anonymity. No identities will be known and no respondents will be identifiable in any publication.

ii. Questionnaire (Piloted)

1. i. Please indicate your line of profession: ....

   ii. Years of experience: ....

2 Please indicate number of radiology request forms/frameworks designs that are in use in your department?

[………]

3 Please indicate CPD courses that you may have attended and year

Year	Area covered
1.	
2.	
3.	

4 What is the average service transaction time for:

Accounts [.......]

Registration [.......]

Equip. prep. [........]

Positioning [........]

Examination [.........]

Image processing [.......]

Image interpretation [.........]

Patient dismissal [.......]

5 i. What would you consider as bottlenecks in the provision of the radiology services?

Accounts [ ] Registration [ ] Patient factors [ ] Equip. prep. [ ] Positioning [ ] Equip. capacity [ ] Personnel capacity [ ] Image processing [ ] Image interpretation [ ]

Policy factors (explain):...

Other (Explain): ………..

ii. Which stage in the patient pathway generally has the longest queue?
Accounts [ ] Registration [ ] Patient prep. [ ] Imaging rooms [ ] Image

interpretation [ ] Dismissing [ ]

iii. Which part of the patient pathway generally has the longest waiting time?

Accounts [ ] Registration [ ] Patient prep. [ ] Imaging rooms [ ] Image interpretation [ ] Dismissing [ ]

6. i. What is the average number of patients per day that are sent away without receiving radiology service?

Accounts related problem [ ]

Equipment related problems [ ]

Personnel related problems [ ]

Consumables related problems [ ]

Other (explain):
…………………………………………………..
....
....

ii. What is the average number of patients per day received on call? ....

If any of the correspondents completing this survey are interested in obtaining results of this study please feel free to contact me at:

lidionsibanda@gmail.com

A BIG THANK YOU TO ALL WHO TOOK THE TIME TO COMPLETE AND RETURN THIS QUESTIONNAIRE.

iv. Interview questions: English (Patients)

Where did you get this request for radiology from? ....

What was the clinical diagnosis made by your doctor?
....

What is the clinical history of your current condition? (Key words: indications for requested radiology)
....

....
....
....

What is your family history regards this clinical condition?
....

If radiology results confirm or reject the diagnosis what will be the next step in the management of your clinical condition?
....

How do you think this requested examination can help your clinical situation?
....
...

Did you suggest this to your referring doctor before he could write the radiology request?
....

v. Interview questions: Ndebele (Patients)

Udokotela okulobele lesi isicelo sokuba uhlolwe nge ”x-ray” ngowasiphi isbhedlela?
....

Udokotela wakho ubecabanga ukuthi ungabe ukhathazwa yini?
....

Ngicela ungilandisele inganekwana yokugula kwakho okukulethe esibhedlela namhlanje?
....
....
....
....

Ngicela ungilandisele ukwazi ukuthi izihlobo zakho zingaki ezake zehlelwa yiloludubo okhangelane lalo? ....

Kambe ma impumelo ye”X-ray” ingatsho ukubana ukhathazwa yini, ungabe ulolwazi olunganani lokuthi okuzalandela kungaba yintoni ekulatshweni kwakho?
....

Wena ngokwakho ungaba lolwazi olunganani ukuthi impumela ye-“X-ray” ingakunceda ngani kulolu daba?
....
...

Kambe ungabe ukhombise udokotela wakho lolu lwazi andubana ebhale isicelo se”X-ray”?
....

vi. Interview questions: Shona (Patients)

Pepa rinokumbira kuti muitwe “X-ray” makarinyorerwa muchipatara chipi?
....

Chiremba wenyu aifungidzira kuti muriku netswa neyi?
....

Ndinokumbira kuti mundiwudze nhoroondo yekurwara kwenyu?
....
....
....
....

Ndino kumbira kuti mundiwudze kana pane hama dzenyu ngani dzakambo wirwa netambudziko serenyu iri? ....

Kana zvichabuda pama ”X-ray” zvichenderana kana kusaenderana nezvanga zvichifungidzirwa na chiremba wenyu mberi muchirapwa sei?
....

Imimi pachenyu muneruzivo here kuti hongoro iyi inogona kukupatsirai sei patambudziko ramunaro?
....
...

Makapa here chiremba wenyu mazano okuti mutorwe “X-ray” asati akunyorerai pepa iri?
....

vii. Interview questions (Radiographers)

What information do you consider a “must have information” in request forms?
....

What do you understand by “clinical diagnosis”? ....

What do you understand by “clinical indication as referred to in radiology examinations”?
....

How may documented treatment plan for radiology patients help in the justification of exposures?
....
...

How does the clinical history of a patient help you in managing radiology patients?
....
....
....
....

What is your role in radiation protection to patients especially with respect to justification of requests? ....

What is your opinion in radiographing self referral patients?

....
...

What do you consider important regards reducing unwanted radiology examinations?

....

How does radiography practice compare with radiography curricula?

....

....

How does radiography practice compare with radiography scope of practice?

....

....

viii. Patient Statistics instrument

Part A. Month on month statistical data: Year.................................

Data collection centre code: **............**	Health care Level		Province		District		
Number of radiologists:	Number of radiographers:...............			X-ray operators		....	
Number of hand-offs in pathway	1..........	2.......	3...........	4.......	5.......	6.......	
Who is involved at each of these levels? e.g. Admin.							
Doing what? e.g. patient registration							
Eqpment involved at each of these levels e.g pII comp							
Month on month statistical data number of patients							

	Master code					
	Month Number					
Total number of patients for the month						
Distribution by age	0-16					
	16+(Adult)					
Distribution by sex	Male					
	Female					
Distribution by anatomical region	Appendicular					
	Axial					
	Chest					
	Other					

Incidental discoveries	....	

ix. Part B. Identification of bottlenecks in the system: Year..

Data collection centre code:	Health care Level	Province	District	

Number of radiologists:	Number of radiographers	
Number of nurses:	Number of x-ray operators	

Number of hand-offs in pathway	1..........	2.......	3...........	4.......	5.......	6.......	7....... .
Doing what? e.g. patient registration							
Eqpment involved at each of these levels e.g pII comp							

Patient I.D. code													
Referred: Number of days ago													
Patient’s information	0-16yrs												
	16+(Adult)												
	Male												
	Female												
	Ambulant												
Waiting time:	Level 1												
	2												
	3												
	4												
	5												
	6												
	7												
Service time:	Level 1												
	2												
	3												

	4												
	5												
	6												
Dismissal	level 7												
Region examined	Appendicular												
	Spine												
	Head												
	Chest												
	Abdomen												
	Multiple												
Exam performed													
Exam rebooked													
Patient examined & refereed													
Patient sent back without exam													

x. Justification of requests instrument (Plain skull)

Refined IAEA and WHO minimum radiological examination request information	***Researcher generated Request form ID.***												
Patient & exam information provided on request form.	1. i. Name												
	ii. Surname												
	2. Age												
	3. i. Contact e.g Hosp. No.												
	ii. Address												
	4. i. Pregnancy status/ LMP												
	ii. Sex												
	5. Allergies												
	6. i. Study requested												
	ii. Accuracy												
	7. i. Clinical history												
	ii. Clinical indication												
	iii. Clinical diagnosis												
	8. Date of request												
	9. X ray number												
	10.Number of Films taken												
	11. Previous x-rays												
	12. Surgical operations												
	13. Walking/stretcher/chair												
Referrer identification provided on request form	14. i. Name												
	ii. Surname												
	15. Contact/ bleep no.												
	16. Signature												
	17. Legibility												

Justification of examination on request form **(**Skull trauma cases)	**18. Exam Justified**												
	At least one positive justifies exam												
	Loss of consciousness												
	Neurological symptoms												
	Fluid through nose/ ear												
	Penetrating injury												
	Alcohol intoxicated												
	Patient vomited												
	Difficult patient												
	Blood through ear/nose												
Justification of examination on request form (Skull -non trauma cases)	Chronic headache with abnormal results on clinical examination												
	Hearing loss												
	Suspected SOL												
	Paranasal Sinusitis >3yrs												
	Police investigations												
NOTES	**Form field completed but not readable will be given zero score. Uncompleted Form field whether applicable or N/a will be given zero score.No form field and information not supplied will be given zero score. No form field but information included elsewhere will be given score of 1.**												

RRF Code	Notes	Comments
	Other: To include any observed justification criterion that was not included in listed criterion	

Appendix C: Descriptive statisctics for multiple imputation

Descriptive statistics –ChestTendency

Data	Imputation	N	Mean	Std. Deviation	Minimum	Maximum
Original Data		129	1622.74	628.716	338.00	2926.00
Imputed Values	1	3	2235.20	504.251	1673.49	2648.83
	2	3	1834.67	330.283	1493.41	2152.75
	3	3	1663.21	302.323	1380.16	1981.68
	4	3	2119.55	334.052	1754.47	2409.92
Complete Data After Imputation	1	132	1636.66	631.275	338.00	2926.00
	2	132	1627.56	623.620	338.00	2926.00
	3	132	1623.66	622.627	338.00	2926.00
	4	132	1634.04	627.263	338.00	2926.00

Descriptive statistics –AppendicTendency

Data	Imputation	N	Mean	Std. Deviation	Minimum	Maximum
Original Data		130	603.81	248.181	128.00	1255.00
Imputed Values	1	2	985.37	52.056	948.56	1022.18
	2	2	843.68	172.716	721.55	965.80
	3	2	636.54	204.851	491.69	781.39
	4	2	824.43	49.735	789.26	859.59
Complete Data After Imputation	1	132	609.59	250.725	128.00	1255.00
	2	132	607.44	248.488	128.00	1255.00
	3	132	604.30	246.961	128.00	1255.00
	4	132	607.15	247.798	128.00	1255.00

Descriptive statistics –AxialTendency

Data	Imputation	N	Mean	Std. Deviation	Minimum	Maximum
Original Data		129	228.16	91.332	35.00	552.00
Imputed Values	1	3	344.75	22.374	325.61	369.35
	2	3	323.88	68.756	283.63	403.27
	3	3	211.60	52.801	152.51	254.16
	4	3	317.73	15.185	300.23	327.42
Complete Data After Imputation	1	132	230.80	91.991	35.00	552.00
	2	132	230.33	91.803	35.00	552.00
	3	132	227.78	90.549	35.00	552.00
	4	132	230.19	91.288	35.00	552.00

Appendix D: Model estimate for predictor variables

<?xml version="1.0" encoding="UTF-8"?>

- <TSCXML xmlns="**http://www.ibm.com/software/analytics/spss/xml/components/time-series**" xmlns:xsi="**http://www.w3.org/2001/XMLSchema-instance**" xsi:schemaLocation="**http://www.ibm.com/software/analytics/spss/xml/components/time-series www.ibm.com/software/analytics/spss/xml/components/time-series-1.0.xsd**">

- <Header>

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</Header>

- <DataDictionary>

- <DateSpecification dateSpecID="**1**" dateSpecDescriptor="**Date specification derived from Statistics time-series date variables**">

- <Periods>

<YearfirstCaseIndex="**2003**" />

<MonthcycleLength="**12**" firstCaseIndex="**0**" />

</Periods>

</DateSpecification>

</DataDictionary>

- <ARIMAModel modelName="**Model_1**" modelDescriptor="**AppendicTendency_ARIMA**" variableID="**AppendicTendency**" dateSpecID="**1**" seasonLength="**12**">

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</ConstantTerm>

- <PredictorEffect variableID="**MONTH_**">

- <Numerator>

- <NonSeasonalFactor>

- <ZeroLagTerm>

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</ZeroLagTerm>

</NonSeasonalFactor>

</Numerator>

</PredictorEffect>

- <ARIMACLSState periodDeficit="0">

<PredictorState/>

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</ARIMACLSState>

- <EstimationInfo periodStartIndex="0" periodLength="132" degreesOfFreedom="130">

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<Statistic type="maxAbsPctErr">366.896124708625</Statistic>

<Statistic type="maxAbsErr">652.995973723247</Statistic>

<Statistic type="rSqr">0.000419816145187182</Statistic>

<Statistic type="normBayesIC">11.0979575265761</Statistic>

<Statistic type="logLikelihood">-913.874628053822</Statistic>

<Statistic type="akaikeIC">1831.74925610764</Statistic>

<Statistic type="bayesIC">1837.51485995282</Statistic>

<Statistic type="stationaryRSqr">0.000419816145187182</Statistic>

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</EstimationInfo>

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- <ARIMAModel modelName="Model_2" modelDescriptor="AxialTendency_ARIMA" variableID="AxialTendency" dateSpecID="1" seasonLength="12">

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    </NonSeasonalFactor>
    </Numerator>
    </PredictorEffect>
-<ARIMACLSState periodDeficit="0">
  <PredictorState/>
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-<EstimationInfo periodStartIndex="0" periodLength="132" degreesOfFreedom="130">
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  <Statistic type="meanSqrErr">8201.85555691395</Statistic>
  <Statistic type="rootMeanSqrErr">90.5640964009135</Statistic>
  <Statistic type="meanAbsPctErr">49.4801038031355</Statistic>
  <Statistic type="meanAbsErr">69.3904172044668</Statistic>
  <Statistic type="maxAbsPctErr">575.773620319075</Statistic>
  <Statistic type="maxAbsErr">313.306632761178</Statistic>
  <Statistic type="rSqr">0.00691542840905302</Statistic>
  <Statistic type="normBayesIC">9.08609754239365</Statistic>
  <Statistic type="logLikelihood">-781.091869097779</Statistic>
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  <Statistic type="bayesIC">1571.94934204073</Statistic>
  <Statistic type="stationaryRSqr">0.00691542840905302</Statistic>
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</ConstantTerm>

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<Statistic type="maxAbsPctErr">353.750637922236</Statistic>

<Statistic type="maxAbsErr">1273.24941724942</Statistic>

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<Statistic type="normBayesIC">12.9512122363477</Statistic>

<Statistic type="logLikelihood">-1036.18943889875</Statistic>

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<Statistic type="bayesIC">2082.14448164267</Statistic>
<Statistic type="stationaryRSqr">0.00886829764482066</Statistic>
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  </EstimationInfo>
  </ARIMAModel>
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- <ConstantTerm>
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  </ConstantTerm>
- <PredictorEffect variableID="MONTH_">
- <Numerator>
- <NonSeasonalFactor>
- <ZeroLagTerm>
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  </NonSeasonalFactor>
  </Numerator>
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<Statistic type="stationaryRSqr">0.00565635745102859</Statistic>

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Appendix E: Model estimate for criterion variable (Seasonal decomposition model)

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- <TSCXML xmlns="http://www.ibm.com/software/analytics/spss/xml/components/time-series" xmlns:xsi="http://www.w3.org/2001/XMLSchema-instance" xsi:schemaLocation="http://www.ibm.com/software/analytics/spss/xml/components/time-series www.ibm.com/software/analytics/spss/xml/components/time-series-1.0.xsd">

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- <DataDictionary>

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<MonthcycleLength="12" firstCaseIndex="0" />

</Periods>

</DateSpecification>

</DataDictionary>

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- <ESSimpleSeasonal seasonLength="12">

- <ParmLevel>

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</ParmLevel>

- <ParmSeason>

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</ESSimpleSeasonal>

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<Statistic type="meanAbsErr">555.328050313627</Statistic>

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<Statistic type="stationaryRSqr">0.565761644631206</Statistic>

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</ExpSmoothingModel>

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- <ESSimpleSeasonal seasonLength="12">

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- <ParmSeason>

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<StateSeason phase="11">-103.193359529518 -50.1930528062002 -41.0111427321397 47.3525208937582 -415.920198326118 36.1707123963929 -78.46565377999 -86.647481793085 125.443394064044 498.443281139662 203.806541055531 -149.364576555306</StateSeason>

</ESSimpleSeasonal>

- <EstimationInfo periodStartIndex="0" periodLength="131" degreesOfFreedom="129">

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\- <ESSimpleSeasonal seasonLength="**12**">

\- <ParmLevel>

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\- <ParmSeason>

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-<ESSimple>

-<ParmLevel>

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<Statistic type="**meanAbsPctErr**">**23.2666644019028**</Statistic>

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<Statistic type="**maxAbsErr**">**3.30857727552191**</Statistic>

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<Statistic type="**normBayesIC**">**-0.208940411886916**</Statistic>

<Statistic type="**logLikelihood**">**-166.634559956003**</Statistic>

<Statistic type="**akaikeIC**">**335.269119912007**</Statistic>

<Statistic type="**bayesIC**">**338.128932316368**</Statistic>

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</EstimationInfo>

</ExpSmoothingModel>

</TSCXML>

Appendix F: Statistics and Ten year Forecasts for total number of patients

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DATASET NAME DataSet1 WINDOW=FRONT.

DESCRIPTIVES VARIABLES=Site_one Site_two Site_Three Site_four Site_five Total_of_sites

/STATISTICS=MEAN SUM MIN MAX SEMEAN.

Descriptives

Notes

Output Created		28-AUG-2016 07:04:48
Comments		
Input	Data	C:\Users\Sibanda\Desktop\SpreadSheet28Aug2016.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	167
Missing Value Handling	Definition of Missing	User defined missing values are treated as missing.
	Cases Used	All non-missing data are used.
Syntax		DESCRIPTIVES VARIABLES=Site_one Site_two Site_Three Site_four Site_five Total_of_sites /STATISTICS=MEAN SUM MIN MAX SEMEAN.
Resources	Processor Time	00:00:00.00
	Elapsed Time	00:00:00.02

[DataSet1] C:\Users\Sibanda\Desktop\SpreadSheet28Aug2016.sav

Descriptive Statistics

	N	Minimum	Maximum	Sum	Mean	
	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error
Number_of_patientsSite1	132	122	2452	107227	812.33	32.364
Number_of_patientsSite2	132	63	1181	55303	418.96	19.865
Number_of_patientsSite3	132	11	2068	105434	798.74	44.435
Number_of _patients_site 4	132	11	1748	117365	889.13	45.935
Number_of_patientsSite5	132	26	946	33994	257.53	14.154
Working number of patients 1_5	132	676	5329	419323	3176.69	101.811
Valid N (listwise)	132					

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  /COMPRESSED.



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PREDICT THRU YEAR 2025 MONTH 12.
* Apply Time Series Models.
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   /MODELSTATISTICS  DISPLAY=YES MODELFIT=[ SRSQUARE]
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/SERIESPLOT FORECAST FORECASTCI
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Forecast

Model		Dec 2014	Jan 2015	Feb 2015	Mar 2015
Working number of patients 1_5-Model_1	Forecast	.	3395	3448	3458
	UCL	.	4780	5138	5406
	LCL	.	2011	1758	1510
Totalpatients lagged by 1 factor-Model_2	Forecast	3166	3212	3265	3274
	UCL	4555	4908	5220	5457
	LCL	1777	1517	1310	1091
Adjusted Predicted Value-Model_3	Forecast	.	3683.78020	3675.70670	3734.06737
	UCL	.	4770.95898	5067.95657	5375.64031
	LCL	.	2596.60141	2283.45682	2092.49442
Standard Error of Predicted Value-Model_4	Forecast	.	2.37433	2.37433	2.37433
	UCL	.	4.12346	4.22414	4.31962
	LCL	.	.62520	.52451	.42904

Forecast

Model		Apr 2015	May 2015	Jun 2015	Jul 2015
Working number of patients 1_5-Model_1	Forecast	3546	3083	3535	3420
	UCL	5722	5464	6106	6168
	LCL	1370	701	963	672
Totalpatients lagged by 1 factor-Model_2	Forecast	3363	2899	3351	3237
	UCL	5752	5479	6109	6160
	LCL	973	319	594	313
Adjusted Predicted Value-Model_3	Forecast	3722.41713	3571.35511	3514.21521	3813.52222
	UCL	5580.14793	5622.59029	5742.21157	6205.25168
	LCL	1864.68632	1520.11994	1286.21885	1421.79277
Standard Error of Predicted Value-Model_4	Forecast	2.37433	2.37433	2.37433	2.37433
	UCL	4.41062	4.49773	4.58141	4.66202
	LCL	.33803	.25092	.16725	.08663

Forecast

Model		Aug 2015	Sep 2015	Oct 2015	Nov 2015
Working number of patients 1_5-Model_1	Forecast	3412	3624	3997	3702
	UCL	6326	6695	7217	7065
	LCL	498	553	777	340
Totalpatients lagged by 1 factor-Model_2	Forecast	3229	3441	3814	3519
	UCL	6310	6672	7188	7030
	LCL	148	210	440	8
Adjusted Predicted Value-Model_3	Forecast	3702.55753	3693.86049	4088.53759	4000.43298
	UCL	6247.50779	6383.31653	6915.12137	6957.79292
	LCL	1157.60728	1004.40444	1261.95382	1043.07303
Standard Error of Predicted Value-Model_4	Forecast	2.37433	2.37433	2.37433	2.37433
	UCL	4.73989	4.81528	4.88841	4.95947
	LCL	.00876	-.06663	-.13975	-.21081

Forecast

Model		Dec 2015	Jan 2016	Feb 2016	Mar 2016
Working number of patients 1_5-Model_1	Forecast	3389	3395	3448	3458
	UCL	6889	7027	7207	7339
	LCL	-110	-236	-310	-424
Totalpatients lagged by 1 factor-Model_2	Forecast	3166	3212	3265	3274
	UCL	6809	6983	7159	7288
	LCL	-478	-559	-629	-740
Adjusted Predicted Value-Model_3	Forecast	3684.34375	3683.78020	3675.70670	3734.06737
	UCL	6766.93679	6886.71599	6994.62214	7165.04416
	LCL	601.75071	480.84440	356.79125	303.09058
Standard Error of Predicted	Forecast	2.37433	2.37433	2.37433	2.37433

Value-Model_4	UCL	5.02862	5.09603	5.16180	5.22605
	LCL	-.27997	-.34737	-.41315	-.47740

Forecast

Model		Apr 2016	May 2016	Jun 2016	Jul 2016
Working number of patients 1_5-Model_1	Forecast	3546	3083	3535	3420
	UCL	7546	7199	7763	7758
	LCL	-455	-1034	-694	-918
Totalpatients lagged by 1 factor-Model_2	Forecast	3363	2899	3351	3237
	UCL	7493	7142	7704	7697
	LCL	-767	-1344	-1001	-1223
Adjusted Predicted Value-Model_3	Forecast	3722.41713	3571.35511	3514.21521	3813.52222
	UCL	7261.90914	7216.13299	7261.32180	7660.23638
	LCL	182.92511	-73.42276	-232.89137	-33.19193
Standard Error of Predicted Value-Model_4	Forecast	2.37433	2.37433	2.37433	2.37433
	UCL	5.28889	5.35041	5.41067	5.46977
	LCL	-.54024	-.60175	-.66202	-.72111

Forecast

Model		Aug 2016	Sep 2016	Oct 2016	Nov 2016
Working number of patients 1_5-Model_1	Forecast	3412	3624	3997	3702
	UCL	7857	8174	8649	8454
	LCL	-1033	-926	-655	-1049
Totalpatients lagged by 1 factor-Model_2	Forecast	3229	3441	3814	3519
	UCL	7794	8108	8581	8385
	LCL	-1336	-1227	-954	-1347
Adjusted Predicted Value-Model_3	Forecast	3702.55753	3693.86049	4088.53759	4000.43298
	UCL	7646.36430	7732.42630	8219.68947	8222.14090

	LCL	-241.24923	-344.70532	-42.61428	-221.27495
Standard Error of Predicted Value-Model_4	Forecast	2.37433	2.37433	2.37433	2.37433
	UCL	5.52775	5.58469	5.64064	5.69564
	LCL	-.77910	-.83604	-.89199	-.94699

Forecast

Model		Dec 2016	Jan 2017	Feb 2017	Mar 2017
Working number of patients 1_5-Model_1	Forecast	3389	3395	3448	3458
	UCL	8239	8341	8488	8589
	LCL	-1460	-1550	-1591	-1674
Totalpatients lagged by 1 factor-Model_2	Forecast	3166	3212	3265	3274
	UCL	8128	8268	8414	8514
	LCL	-1796	-1844	-1884	-1966
Adjusted Predicted Value-Model_3	Forecast	3684.34375	3683.78020	3675.70670	3734.06737
	UCL	7994.70567	8081.01088	8158.12119	8300.07675
	LCL	-626.01816	-713.45049	-806.70780	-831.94202
Standard Error of Predicted Value-Model_4	Forecast	2.37433	2.37433	2.37433	2.37433
	UCL	5.74975	5.80301	5.85545	5.90711
	LCL	-1.00110	-1.05435	-1.10679	-1.15845

Forecast

Model		Apr 2017	May 2017	Jun 2017	Jul 2017
Working number of patients 1_5-Model_1	Forecast	3546	3083	3535	3420
	UCL	8768	8394	8934	8906
	LCL	-1676	-2229	-1864	-2065
Totalpatients lagged by 1 factor-Model_2	Forecast	3363	2899	3351	3237
	UCL	8692	8317	8855	8826
	LCL	-1967	-2518	-2152	-2352

Adjusted Predicted Value-Model_3	Forecast	3722.41713	3571.35511	3514.21521	3813.52222
	UCL	8370.51822	8300.12300	8322.29672	8699.63006
	LCL	-925.68396	-1157.41277	-1293.86629	-1072.58561
Standard Error of Predicted Value-Model_4	Forecast	2.37433	2.37433	2.37433	2.37433
	UCL	5.95802	6.00823	6.05775	6.10661
	LCL	-1.20937	-1.25957	-1.30909	-1.35796

Forecast

Model		Aug 2017	Sep 2017	Oct 2017	Nov 2017
Working number of patients 1_5-Model_1	Forecast	3412	3624	3997	3702
	UCL	8982	9278	9734	9520
	LCL	-2159	-2030	-1740	-2115
Totalpatients lagged by 1 factor-Model_2	Forecast	3229	3441	3814	3519
	UCL	8902	9196	9651	9437
	LCL	-2444	-2315	-2024	-2399
Adjusted Predicted Value-Model_3	Forecast	3702.55753	3693.86049	4088.53759	4000.43298
	UCL	8665.46513	8732.39736	9201.58520	9186.92098
	LCL	-1260.35006	-1344.67638	-1024.51001	-1186.05503
Standard Error of Predicted Value-Model_4	Forecast	2.37433	2.37433	2.37433	2.37433
	UCL	6.15484	6.20246	6.24950	6.29598
	LCL	-1.40619	-1.45381	-1.50085	-1.54732

Forecast

Model		Dec 2017	Jan 2018	Feb 2018	Mar 2018
Working number of patients 1_5-Model_1	Forecast	3389	3395	3448	3458
	UCL	9287	9372	9503	9590
	LCL	-2509	-2582	-2607	-2675
Totalpatients lagged by 1	Forecast	3166	3212	3265	3274

factor-Model_2	UCL	9163	9287	9418	9503
	LCL	-2831	-2863	-2888	-2955
Adjusted Predicted Value-Model_3	Forecast	3684.34375	3683.78020	3675.70670	3734.06737
	UCL	8943.24666	9014.11580	9076.52883	9204.46787
	LCL	-1574.55916	-1646.55541	-1725.11543	-1736.33314
Standard Error of Predicted Value-Model_4	Forecast	2.37433	2.37433	2.37433	2.37433
	UCL	6.34191	6.38731	6.43221	6.47661
	LCL	-1.59325	-1.63866	-1.68355	-1.72796

Forecast

Model		Apr 2018	May 2018	Jun 2018	Jul 2018
Working number of patients 1_5-Model_1	Forecast	3546	3083	3535	3420
	UCL	9754	9366	9892	9851
	LCL	-2662	-3201	-2823	-3011
Totalpatients lagged by 1 factor-Model_2	Forecast	3363	2899	3351	3237
	UCL	9667	9278	9804	9762
	LCL	-2942	-3480	-3101	-3289
Adjusted Predicted Value-Model_3	Forecast	3722.41713	3571.35511	3514.21521	3813.52222
	UCL	9261.52208	9178.32272	9188.23387	9553.80878
	LCL	-1816.68783	-2035.61249	-2159.80345	-1926.76433
Standard Error of Predicted Value-Model_4	Forecast	2.37433	2.37433	2.37433	2.37433
	UCL	6.52054	6.56401	6.60703	6.64962
	LCL	-1.77189	-1.81535	-1.85838	-1.90097

Forecast

Model		Aug 2018	Sep 2018	Oct 2018	Nov 2018
Working number of patients	Forecast	3412	3624	3997	3702

1_5-Model_1	UCL	9916	10200	10644	10419
	LCL	-3092	-2952	-2650	-3015
Totalpatients lagged by 1 factor-Model_2	Forecast	3229	3441	3814	3519
	UCL	9826	10110	10553	10328
	LCL	-3369	-3228	-2926	-3290
Adjusted Predicted Value-Model_3	Forecast	3702.55753	3693.86049	4088.53759	4000.43298
	UCL	9508.35565	9564.43915	10023.18971	9998.47414
	LCL	-2103.24058	-2176.71817	-1846.11453	-1997.60819
Standard Error of Predicted Value-Model_4	Forecast	2.37433	2.37433	2.37433	2.37433
	UCL	6.69179	6.73355	6.77491	6.81589
	LCL	-1.94314	-1.98490	-2.02626	-2.06724

Forecast

Model		Dec 2018	Jan 2019	Feb 2019	Mar 2019
Working number of patients 1_5-Model_1	Forecast	3389	3395	3448	3458
	UCL	10176	10251	10372	10448
	LCL	-3397	-3460	-3475	-3533
Totalpatients lagged by 1 factor-Model_2	Forecast	3166	3212	3265	3274
	UCL	10044	10159	10279	10356
	LCL	-3712	-3735	-3749	-3807
Adjusted Predicted Value-Model_3	Forecast	3684.34375	3683.78020	3675.70670	3734.06737
	UCL	9745.11102	9806.63228	9860.01908	9979.23524
	LCL	-2376.42351	-2439.07189	-2508.60569	-2511.10050
Standard Error of Predicted Value-Model_4	Forecast	2.37433	2.37433	2.37433	2.37433
	UCL	6.85650	6.89674	6.93663	6.97617
	LCL	-2.10785	-2.14809	-2.18797	-2.22751

Forecast

Model		Apr 2019	May 2019	Jun 2019	Jul 2019
Working number of patients 1_5-Model_1	Forecast	3546	3083	3535	3420
	UCL	10604	10207	10724	10675
	LCL	-3512	-4041	-3655	-3835
Totalpatients lagged by 1 factor-Model_2	Forecast	3363	2899	3351	3237
	UCL	10511	10113	10630	10580
	LCL	-3785	-4314	-3928	-4107
Adjusted Predicted Value-Model_3	Forecast	3722.41713	3571.35511	3514.21521	3813.52222
	UCL	10027.85317	9936.48871	9938.49165	10296.40197
	LCL	-2583.01892	-2793.77848	-2910.06123	-2669.35752
Standard Error of Predicted Value-Model_4	Forecast	2.37433	2.37433	2.37433	2.37433
	UCL	7.01537	7.05424	7.09280	7.13104
	LCL	-2.26672	-2.30559	-2.34414	-2.38239

Forecast

Model		Aug 2019	Sep 2019	Oct 2019	Nov 2019
Working number of patients 1_5-Model_1	Forecast	3412	3624	3997	3702
	UCL	10731	11007	11443	11211
	LCL	-3907	-3759	-3449	-3807
Totalpatients lagged by 1 factor-Model_2	Forecast	3229	3441	3814	3519
	UCL	10636	10912	11348	11116
	LCL	-4179	-4031	-3721	-4078
Adjusted Predicted Value-Model_3	Forecast	3702.55753	3693.86049	4088.53759	4000.43298
	UCL	10243.51555	10292.38561	10744.13192	10712.61130
	LCL	-2838.40048	-2904.66463	-2567.05673	-2711.74534
Standard Error of Predicted Value-Model_4	Forecast	2.37433	2.37433	2.37433	2.37433
	UCL	7.16898	7.20662	7.24396	7.28103

	LCL	-2.42032	-2.45796	-2.49531	-2.53238

Forecast

Model		Dec 2019	Jan 2020	Feb 2020	Mar 2020
Working number of patients 1_5-Model_1	Forecast	3389	3395	3448	3458
	UCL	10961	11028	11143	11213
	LCL	-4182	-4238	-4246	-4298
Totalpatients lagged by 1 factor-Model_2	Forecast	3166	3212	3265	3274
	UCL	10825	10932	11046	11116
	LCL	-4493	-4508	-4516	-4567
Adjusted Predicted Value-Model_3	Forecast	3684.34375	3683.78020	3675.70670	3734.06737
	UCL	10452.63303	10507.72024	10554.84615	10667.96682
	LCL	-3083.94553	-3140.15984	-3203.43276	-3199.83209
Standard Error of Predicted Value-Model_4	Forecast	2.37433	2.37433	2.37433	2.37433
	UCL	7.31781	7.35433	7.39058	7.42657
	LCL	-2.56916	-2.60568	-2.64192	-2.67791

Forecast

Model		Apr 2020	May 2020	Jun 2020	Jul 2020
Working number of patients 1_5-Model_1	Forecast	3546	3083	3535	3420
	UCL	11361	10958	11469	11414
	LCL	-4270	-4793	-4400	-4574
Totalpatients lagged by 1 factor-Model_2	Forecast	3363	2899	3351	3237
	UCL	11264	10861	11372	11316
	LCL	-4539	-5062	-4669	-4842
Adjusted Predicted Value-Model_3	Forecast	3722.41713	3571.35511	3514.21521	3813.52222
	UCL	10710.64750	10613.49724	10609.85949	10962.26825
	LCL	-3265.81324	-3470.78701	-3581.42907	-3335.22380

Standard Error of Predicted Value-Model_4	Forecast	2.37433	2.37433	2.37433	2.37433
	UCL	7.46230	7.49778	7.53302	7.56803
	LCL	-2.71365	-2.74913	-2.78437	-2.81937

Forecast

Model		Aug 2020	Sep 2020	Oct 2020	Nov 2020
Working number of patients 1_5-Model_1	Forecast	3412	3624	3997	3702
	UCL	11464	11734	12165	11928
	LCL	-4640	-4486	-4171	-4523
Totalpatients lagged by 1 factor-Model_2	Forecast	3229	3441	3814	3519
	UCL	11366	11636	12067	11829
	LCL	-4909	-4755	-4439	-4791
Adjusted Predicted Value-Model_3	Forecast	3702.55753	3693.86049	4088.53759	4000.43298
	UCL	10904.01376	10947.64390	11394.27341	11357.75435
	LCL	-3498.89869	-3559.92292	-3217.19822	-3356.88840
Standard Error of Predicted Value-Model_4	Forecast	2.37433	2.37433	2.37433	2.37433
	UCL	7.60279	7.63733	7.67164	7.70573
	LCL	-2.85414	-2.88868	-2.92299	-2.95708

Forecast

Model		Dec 2020	Jan 2021	Feb 2021	Mar 2021
Working number of patients 1_5-Model_1	Forecast	3389	3395	3448	3458
	UCL	11672	11734	11843	11908
	LCL	-4893	-4943	-4946	-4993
Totalpatients lagged by 1 factor-Model_2	Forecast	3166	3212	3265	3274
	UCL	11533	11635	11744	11809
	LCL	-5201	-5211	-5214	-5260
Adjusted Predicted Value-	Forecast	3684.34375	3683.78020	3675.70670	3734.06737

Model_3	UCL	11092.89150	11143.20361	11185.66007	11294.21298
	LCL	-3724.20400	-3775.64322	-3834.24668	-3826.07825
Standard Error of Predicted Value-Model_4	Forecast	2.37433	2.37433	2.37433	2.37433
	UCL	7.73961	7.77327	7.80673	7.83997
	LCL	-2.99096	-3.02462	-3.05807	-3.09132

Forecast

Model		Apr 2021	May 2021	Jun 2021	Jul 2021
Working number of patients 1_5-Model_1	Forecast	3546	3083	3535	3420
	UCL	12052	11644	12150	12090
	LCL	-4960	-5478	-5081	-5250
Totalpatients lagged by 1 factor-Model_2	Forecast	3363	2899	3351	3237
	UCL	11952	11544	12051	11990
	LCL	-5227	-5745	-5348	-5516
Adjusted Predicted Value-Model_3	Forecast	3722.41713	3571.35511	3514.21521	3813.52222
	UCL	11332.42394	11230.89855	11222.97696	11571.19003
	LCL	-3887.58969	-4088.18832	-4194.54654	-3944.14558
Standard Error of Predicted Value-Model_4	Forecast	2.37433	2.37433	2.37433	2.37433
	UCL	7.87302	7.90587	7.93853	7.97100
	LCL	-3.12437	-3.15722	-3.18988	-3.22234

Forecast

Model		Aug 2021	Sep 2021	Oct 2021	Nov 2021
Working number of patients 1_5-Model_1	Forecast	3412	3624	3997	3702
	UCL	12136	12402	12828	12586
	LCL	-5312	-5154	-4834	-5182
Totalpatients lagged by 1 factor-Model_2	Forecast	3229	3441	3814	3519
	UCL	12036	12301	12728	12486

	LCL	-5579	-5420	-5100	-5448
Adjusted Predicted Value-Model_3	Forecast	3702.55753	3693.86049	4088.53759	4000.43298
	UCL	11508.82500	11548.42691	11991.10779	11950.71711
	LCL	-4103.70993	-4160.70594	-3814.03261	-3949.85116
Standard Error of Predicted Value-Model_4	Forecast	2.37433	2.37433	2.37433	2.37433
	UCL	8.00327	8.03537	8.06728	8.09902
	LCL	-3.25462	-3.28672	-3.31863	-3.35037

Forecast

Model		Dec 2021	Jan 2022	Feb 2022	Mar 2022
Working number of patients 1_5-Model_1	Forecast	3389	3395	3448	3458
	UCL	12326	12384	12490	12551
	LCL	-5547	-5594	-5593	-5635
Totalpatients lagged by 1 factor-Model_2	Forecast	3166	3212	3265	3274
	UCL	12185	12284	12389	12449
	LCL	-5853	-5859	-5858	-5901
Adjusted Predicted Value-Model_3	Forecast	3684.34375	3683.78020	3675.70670	3734.06737
	UCL	11682.05716	11728.64425	11767.44567	11872.41128
	LCL	-4313.36966	-4361.08386	-4416.03228	-4404.27655
Standard Error of Predicted Value-Model_4	Forecast	2.37433	2.37433	2.37433	2.37433
	UCL	8.13058	8.16197	8.19319	8.22424
	LCL	-3.38193	-3.41332	-3.44454	-3.47559

Forecast

Model		Apr 2022	May 2022	Jun 2022	Jul 2022
Working number of patients 1_5-Model_1	Forecast	3546	3083	3535	3420
	UCL	12690	12278	12781	12717
	LCL	-5599	-6113	-5712	-5877

Totalpatients lagged by 1 factor-Model_2	Forecast	3363	2899	3351	3237
	UCL	12589	12177	12680	12616
	LCL	-5864	-6378	-5977	-6142
Adjusted Predicted Value-Model_3	Forecast	3722.41713	3571.35511	3514.21521	3813.52222
	UCL	11907.10061	11802.11727	11790.79951	12135.67638
	LCL	-4462.26635	-4659.40704	-4762.36909	-4508.63193
Standard Error of Predicted Value-Model_4	Forecast	2.37433	2.37433	2.37433	2.37433
	UCL	8.25513	8.28586	8.31643	8.34684
	LCL	-3.50648	-3.53720	-3.56777	-3.59819

Forecast

Model		Aug 2022	Sep 2022	Oct 2022	Nov 2022
Working number of patients 1_5-Model_1	Forecast	3412	3624	3997	3702
	UCL	12760	13022	13445	13199
	LCL	-5936	-5774	-5451	-5795
Totalpatients lagged by 1 factor-Model_2	Forecast	3229	3441	3814	3519
	UCL	12658	12920	13343	13098
	LCL	-6201	-6039	-5715	-6059
Adjusted Predicted Value-Model_3	Forecast	3702.55753	3693.86049	4088.53759	4000.43298
	UCL	12070.03336	12106.41383	12545.92819	12502.42438
	LCL	-4664.91830	-4718.69286	-4368.85301	-4501.55842
Standard Error of Predicted Value-Model_4	Forecast	2.37433	2.37433	2.37433	2.37433
	UCL	8.37710	8.40720	8.43716	8.46697
	LCL	-3.62844	-3.65855	-3.68851	-3.71832

Forecast

Model		Dec 2022	Jan 2023	Feb 2023	Mar 2023
Working number of patients	Forecast	3389	3395	3448	3458

1_5-Model_1	UCL	12936	12991	13093	13150
	LCL	-6157	-6200	-6196	-6235
Totalpatients lagged by 1 factor-Model_2	Forecast	3166	3212	3265	3274
	UCL	12794	12889	12990	13048
	LCL	-6462	-6465	-6460	-6500
Adjusted Predicted Value-Model_3	Forecast	3684.34375	3683.78020	3675.70670	3734.06737
	UCL	12230.70320	12274.27946	12310.11922	12412.17094
	LCL	-4862.01570	-4906.71907	-4958.70583	-4944.03621
Standard Error of Predicted Value-Model_4	Forecast	2.37433	2.37433	2.37433	2.37433
	UCL	8.49663	8.52616	8.55554	8.58478
	LCL	-3.74798	-3.77750	-3.80688	-3.83612

Forecast

Model		Apr 2023	May 2023	Jun 2023	Jul 2023
Working number of patients 1_5-Model_1	Forecast	3546	3083	3535	3420
	UCL	13287	12872	13372	13305
	LCL	-6195	-6707	-6302	-6465
Totalpatients lagged by 1 factor-Model_2	Forecast	3363	2899	3351	3237
	UCL	13185	12769	13269	13202
	LCL	-6460	-6971	-6566	-6729
Adjusted Predicted Value-Model_3	Forecast	3722.41713	3571.35511	3514.21521	3813.52222
	UCL	12443.99288	12336.18744	12322.09167	12664.23348
	LCL	-4999.15863	-5193.47721	-5293.66125	-5037.18903
Standard Error of Predicted Value-Model_4	Forecast	2.37433	2.37433	2.37433	2.37433
	UCL	8.61388	8.64285	8.67169	8.70039
	LCL	-3.86523	-3.89420	-3.92303	-3.95174

Forecast

Model		Aug 2023	Sep 2023	Oct 2023	Nov 2023
Working number of patients 1_5-Model_1	Forecast	3412	3624	3997	3702
	UCL	13344	13603	14023	13775
	LCL	-6520	-6355	-6029	-6371
Totalpatients lagged by 1 factor-Model_2	Forecast	3229	3441	3814	3519
	UCL	13241	13501	13920	13672
	LCL	-6784	-6619	-6293	-6634
Adjusted Predicted Value-Model_3	Forecast	3702.55753	3693.86049	4088.53759	4000.43298
	UCL	12595.89727	12629.62535	13066.52711	13020.44948
	LCL	-5190.78221	-5241.90438	-4889.45192	-5019.58353
Standard Error of Predicted Value-Model_4	Forecast	2.37433	2.37433	2.37433	2.37433
	UCL	8.72897	8.75741	8.78573	8.81393
	LCL	-3.98031	-4.00876	-4.03708	-4.06528

Forecast

Model		Dec 2023	Jan 2024	Feb 2024	Mar 2024
Working number of patients 1_5-Model_1	Forecast	3389	3395	3448	3458
	UCL	13509	13561	13660	13715
	LCL	-6730	-6770	-6764	-6800
Totalpatients lagged by 1 factor-Model_2	Forecast	3166	3212	3265	3274
	UCL	13366	13458	13557	13612
	LCL	-7034	-7034	-7027	-7064
Adjusted Predicted Value-Model_3	Forecast	3684.34375	3683.78020	3675.70670	3734.06737
	UCL	12746.19234	12787.26951	12820.64626	12920.27015
	LCL	-5377.50483	-5419.70911	-5469.23287	-5452.13542
Standard Error of Predicted Value-Model_4	Forecast	2.37433	2.37433	2.37433	2.37433
	UCL	8.84200	8.86995	8.89779	8.92550

	LCL	-4.09335	-4.12130	-4.14913	-4.17685

Forecast

Model		Apr 2024	May 2024	Jun 2024	Jul 2024
Working number of patients 1_5-Model_1	Forecast	3546	3083	3535	3420
	UCL	13849	13432	13929	13859
	LCL	-6758	-7266	-6859	-7019
Totalpatients lagged by 1 factor-Model_2	Forecast	3363	2899	3351	3237
	UCL	13746	13328	13826	13756
	LCL	-7021	-7530	-7123	-7283
Adjusted Predicted Value-Model_3	Forecast	3722.41713	3571.35511	3514.21521	3813.52222
	UCL	12949.69861	12839.53324	12823.11030	13162.95695
	LCL	-5504.86436	-5696.82301	-5794.67987	-5535.91250
Standard Error of Predicted Value-Model_4	Forecast	2.37433	2.37433	2.37433	2.37433
	UCL	8.95310	8.98058	9.00795	9.03520
	LCL	-4.20445	-4.23193	-4.25930	-4.28655

Forecast

Model		Aug 2024	Sep 2024	Oct 2024	Nov 2024
Working number of patients 1_5-Model_1	Forecast	3412	3624	3997	3702
	UCL	13896	14153	14570	14320
	LCL	-7072	-6905	-6576	-6915
Totalpatients lagged by 1 factor-Model_2	Forecast	3229	3441	3814	3519
	UCL	13793	14049	14467	14217
	LCL	-7336	-7168	-6840	-7178
Adjusted Predicted Value-Model_3	Forecast	3702.55753	3693.86049	4088.53759	4000.43298
	UCL	13092.35688	13123.85167	13558.55004	13510.29826
	LCL	-5687.24181	-5736.13070	-5381.47485	-5509.43231

Standard Error of Predicted Value-Model_4	Forecast	2.37433	2.37433	2.37433	2.37433
	UCL	9.06235	9.08938	9.11631	9.14313
	LCL	-4.31370	-4.34073	-4.36766	-4.39448

Forecast

Model		Dec 2024	Jan 2025	Feb 2025	Mar 2025
Working number of patients 1_5-Model_1	Forecast	3389	3395	3448	3458
	UCL	14051	14101	14198	14251
	LCL	-7272	-7310	-7301	-7336
Totalpatients lagged by 1 factor-Model_2	Forecast	3166	3212	3265	3274
	UCL	13908	13998	14094	14147
	LCL	-7576	-7574	-7564	-7599
Adjusted Predicted Value-Model_3	Forecast	3684.34375	3683.78020	3675.70670	3734.06737
	UCL	13233.89556	13272.85511	13304.14165	13401.70212
	LCL	-5865.20806	-5905.29471	-5952.72826	-5933.56738
Standard Error of Predicted Value-Model_4	Forecast	2.37433	2.37433	2.37433	2.37433
	UCL	9.16984	9.19645	9.22296	9.24936
	LCL	-4.42119	-4.44780	-4.47430	-4.50071

Forecast

Model		Apr 2025	May 2025	Jun 2025	Jul 2025
Working number of patients 1_5-Model_1	Forecast	3546	3083	3535	3420
	UCL	14382	13962	14458	14386
	LCL	-7291	-7797	-7388	-7546
Totalpatients lagged by 1 factor-Model_2	Forecast	3363	2899	3351	3237
	UCL	14279	13859	14354	14282
	LCL	-7554	-8060	-7651	-7809
Adjusted Predicted Value-	Forecast	3722.41713	3571.35511	3514.21521	3813.52222

Model_3	UCL	13429.09337	13316.91645	13298.50710	13636.39195
	LCL	-5984.25911	-6174.20622	-6270.07667	-6009.34750
Standard Error of Predicted Value-Model_4	Forecast	2.37433	2.37433	2.37433	2.37433
	UCL	9.27566	9.30186	9.32797	9.35397
	LCL	-4.52701	-4.55321	-4.57931	-4.60532

Forecast

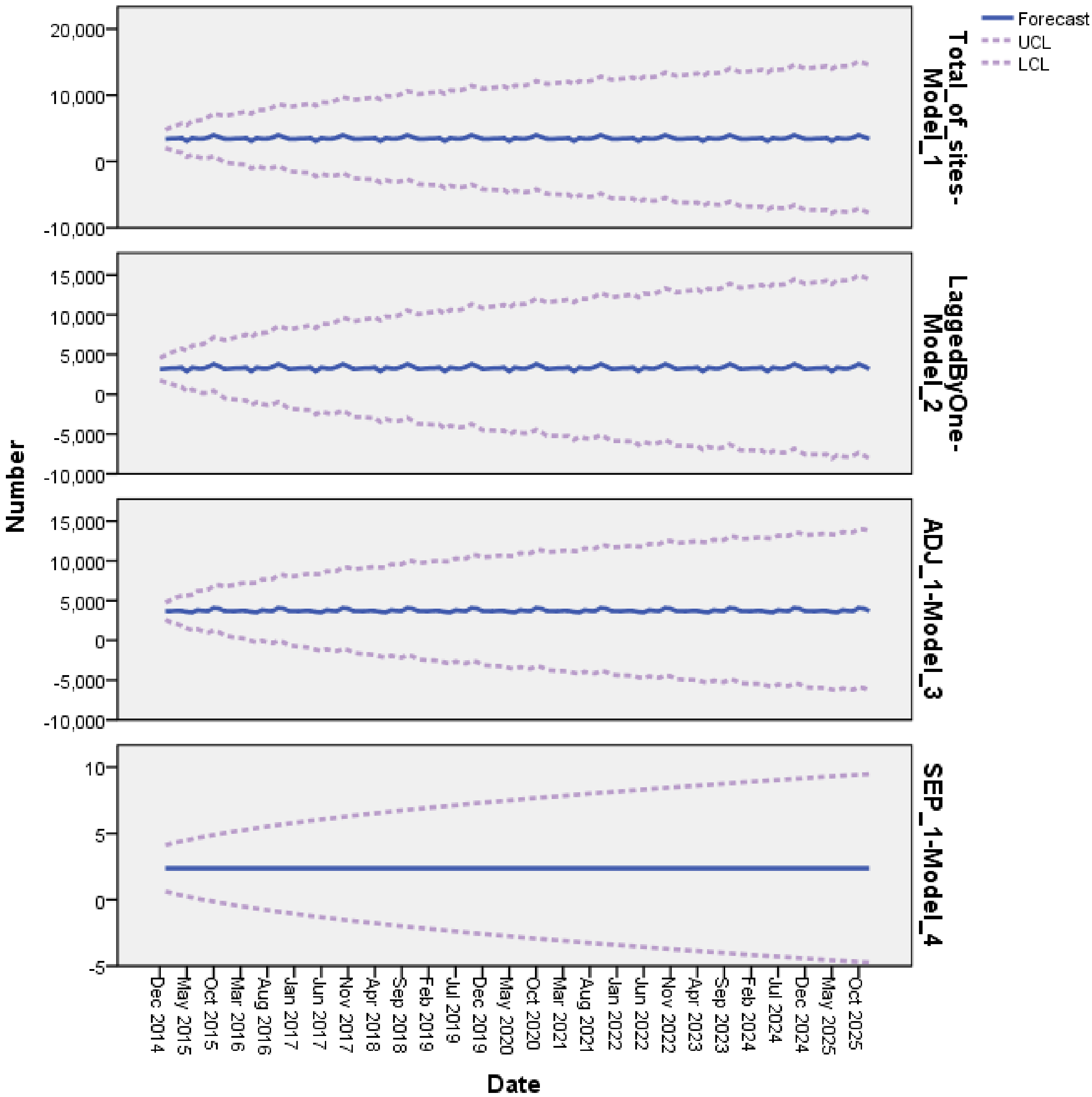
Model		Aug 2025	Sep 2025	Oct 2025	Nov 2025
Working number of patients 1_5-Model_1	Forecast	3412	3624	3997	3702
	UCL	14420	14675	15090	14838
	LCL	-7597	-7427	-7096	-7433
Totalpatients lagged by 1 factor-Model_2	Forecast	3229	3441	3814	3519
	UCL	14317	14571	14987	14734
	LCL	-7860	-7690	-7359	-7696
Adjusted Predicted Value-Model_3	Forecast	3702.55753	3693.86049	4088.53759	4000.43298
	UCL	13563.85419	13593.43491	14026.24235	13976.12231
	LCL	-6158.73912	-6205.71393	-5849.16716	-5975.25636
Standard Error of Predicted Value-Model_4	Forecast	2.37433	2.37433	2.37433	2.37433
	UCL	9.37988	9.40570	9.43142	9.45704
	LCL	-4.63123	-4.65704	-4.68276	-4.70839

Forecast

Model		Dec 2025
Working number of patients 1_5-Model_1	Forecast	3389
	UCL	14567
	LCL	-7788
Totalpatients lagged by 1 factor-Model_2	Forecast	3166
	UCL	14423

	LCL	-8091
	Forecast	3684.34375
Adjusted Predicted Value-Model_3	UCL	13697.87359
	LCL	-6329.18608
	Forecast	2.37433
Standard Error of Predicted Value-Model_4	UCL	9.48258
	LCL	-4.73392

For each model, forecasts start after the last historical period that was used in estimation of the models applied, and end at the end of the requested forecast period (year 2025).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