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# Optimising cardiac services using routinely collected data and discrete event simulation

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## ABSTRACT

**Background:** The current practice of managing hospital resources, including beds, is very much driven by measuring past or expected utilisation of resources. This practice, however, doesn't reflect variability among patients. Consequently, managers and clinicians cannot make fully informed decisions based upon these measures which are considered inadequate in planning and managing complex systems.

**Aim:** to analyse how variation related to patient conditions and adverse events affect resource utilisation and operational performance.

**Methods:** Data pertaining to cardiac patients (cardiothoracic and cardiology, n=2241) were collected from two major hospitals in Oman. Factors influential to resource utilisation were assessed using logistic regressions. Other analysis related to classifying patients based on their resource utilisation was carried out using decision tree to assist in predicting hospital stay. Finally, discrete event simulation modelling was used to evaluate how patient factors and postoperative complications are affecting operational performance.

**Results:** 26.5% of the patients experienced prolonged Length of Stay (LOS) in intensive care units and 30% in the ward. Patients with prolonged postoperative LOS had 60% of the total patient days. Some of the factors that explained the largest amount of variance in resource use following cardiac procedure included body mass index, type of surgery, Cardiopulmonary Bypass (CPB) use, non-elective surgery, number of complications, blood transfusion, chronic heart failure, and previous angioplasty. Allocating resources based on patient expected LOS has resulted in a reduction of surgery cancellations and waiting times while overall throughput has increased. Complications had a significant effect on perioperative operational performance such as surgery cancellations. The effect was profound when complications occurred in the intensive care unit where a limited capacity was observed. Based on the simulation model, eliminating some complications can enlarge patient population.

**Conclusion:** Integrating influential factors into resource planning through simulation modelling is an effective way to estimate and manage hospital capacity.

## DECLARATION OF ORIGINALITY

I hereby declare that this thesis and the work reported herein was composed by and originated entirely from me. Information derived from the published and unpublished work of others has been acknowledged in the text and references are given in the list of sources.

**Ahmed Almashrafi**

## COPYRIGHT DECLARATION

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## ABBREVIATION LIST

| | |
|---|---|
| **A&E** | Accident and Emergency |
| **AF** | Atrial Fibrillation |
| **CABG** | Coronary Artery Bypass Graft surgery |
| **CART** | Classification and Regression Tree |
| **Cath Lab** | Catheterisation Laboratory |
| **CCU** | Coronary Care Unit |
| **CI** | Confidence Interval |
| **CICU** | Cardiac Intensive Care Unit |
| **CPB** | Cardiopulmonary Bypass |
| **DES** | Discrete Event Simulation. |
| **DRG** | Diagnosis related groups |
| **ED** | Emergency Department |
| **EuroSCORE** | The European System for Cardiac Operative Risk Evaluation |
| **HIS** | Hospital Information System |
| **ICU** | Intensive Care Unit |
| **K-S** | Kolmogorov-Smirnov test |
| **LOS** | Length of Stay |
| **MI** | Myocardial Infarction |
| **OR** | Operating Room |
| **PTCA** | Percutaneous Transluminal Coronary Angioplasty |
| **RH** | Royal Hospital |
| **ROC** | Receiver Operating Characteristic curve |
| **SE** | Standard Error |
| **SQUH** | Sultan Qaboos University Hospital |
| **STS** | Society of Thoracic Surgeons |
| **UA** | Unstable Angina |

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# Chapter 1

# INTRODUCTION

## 1.1 CHAPTER OVERVIEW

The chapter outlines several areas that will be covered in the thesis. I will discuss justification for the study and provide a summary of the research layout. I will also discuss some elements concerning the overall management of resources in hospitals. I then provide the justification for using simulation modelling as a tool in this research. Finally, I will introduce the research questions which will be supported by a series of more specific objectives.

## 1.2 JUSTIFICATION FOR THE STUDY

Cardiac interventions are associated with high cost and extensive use of hospital resources (e.g. intensive care beds). For example, Coronary Artery Bypass Graft (CABG) - despite its decline in recent years[1] - is still among the most performed major operation in many countries such as the United States and accounts for more resources than most surgical procedures.[2] Considerable research has been done to improve resource allocation for patients with cardiac care. However, little is known about how patient variation affects hospital resource management. The current practice of managing hospital resources, including beds, is very much driven by measuring past or expected utilisation of resources (e.g. average length of stay, average occupancy).[3] This practice, however, doesn't reflect variability among patients nor does it allow for managing resources based on variability expected among cardiac patients. Consequently, managers and clinicians cannot make fully informed decisions based upon these measures which are considered inadequate in planning and managing complex stochastic systems.[4-6] The dynamic nature of patient flows and hospital operations means more flexible models are needed to reflect complexity, uncertainty, variability and limited resources.[7]

Understanding how factors related to patients, treatment and iatrogenic events affect Length Of Stay (LOS) might aid in the management of complex hospital systems.[8] Therefore, the ability to predict resource consumption based on patient condition would allow for better planning of hospital resources. As such, decisions should be enhanced by data-driven evidence that should overcome a limitation of traditional resource allocation practices that often consider patients as homogenous entities with similar needs.[2] By knowing the explanatory variables that describe an operational process, variances in resource allocation can be discovered.[9]

Aside from this, demand for cardiac services in Oman has increased due to an aging population and high prevalence of risk factors for cardiovascular disease.[10] Coupled with increased demand is a shortage in supply as there are currently only two government hospitals that provide more than 95% of the cardiac interventions in the country. Day-to-day resource allocations in the hospitals are based on traditional first come, first served without regard to patient variation. This practice is undoubtedly one of the reasons for some inefficiency in the Omani hospitals. Providing efficient care, and yet safe, is a major challenge facing the Omani healthcare system.

The overall aim of this research is to investigate how patient flow in cardiac care services can be optimised by understanding variations among patients and their relationship with resource utilisation. LOS was used as surrogate of resource utilisation. The factors that are deemed to influence the hospital resource utilisation can be divided into two groups. The first is related to patient and treatment characteristics and the second is related to adverse events that may develop during hospitalisation. The LOS associated with any of these two types of factors is known to increase cost. However, existing research has to date been limited on how this variability impacts upon operational performance (e.g. waiting time, surgery cancellation, and throughput). This research attempts to understand these relationships and investigate possible strategies that can be implemented to improve patient flow and resource utilisation.

## 1.3 ORIGINALITY AND CONTRIBUTIONS

I would justify the originality of this research in the following terms. The research is the first empirical study on resource utilisation among cardiac care patients in Oman. The Omani population as well as the hospitals settings have some unique characteristics that will be discussed subsequently. Second, the research provides evidence on the need to incorporate patient variation (i.e. natural variation) into resource planning in hospitals, thus permitting the exploration of different resource management strategies that are overlooked by traditional planning practices. This is important managerially, because it may prove the hypothesis that resource management decisions cannot be made in isolation from patient characteristics. While previous studies have confirmed that individual patient characteristics can significantly impact resource use in hospitals, they have not demonstrated how this knowledge can be of value to hospital resource planning. I used Discrete Event Simulation (DES) to incorporate factors influential to prolonged LOS and test strategies to optimise the use of resources. Third, a further important and original aspect of my findings will be a contribution toward understanding how adverse events impact operational performance. This could be a key to quantifying the effect of complications beyond costs and resource utilisations. Existing practices in hospital resource management do not view complications as a source of risk to the patient flow and to the patient journey as a whole. Every single bed that is occupied by a patient with complications can limit the hospital's ability to admit new patients. The collective effect of excess LOS due to complications on hospital performance can be significant.

This study was the first in Oman to assess the utility of cardiac risk stratification systems for predicting LOS. I was also able to create and externally validate a model for predicting Cardiac Intensive Care Unit (CICU) LOS classes based on simple variables. I chose to put more emphasis on factors affecting CICU LOS because it is a limiting bottleneck for operating theatre utilisation and consequently a major area for operational performance improvement.

I should also make it clear in this introductory chapter that the thesis seeks to provide more than a solution to specific existing operational problems in the studied hospitals such as that expected from some consultancy studies. Rather, my research attempts to contribute towards the general application of concepts that are less researched which can be applicable to wider settings.

## 1.4 THE CHALLENGE OF HOSPITAL RESOURCE MANAGEMENT

Expenditure on hospital services comprises one of the largest shares of total health spending in all countries, regardless of their income.[11] Hospital managers are frequently required to devise plans for allocating resources. In a survey of healthcare executives in America, two-thirds of the executives said that they had no effective way to predict their capacity needs or to match capacity with demand in the next five years.[12] This is the case because many factors are responsible for healthcare resource demand (i.e. utilisation) including patients and intrinsic organisational characteristics which may or may not be apparent. Within hospital systems, traditional allocation of resources has resulted in a capacity imbalance in which some units have over-capacity while others strive to deal with the stress of under-capacity, resulting in bottlenecks or under-utilisation (Mango and Shapiro, 2001 as cited in Hall, Randolph[13]).

A major task of hospital management is to create a balance between capacity and demand so that expensive resources are wisely managed.[14] "Capacity utilisation" addresses the important question of whether more flexible use of certain inputs could improve performance.[15] The difficulty is that publicly owned hospitals don't get to select their patients. Once patients are admitted they tend to vary in their use of resources.[16] Some patients will need a brief admission while others will require several weeks of hospital stay. This variation can put pressure on hospitals that have to respond to urgent cases. The wide range of comorbidities, severity of illness, and treatments can confound a simple planning process of allocating resources. Thus, the ability to estimate patient needs for hospital resources is an important element in planning.[17]

### 1.4.1 Managing natural variations

Some of the most important factors that affect efficient resource allocation are related to patients, uncertainty, and resource availability. Hospitals are expected to deliver care for patients with many different type of diseases. Even patients with the same disease exhibit significant differences in their degree of illness and response to treatment (clinical variability). Patient demand for care may also appear in a random fashion with different mean and standard deviations of arrival rate (flow variability).[18] In addition, clinicians deliver care differently (professional variability). The presence of clinical, flow and professional variability increases complexity and adds cost to the healthcare system.[18] Collectively, this variation can be labelled as "natural variability". Another type of variability in hospitals is "artificial variability" that is introduced into the system because of scheduling practice, resource shortage, incompetent staff, admission and discharge planning, etc. Compared with natural variability, artificial variability is non-random, yet it is also unpredictable.[18] The convention in hospital management is that artificial variation is controllable and should be eliminated.[19, 20] However, the remaining natural variation, which are largely patient and disease driven (e.g. complications, severity, urgency level), should be optimally managed because it might not be possible to reduce without advances in new medical knowledge or technology. The first step in managing natural variability is to identify homogenous subgroups. Common divisions of patients are based on urgency level (elective vs. emergent) or disease type (cardiac, orthopaedic, etc.). In this research, I attempt to group patients whose clinical characteristics dictate resource consumption (e.g. normal LOS vs. prolonged LOS). Such division allows more focus on different strategies which can be developed to optimally manage these subgroups.

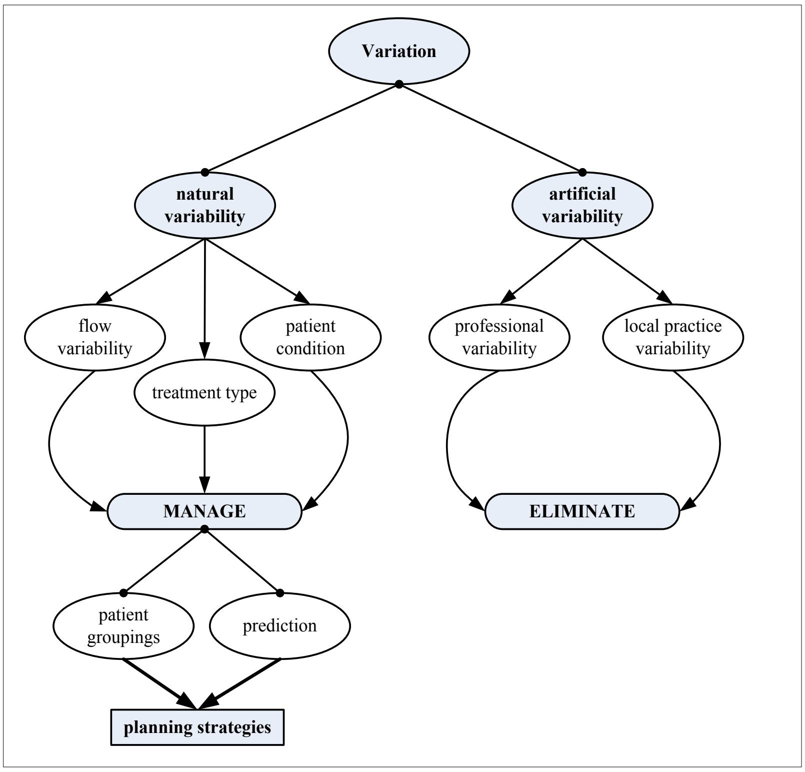



**Figure 1-1 The relationship between natural variation and resource planning**

I illustrated the two types of variation in Figure 1-1. The focus of this thesis is on the natural variability namely flow variability and clinical variability. Treatment and patient condition variability are related to the clinical variability. Treatment type such as surgery and the use of cardiopulmonary bypass machine during operation may affect patient outcome and hospital stay. The same thing can be said about patient condition. For the purpose of hospital resource planning, variability can be assessed through prediction and patient groupings. The former involves understanding factors associated with resource use while the latter involves classifying patients based on their prospect of hospital resource utilisation. The two approaches differ in their methodology, yet share a similar outcome. Knowledge gained from understanding natural variation can be used to formulate resource planning strategies.

### 1.4.2 The challenge of managing variation among cardiac patients

There are two difficulties associated with estimating resource use for cardiac care patients. First, there is a wide range of predictors that could explain variation in resource use. For example, Messaoudi et al[21] reported in a systematic review of factors prolonging Intensive Care Unit (ICU) stay that the number of predictors among the reviewed studies ranged from 1 to 16 (with an average of 6 predictors). Second, the dynamic nature of patient flow and the interrelationship between hospital services[22] make resource utilisation prediction, and thus resource planning, a difficult task. Cardiac care is characterised by occurrence of several uncertainties including admission of emergency patients (chest pain is a common cause for emergency visits in hospitals) and postoperative complications. Due to the invasive nature of heart surgeries and relatively higher ages of most patients, LOS tend to be higher than most other types of hospital admissions.

## 1.5 MEASURING PATIENT VARIATION IN RESOURCE UTILISATION

Resource consumption can be measured as the number of services provided to patients, such as the number of diagnostic tests.[23] Cost estimates can also be used for measuring the level of resource utilisation, but cost data vary substantially based on different accounting methods, coding, and billing patterns in use.[24] It is widely accepted that the simplest predictor of costs is LOS.[25] Rapoport and colleagues found that LOS can explain approximately 85 to 90% of variation in hospital costs.[25] Similarly, another study found that there is a strong correlation between LOS and hospitals costs.[26]

The use of LOS as a proxy measure of resource consumption is well supported in research. It has also been used as a proxy for hospital efficiency.[27] LOS data are routinely collected by hospitals and they are easy to retrieve. However, LOS is likely to be the outcomes of several complex social, medical practice and hospital characteristics.[28] This will be discussed as a limitation in this research.

### 1.5.1 Resource utilisation prediction models

At the population level, several risk stratification models are used for predicting events such as unplanned admissions, future risk of diabetes, and risk of developing cardiovascular disease.[29] Patients identified at the highest risk are then linked to the most appropriate evidence-based integrated care strategies. Among these risk stratifications is the LACE (LOS, acuity of admission, comorbidities, emergency department visits) tool administered at discharge to quantify and predict early death or unplanned readmission.[30] There is equivocal evidence to suggest that the use of risk stratification tools has a positive effect on patient outcomes.[29]

Several measures such as prediction of patient discharge by clinicians remains subjective and susceptible to high variability.[31] On the other hand, models proposed to predict prolonged LOS in the literature remain mostly deterministic which places a major limitation upon the ability of managers to conduct what-if analysis. Moreover, it is difficult to assess whether stratification systems of this nature will produce operational benefits as there is lack of research discussing implementation. A validated model that is based on routinely available clinical data can replace intuitions and subjective judgements about patients expected resource use.

It would be safe to assume that the existing hospital resource prediction models can only be applied to the local settings where they have been originally designed. This means that resource use is an institution-specific phenomena and, therefore a universal prediction tools should not be valid. A similar caution was noted in predicting patients for case management using data from other facilities.[32]

### 1.5.2 The use of cardiac risk stratifications for predicting resource utilisation

Risk stratification systems such as the European System for Cardiac Operative Risk Evaluation (EuroSCORE) are commonly available in many hospitals. However, their utility for predicting workload and resource utilisation is unknown as they are designed and validated to predict mortality.[33] A basic premise in this thesis is that these prognostic systems reflect patient clinical severity[34, 35] which has been found to correlate with hospital resource use.[36] Thus, a composite score of risk may be used in predicting resource utilisation. However, none of the risk scores have been validated in the Omani population for either mortality or resource utilisation. As such, a risk prediction algorithm may be valid for one population and invalid for another. For example, North American risk algorithms were found not to be useful for predicting mortality in patients with CABG surgeries in the United Kingdom.[37] Another reason why I decided to assess the usefulness of cardiac risk stratification systems such as the Society of Thoracic Surgeons (STS), EuroSCORE, and Parsonnet for predicting resource use is that they are composed of a wide range of clinical variables that are otherwise difficult to collate from patient records. The validity of risk stratification systems in predicting LOS could mean further application in beds and patient flow management.

### 1.5.3 The effect of complications on resource utilisation and patient flow

My informal discussion with the managerial and clinical staff revealed that the hospitals had no estimate of the impact of patient mix and complications on LOS and resource expenditure. A continuing evaluation of factors affecting LOS remains important for allocating resources. Therefore, one of the objectives of this thesis is to create a meaningful estimate of the resource use associated with adverse events and patient mix that will assist hospitals to evaluate their impact on various operational performance (e.g. surgery cancellation, waiting times, bed turnover rate).

A major limitation of much literature around assessing LOS is the deficiency in considering the effect of complications that have been recognised to extend hospital stay.[38-40] The relationship between complications and resource utilisation is not always straightforward. Several factors interact to influence this relationship which mean that these potential confounding factors need to be separated. Complications are known to prolong LOS (readers are referred to chapter 3 for more detail). The lost-bed days associated with complications may limit patient flow and eventually may lead to extended waiting times. The extent to which postoperative complications affect resource utilisation will be investigated in more detail in chapter 7 where I will discuss how complications affect resource availability and operational performance such as surgery cancellations.

## 1.6 PLANNING INPATIENT CARDIAC CARE RESOURCES

Resource planning for cardiac care services is challenging because several different parameters affect resource use. For instance, the presence of emergency cases raises uncertainty in the system.[41] Urgent cases can also introduce a considerable impact on elective patient scheduling. Emergency admissions have received considerable attention in operational research. However, the role of variability related to patient and treatment were given little attention. These factors should not be ignored in designing resource management systems.

Once a patient is deemed to require a cardiac intervention, he or she will be placed on a waiting list. The convention in scheduling is usually based on first come first served, unless urgency level dictates that patients should be given priority.[42] Patients with potentially life-threatening conditions will be admitted regardless of the status of resource availability. Frequently, hospitals do not have dedicated catheter labs or operating rooms for emergency cases.

Hospitals take several measures to reduce resource utilisation. First, it is common to minimise preoperative LOS by assessing patients in outpatient clinics rather than in more expensive inpatient setting. Second, there is a tendency to admit cardiac patients on the day of the procedure to reduce LOS. Third, some hospitals adopt strategies whereby patients are transferred to other settings (e.g. community care) or other hospitals (e.g. regional) to free up some capacity.

Throughout this research the term “resource allocation” means the selection of an operational, tactical or strategic alternative that would maximise the use of resources and improve patients flow. This could be related to scheduling patients, increasing number of beds, reducing infections, mitigating preoperative comorbidities, etc.

## 1.7 SYSTEMS THINKING THEORY

Many healthcare organisations recognise that their delivery of care is often overly complex and unstandardized. As such, decision makers have to gain knowledge about several system and patient variables to analyse their interactions. This stresses the need to make decisions from a system-wide view. The fundamental philosophy of system thinking theory centres on this perspective. It explains how the dynamics and behaviour of health systems are shaped by multiple and complex interactions rather than by a single behaviour.[43] Therefore, system dynamics is an approach to problem solving that views “problems” as part of a wider, dynamic system.[43] It was originated in the 1930s by the biologist Von Bertalanffy to describe systems with interacting components.[44] The theory fits appropriately with the main concept discussed in this thesis. Therefore, the research was conceptualised within this theory.

In healthcare, system thinking is mostly discussed at the macro-level. However, it can be applied to the hospital system where complex adaptive systems interact. A system is a collection of independent but interrelated elements or components organised to accomplish an overall goal.[45] A hospital can be seen as part of the whole healthcare system, while a hospital itself is composed of several subsystems. Within these subsystems, several processes are coordinated to accomplish the objectives of the subsystems. In turn, these processes are affected by several elements such as patients developing complications. In general, patients are the most important actors in the system. Their outcomes influence the delivery of the system (e.g. readmission triggers use of resources). In hospitals, a consistent degree of system understanding is an overwhelming task due to uncertainty and interdependencies. An important principle in this thesis is that several patient factors affect processes which in turn affect other parameters in the system such as waiting times and the number of admitted patients.

## 1.8 THE COUNTRY CONTEXT

Oman is a country that is located in the south eastern corner of the Arabian Peninsula and has a population of 4.4 million people. The total area of Oman is approximately 309,500 square kilometres. The discovery of oil in Oman in the late 1950s has assisted the government to modernise infrastructure and to set various development programs including eradication of illiteracy. Today, Oman's economy is still largely reliant on oil export. The current Gross Domestic Products of the country is 58 USD billions.[46] Health services are provided for free to citizens and foreign employees working for the government. Since there is no income taxation in Oman, the public healthcare sector is funded through the general revenue. The total health expenditure accounts for 2.7% of the Gross Domestic Products.[47]

## 1.9 CARDIAC CARE SERVICES IN OMAN

The drastic improvement of healthcare services in Oman over the past four decades has increased life expectancy and other health indicators. However, such achievement is overshadowed by dramatic increase of chronic health problems, including cardiovascular diseases.[10] Life style risk factors such as diabetes and obesity are common in the gulf countries.[48] It is estimated that 12% of the Omani population has diabetes, 30% are overweight, 20% are obese, 41% have high cholesterol, and 21% have metabolic syndrome.[49] These risk factors not only increase the risk of cardiovascular diseases, but also place pressure on healthcare resources. The demand on cardiac procedures such as Percutaneous Coronary Intervention (PCI) and cardiac surgery is intensifying as a result. Waiting lists have increased, risking patients' wellbeing. Despite this, there are no national stipulated waiting time targets (e.g. the time from point of referral to the point of admission) that hospitals are required to achieve. Investment in capacity has been limited due to physical space in hospitals and scarcity of qualified staff.

The growth of cardiac care services in Oman has been slow relative to the population density and increase in prevalence of heart diseases. This is reflected by the limited number of facilities dedicated to cardiac interventions. At the time of this writing, there are only two public hospitals in Oman that provide cardiac procedures. Patients from all over the country are referred to these hospitals. Another issue facing the delivery of cardiac care services in the country is the lack of a national strategy that outlines quality and directions for services. An example of an effective strategy was the UK national service framework for coronary heart disease which set several countrywide reform initiatives.[50] Since its introduction, some major achievements including reduction in waiting times have been reported.[51]

Treatments and surgical services provided to cardiac patients are among the most expensive in Oman. The limited resources have resulted in several operational issues including prolonged waiting times (e.g. an average of 4 months for an echocardiogram) and an increase in the number of cancelled procedures. The availability of CICU beds is another issue. There are only 10 CICU beds in the country at the time of my data collection. The problem is aggravated by lack of intermediate care services such as step-down units. Emergency cases often tend to disturb normal patient flow in both hospitals. Patients in Oman are exclusively scheduled on the basis of their urgency. Scheduling of elective patients for heart procedure is rarely based on consideration related to patient factors. Instead it is driven by factors such as physician working schedule and availability of beds. The existing resource planning doesn't have the capacity to cope with constraints introduced into the system by patients and thus it lacks robustness. Therefore, it can be said that some sources of inefficiency in the existing system may be due to ineffective resource management.

There is lack of national statistics regarding the number of patients who are diagnosed with cardiac disease such as Coronary Artery Disease or Ischemic Heart Disease. There is no national registry that tracks the prevalence of heart diseases in Oman. It is also difficult to speculate on the number of patients who are diagnosed with these diseases, but don't receive the required interventions.

## 1.10 THE TWO HOSPITALS CONTEXT

The Royal Hospital (RH) is the largest hospital in Oman and it comes under the umbrella of the Ministry of Healthcare. The hospital has 624 beds and over 3000 full time employees. In 2013, 182,000 outpatient visits were made by patients. Bed occupancy rate was 84% for cardiology and 68% for cardiothoracic surgery.[52] Around 10,000 major and minor surgeries are performed per year in the hospital. It is the first hospital in the country that was authorised to perform heart operations. Every day, patients are referred to this hospital for treatment from all over the country. It has a high degree of specialisation in areas such as oncology, cardiology, infectious diseases, and neurology. The RH receives between 70 to 100 referrals request for cardiac procedures per week.

On the other hand, the Sultan Qaboos University Hospital (SQUH) is an academic institution that is affiliated with the largest university in the country. The hospital treats employees of the university and their families as well as referred patients from different hospitals. For the past twenty-three years, the hospital has supported medical education through training and supervision of medical students. The SQUH is a fully-fledged national referral hospital with the capacity to treat complicated cases and emergencies. Continuous government funding has assisted the hospital to earn a reputation as a centre of excellence in medical teaching and patient care. All services are provided free of charge. In recent years, demand for hospitals services has increased due to an increase of beneficiaries from within the affiliated university and the population in general. Expanding services beyond the current physical boundaries of the hospital is challenging due to existing limitation and shortage of space outside the main hospital building.

Both hospitals are situated in Muscat, the capital city of Oman and are equipped with the most modern medical equipment required for diagnostic and treatment purposes. The two hospitals operate under autonomous managements with discretion to manage human and financial resources. Management in each hospital was seeking means to increase efficiency and improve quality. The hospitals perform the majority of the cardiac procedures in the country (around 95%), while the remaining 5% are performed by a private hospital.

## 1.11 HEART DISEASE INTERVENTIONS

Several care services are provided to patients with cardiac care. Coronary artery disease is a common disease that affects many people around the world.[53] The disease starts as one of the heart vessels get occluded preventing the heart from receiving a normal blood supply. The disease can affect patient life expectancy and inflict great physical and psychological changes. Another common disease that requires intervention is valve disease. Heart valves function to ensure coordinated forward blood flow during the cardiac cycle.[54] Malfunctions of valves can occur if the valves can’t control normal blood flow either due to valve narrowing or incompetence. There are four types of valves that control cardiac blood flow: aortic, mitral, pulmonary and tricuspid valves.

Patients complaining of chest discomfort constitute a large number of users of Accident and Emergency (A&E). Approximately half of the patients with ST-segment depression will develop Myocardial Infraction (MI) within hours after presentation to the A&E.[55] A substantial portion of patients with unstable angina (UA) and non-ST-segment Elevation Myocardial Infarction (NSTEMI) will be hospitalised. The 12-lead ECG and cardiac biomarkers are key diagnostic tests that should be obtained either prior to A&E arrival or during early presentation.

The two most common interventions are: Percutaneous Transluminal Coronary Angioplasty (PTCA) and CABG. PTCA, also known as Percutaneous Coronary Intervention (PCI) or angioplasty, is often preceded by diagnostic catheterization (angiography) in which a catheter is introduced into a vein or artery and advanced toward the heart. With the injection of a contrast fluid, the coronary arteries can be visualised using x-ray machine. The interventionist cardiologist can accurately determine the level of occlusion and whether a therapeutic procedure is required. Angioplasty can be performed during the diagnostic session or it may be scheduled for a later date. The decision to delay the procedure is primarily left to the patient unless there is an immediate risk to his or her life.

CABG is performed to replace one or more vessels. The procedure involves grafting a vein and attaching it to the heart. The operation is done frequently with the support of a heart and lung machine known as Cardiopulmonary Bypass (CPB) machine. The surgery can also be performed with a beating heart (off pump). A team of several specialists is required during heart surgery which include surgeons, scrub nurses, perfusion technicians, and anaesthetists.

Timing of care is crucial. For myocardial infarction (i.e. STEMI) patients, a thrombolytic agent should be administered in less than 30 minutes, alternatively if PTCA is chosen, the delay from patient arrival to the A&E to balloon inflation should be less than 90 minutes.[55] Any patient at high risk for unstable angina or NSTEMI should undergo coronary angiography and revascularisation within 12 to 48 hours after presentation to the A&E department.[56]

## 1.12 DESCRIPTION OF THE CARDIAC CARE SYSTEM

The cardiac care systems in Oman are divided into two major specialities: cardiothoracic surgery and cardiology. Care is delivered through six main components: outpatient clinics, cardiac Catheterization Laboratory (Cath Lab), Cardiac Care Unit (CCU), operating theatres, cardiac intensive care unit, and inpatient wards. Cardiac departments in Oman receive patients from three different sources: 1) internal referral from other departments, 2) Accident and Emergency, and 3) other hospitals (elective referrals). Referral requests go through a review process that may take a few hours to several days. The decision to “accept” patients takes two factors into consideration: the state of the cardiac unit and the condition of the patient. The state of the cardiac unit refers to the availability of resources such as beds necessary to admit patients while patient’s characteristics include factors such as severity of disease, age, and the probable outcomes.

Patient encounters with the cardiac system usually start with referral to the cardiology department. Patients will be either treated medically, admitted to the cardiac wards, or referred for cardiothoracic surgery. In Oman, surgical patients are admitted for assessment prior to their procedure as there is no “pre-assessment clinic” in both hospitals. An Anaesthetist will assess patient’s fitness for surgery. Late cancellation due to unsuitability for surgery can arise. Patients are selected for surgery based on availability of CICU beds, patients' preferences, and fitness for surgery. Cardiology departments are usually major gateways to cardiothoracic surgery.[1] In Oman, there is a resource sharing arrangement between the two departments. For example, it is common to share resources such as beds when their availability is an issue.

After surgery, patients will be transferred to CICU if they need intensive monitoring and care. Patients are normally monitored in this unit for 48 hours. The decision to transfer patients from CICU to lower level of care is complex and is evaluated based on multiple prognosis signs.[57] Patients can't be checked into the OR unless a CICU bed is available. Accordingly, the CICUs are major bottlenecks to the OR and have restricted the number of surgeries in both hospitals in the past. Occasionally, other non-surgical patients are also admitted to the CICU. Patients will continue their recovery in the cardiothoracic ward which is the last place before discharge. Patients who develop complications will stay longer in hospital for several days or even months.

In Oman, the current model of scheduling patients remains a one-size-fits-all system, whether the patient is healthy or a complex case. Patients are admitted or scheduled for surgery based on first-come-first-serve basis in most cases. Even though there is no prior study assessing the consequences of this practice, I expect it to be a major factor for operational and financial inefficiency.

## 1.13 WHAT IS DISCRETE EVENT SIMULATION?

Perhaps, the most commonly used type of simulation modelling in healthcare application is the DES. DES was introduced in the early 1960s whereby it came together with General Purpose Simulation System, an early programming language for simulation.[58] As applications of DES

[1] Surgeons in the hospitals under study estimate that about 50% of all surgical cases are referred from internal cardiology departments.

increased, there has also been an increase in the development of DES proprietary packages that enabled more ideas to be tested in risk-free environment without extensive programming.

The main focus of DES is a representation of an entity (e.g. patient) though a sequence of events driven by certain logic. The simulation is driven by entities that move through locations (e.g., waiting room, OR, etc.) while requesting resources (e.g., staff, beds, etc.) as needed. An entity will have the tendency to trigger certain events and resources. For an event, it can be described as an activity such as treatment and transport. A resource might be an inpatient bed, staff, or medical equipment. The simulation stores the desired model inputs (e.g. patient arrivals, LOS, number of tests, etc.). These inputs are also known as "event list".[59] The simulation then moves from one discrete event to the next, updating the system clock and system variables. Events are randomly generated, based on input probabilities. The flow is defined by the user and can include several patterns. The simulation model uses statistical sampling rather than mathematical formula and therefore the choice of run length affects the accuracy of the estimate.[59]

## 1.14 REFLECTING PATIENT VARIATION IN HOSPITAL RESOURCE PLANNING

One possible strategy to optimise use of resources is to manage patients with similar resource consumption. Case mix methodologies categorise patients into groups based on clinical information, commonly to identify cost differences.[60] The most common case mix system is the Diagnosis Related Group (DRG). Many hospitals in the United States and Europe are reimbursed based on the mean cost of the case mix group.[61] In Oman, the DRG, or its variants, are not in use by hospitals. In addition, the DRG would be too broad for use in classifying patients based on resource use in a single speciality such as cardiothoracic. In the face of this, existing patient data can offer an alternative means to evaluate the role of patient variation in resource utilisation.

### 1.14.1 Capturing variation in simulation models

Paul Harper[62] discusses four approaches of capturing patient variability in healthcare models:

1. Ignore variability: in this type of models, patients are considered homogenous and average values are used.
2. Re-sample all individuals: these models attempt to replicate the real-life experience of the patient. This is a time-consuming and still lacks the ability to provide insight for future prediction.
3. Build a stochastic model with one "generic" patient group: distributions are specified for each parameter in the model and individuals are sampled from the entire possible range of (observed) values.
4. Create patient groups: each patient group will have their own set of parameters, distributions, care pathways, etc.

The last approach is preferable for two reasons. Firstly, more insights can be gained in regard to patient and resource relationship. Secondly, when simulation is used for modelling capacity problems, different strategies can be tested which allows selection of the best strategy that meets the requirement of a particular group of patients. This can be more cost effective than implementing resource allocation strategies for all users of services.

## 1.15 RESEARCH QUESTIONS AND OBJECTIVES

The main aim of this study is to understand how factors related to patient and treatment can be incorporated into hospital resource planning to improve performance. Therefore, the empirical objectives can be divided into three main headings:

1) Identification of patient factors influential to resource utilisation, 2) Evaluation of the role of complications (as a source of variation) on resource utilisation and operational performance, and 3) Evaluation of strategies to accommodate patient variation.

This research is guided by the following research questions:

**RQ1: What factors are influencing resource utilisation among patients with cardiac interventions in Oman?**

- Objective 1: To survey literature on resource utilisation among cardiac care patients undergoing cardiac interventions.
- Objective 2: To identify independent factors for prolonged postoperative LOS among patients undergoing cardiac surgery in Oman.
- Objective 3: To identify independent factors for admission following outpatient cardiac angiography.

**RQ2: Can existing cardiac risk stratification systems explain variation in resource use among the Omani patients?**

- Objective 4: To validate existing risk stratification models for predicting prolonged LOS.

**RQ3: How variation around patient and treatment can be incorporated into hospital resource planning?**

- Objective 5: To survey literature on the use of DES in planning resources in healthcare facilities and to investigate the extent to which DES models account for patient variability.
- Objective 6: To construct a DES model to examine resource allocation strategies that can improve operational performance.
- Objective 7: To evaluate the utility of resource prediction models using DES.

**RQ4: Do complications exert an influence on hospital operational performance? If so, how can this knowledge be utilised to optimise resources in order to improve productivity?**

- Objective 8: To quantify excess LOS associated with postoperative complications.
- Objective 9: To quantify the effect of complications on operational performance using DES and suggest resource planning strategies to mitigate the effect of complications on operational performance.

### 1.16 THESIS LAYOUT

In this section I provide an overview of the layout of the thesis, chapter by chapter, in order to inform the reader at the outset how the study parts are connected (Figure 1-2)

**Chapter 1** describes the importance of the subject and it presents an overview of the hospitals under investigation. The chapter also introduces the research questions and its objectives.

**Chapter 2 and 3** provide literature review which is most related to two bodies of research: 1) factors affecting resource utilisation among cardiac care patients, and 2) the use of DES in healthcare facilities. The literature review chapters were an essential background information that facilitated the selection of variables, interpretation of results, and addressing how the research questions should be approached. Chapter 2 reviews existing uses of DES in healthcare facilities and how patient variation was addressed in simulation models. Chapter 3 sets the tone for variable selection and further data collection from the two Omani hospitals

**Chapter 4** is about methodology which includes detail related to data collection, techniques of data analysis, and description about the hospital settings.

**Chapter 5 to 8** are the results of the thesis. In chapter 5, I provide general descriptive statistics about the patients and use of services. Chapter 6 presents models for predicting resource use among patients. In chapter 7 I built DES models to test how patient variability can be incorporated into resource planning in hospitals. In chapter 8 I introduced the concept of quantifying the effect of complications on operational performance.

**Chapter 9** provides a general discussion which includes contributions of the research, limitations, and recommendations.

Finally, **Chapter 10** concludes the thesis and highlights future work.

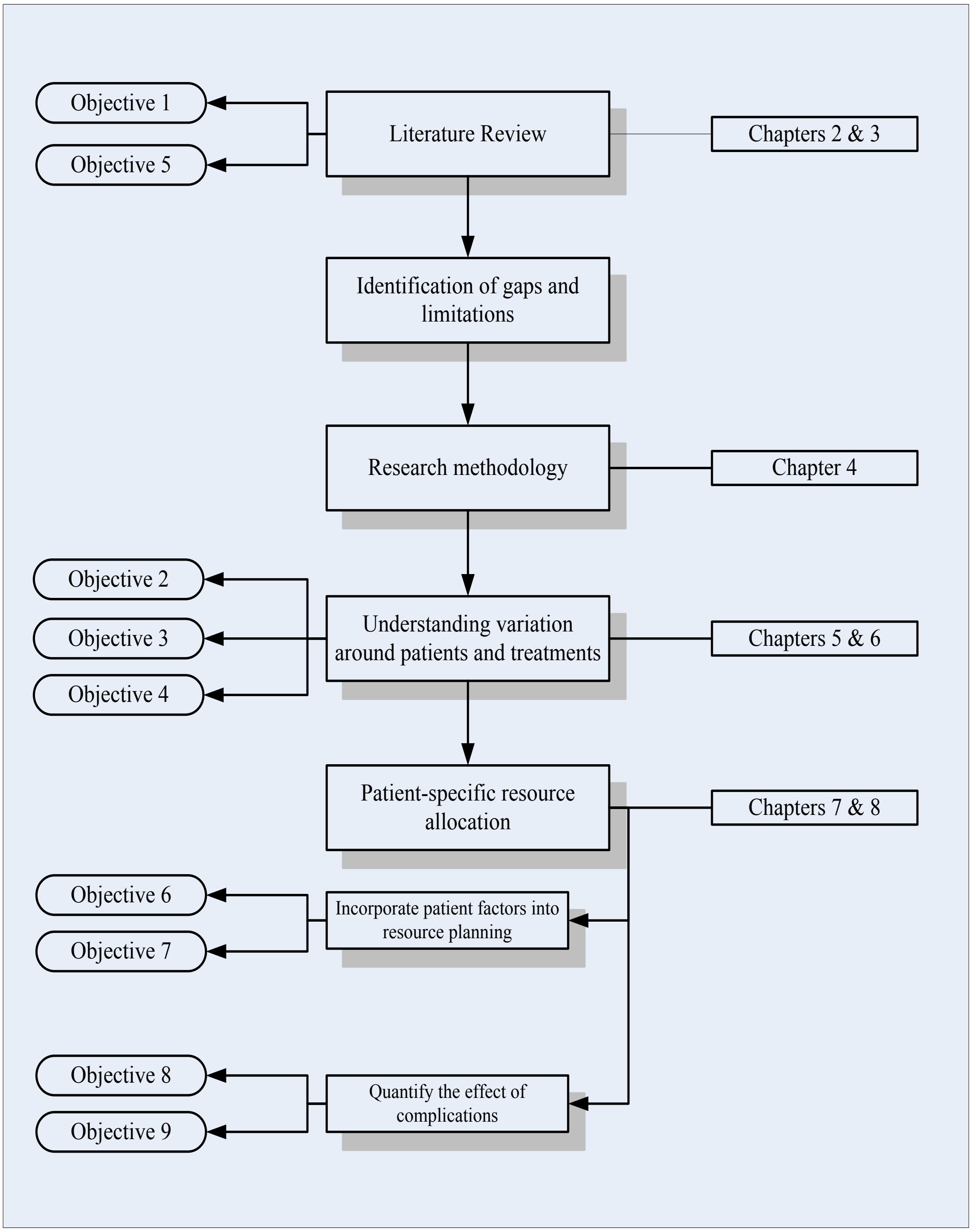



**Figure 1-2 Thesis structure in relation to its objectives**

# Chapter 2

# LITERATURE REVIEW: DES MODELLING FOR PERFORMANCE IMPROVEMENT IN HEALTHCARE FACILITIES

## 2.1 CHAPTER OVERVIEW

This chapter provides an overview of existing literature on the application of simulation modelling in healthcare organisations. Firstly, I explore the applications of DES in healthcare settings. Secondly, I assess the level of detail in simulation studies and the extent to which patients and treatment factors associated with variation are represented in these studies.

## 2.2 INTRODUCTION

The enthusiasm for the increased use of simulation in healthcare stems from its flexibility in incorporating several stochastic and dynamic elements common in complex healthcare processes.[63] Computer simulation can allow decision makers to quantify effects of an intervention on interdependent processes before expensive schemes can be implemented. As a result, it has been applied to a wide range of issues from optimising capacity in a single hospital unit to improving performance of a wider healthcare system. Considering the substantial growth of healthcare simulation papers in recent years,[64] I anticipate a similar increase in applications to wider healthcare settings and issues.

The desire to improve efficiency and reliability in healthcare has resulted in adoption of system engineering techniques. These tools have substantially improved performance in other industries from manufacturing to aviation, and hold similar promise for healthcare.[65] Techniques such as six sigma, Plan-Do-Study-Act, and health failure modes and effect analysis are being used in healthcare to achieve improved quality and efficiency.[66] Although adopting an industrial process philosophy to healthcare may seem straightforward, this is often not the case.[67] Patients exhibit variation in severity and use of resources. Variation is known to be intrinsic in healthcare.[19, 62] Consequently, achieving a realistic simulation modelling with adequate representation of variation can be challenging.

If we assume it is a common intention of modellers to produce models that resemble reality as much as possible, then some basic patient characteristics should be incorporated into models. For example, a model concerning resource allocation should account for the fact that younger patients are expected to recover faster than older people after a surgery and thus aggregating patients in a single group might not echo reality. Models can suffer from "data gap" if several data were aggregated.

### 2.2.1 Complexity of healthcare processes and the role of simulation

Healthcare organisations can be viewed as complex adaptive systems.[68] They are collection of individuals who are free to act in ways that are not totally predicable.[69] Respectively, daily operations are likely to be impacted by occurrence of uncertain events such as arrival of emergency cases or patients developing adverse events while receiving care. This state of uncertainty exerts pressure on existing resources which have to be effectively managed to ensure a certain level of quality.

Interaction between patients' clinical factors such as severity of disease and hospital resources (e.g. utilisation of ICU bed) constitutes an example of healthcare complexity. Patient related factors can alter the course of the treatment and induce variation in resources requirements. Despite this, resources are allocated based on their average utilisation (e.g. bed occupancy rate) which are not a good measure of services provided inside hospitals.[3] The wide variation in case mix and thus cost of those occupying the beds are simply not reflected in many traditional resource planning practices.

Computer simulation models have the capability to investigate improvement strategies from a system-wide perspective. In hospital operation for instance, inefficiency in a downstream area can slow down or even halt activities at an upstream service. Moreover, patient interactions in healthcare systems do not conform to linear or simple patterns. This dynamic complexity adversely can affect resource utilisation[70] and makes resource planning a challenging task. Computer simulation, however, can aid decision making by effectively incorporating patient journeys along with influencing factors such as resource availability, priority of care, and uncertain events. It accounts for how changes in one part of the patient's pathway might impact other system components. Such tools mostly seek to maximise throughput subject to budget and capacity constraints.

However, attempting to reflect complex system and patient elements in simulation models are easier said than done. First, there is an immense complexity in healthcare systems and including a greater level of detail to improve credibility of the model can be challenging.[71] As more elements of the system get included in a model, data requirements exponentially increases. In general, modellers chose a level of abstraction and scope that they think is appropriate.[63] It might be the case that capturing the essence of the system instead of modelling every detail will suffice.[72] However, in healthcare this is often overshadowed by the existence of complex and interrelated processes that are simply difficult to disregard.

I hypothesised that patients and treatment factors are overlooked in simulation models. I will discuss why this level of detail is crucial for resource planning in hospitals.

## 2.3 AIMS AND OBJECTIVES OF LITERATURE REVIEW

The aim of this chapter is to explore how computer simulation is being used as a tool for improving performance in healthcare organisations. Particular emphasis is given on how variation surrounding patient mix is represented in simulation models. Findings from this literature review will be used to support the theoretical basis of this thesis.

By reviewing recent works on healthcare simulation modelling, this review attempts to achieve the following objectives:

1) To explore different applications of simulation studies, their objectives and proposed interventions, 2) To assess the extent to which clinical factors or patient characteristics are represented in simulation models with a view to inform future models building, and 3) To determine any emerging new uses of computer simulation for healthcare performance improvement.

## 2.4 METHODS

### 2.4.1 Search strategy

I searched three electronic databases (PubMed, SCOPUS, and the Web of Science) to capture relevant literature on the applications of DES in healthcare facilities. A broad set of search keywords were used: (discrete event simulation) OR (Model*) AND (hospital) OR (clinic) OR (patient flow) OR (health*) OR (operation) OR (emergency) OR (service). The search was restricted to a period of 11 years (2004-2014).

The following information was recorded in a data collection form:

- The paper detail (e.g. title, year of publication, simulation approach, type of publication).
- Healthcare settings (application area).
- Modelling objectives (e.g. type of performance improvement, proposed interventions).
- Patient factors representation (whether the paper describes a patient flow, the level of representation, and list of any clinical factors represented in the model).

### 2.4.2 Study selection and exclusion criteria

I included studies if they met the following criteria: 1) the study has to be available as a full text in English language, 2) Only studies where the primary method of analysis is DES with the aim of optimising performance of a process or multiple processes in healthcare, and 3) the publication date is between 2004 and 2014. I excluded papers based on the following criteria: 1) papers with the main tool of analysis is not simulation such as descriptive, analytical, and qualitative models, 2) studies which are intended to improve provision of care at the population level with no reference to patient flow in a particular healthcare organisation, and 3) papers that are published in conference proceedings.

## 2.5 RESULTS

A search of electronic databases identified 948 publications. After a review of titles, 823 articles were retrieved for further inspection and 53 were included in the final review (Figure 2-1).

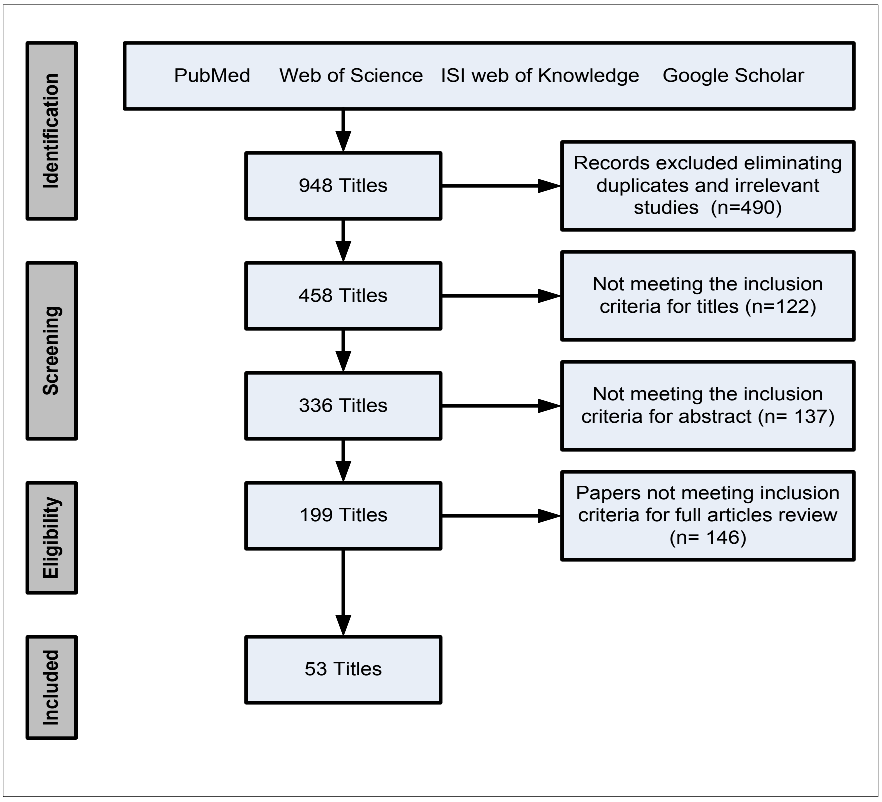



**Figure 2-1 Flow chart of studies selection process**

The reviewed papers were examined based on the objectives and scope and their representation of patient clinical factors (Table 2-1).

**Table 2-1 Characteristics of the simulation studies**

| First author | Healthcare setting | Scope and interrelationship with care setting | Patient clinical characteristics | Investigated area(s) of improvement |
|---|---|---|---|---|
| Antuela A Tako (2013) | Speciality clinic | Multiple micro-systems | None | RP |
| Peter T VanBerkel (2007) | Surgery/ OR | Multiple micro-systems | Diagnostic category | RP |
| Borjorn Berg (2010) | Diagnostic service | Single micro-system | None | RP |
| Waressara Weerawat (2013) | Outpatient clinic | Multiple micro-systems | None | RP, S |
| Jeroen M Van Oostrum (2008) | ED | Single micro-system | safety intervals for postponing surgery | RP |
| Solmaz Azari-Rad (2014) | Surgery/ OR | Multiple micro-systems | acuity/ priority level | RP, S |
| C. Vasilakis (2007) | Surgery/ Outpatient | Single micro-system | surgical priority | S |
| Zhen Zeng (2012) | ED | Single micro-system | acuity/ priority level | RP |
| R.S Maull (2009) | ED | Single micro-system | acuity/ priority level | PM |

| First author | Healthcare setting | Scope and interrelationship with care setting | Patient clinical characteristics | Investigated area(s) of improvement |
|---|---|---|---|---|
| S Vanderby (2009) | ED | Multiple micro-systems | acuity/ priority level | RP, DM |
| John Bowers (2013) | Surgery/ OR | Multiple micro-systems | none | RP |
| Beate Jahn (2010) | Cath Lab | Single micro-system | patients groups | RP |
| Diwakar Gupta (2007) | Cath Lab | Single micro-system | acuity/ priority level | RP |
| Juha-Matti Lehtonen (2007) | Surgery/ OR | Single micro-system | none | PM |
| Gerhard Wullink (2007) | Surgery/ OR | Single micro-system | none | RP, PM |
| Geoffrey R. Hung (2007) | ED | Single micro-system | acuity/ priority level | RP, S |
| Fernando C. Coelli (2007) | Diagnostic service | Single micro-system | none | RP |
| Alan B Storrow (2008) | ED | Single micro-system | none | PM |
| Chantal Baril (2014) | Outpatient clinic | Single micro-system | none | RP, S |
| J.R Villamizar (2011) | Diagnostic service | Single micro-system | none | RP |
| Peter Chemweno (2014) | Speciality clinic | Single micro-system | acuity/ priority level | RP |
| Steffen Bayer (2010) | Speciality clinic | Macro system | none | RP |
| Nathan R. Hoot (2008) | ED | Single micro-system | acuity/ priority level | RP |
| Rodrigo Ferreira (2008) | Surgery/ OR | Multiple micro-systems | none | RP, S |
| Sameer Kumar (2011) | Surgery/ OR | Multiple micro-systems | none | RP |
| Thomas R. Rohleder (2011) | Diagnostic service | Single micro-system | none | RP |
| Jomon Paul (2012) | ED | Single micro-system | acuity/ priority level | RP |
| Yariv Marmor (2013) | ICU | Multiple micro-systems | patients bouncing back to OR or ICU | RP |
| A.K Shahani (2008) | ICU | Single micro-system | patients groups | RP |
| Philip Marc Troy (2009) | ICU | Single micro-system | patients bouncing back to OR or ICU | RP |
| Argelio Santos (2013) | Speciality clinic, rehabilitation | Macro system | complications | RP, PM |
| Thomas R. Rohleder (2011) | Speciality clinic, orthopaedic | Single micro-system | none | RP |
| Murat M. Gunal (2010) | Whole hospital | Multiple micro-systems | none | RP |
| Marie E Matta (2007) | Speciality clinic, Oncology | Multiple micro-systems | none | DM |
| Woan Shin Tan (2009) | Pharmacy service | Single micro-system | none | PM |
| Christine Duguay (2007) | ED | Single micro-system | none | RP |

| First author | Healthcare setting | Scope and interrelationship with care setting | Patient clinical characteristics | Investigated area(s) of improvement |
|---|---|---|---|---|
| Pablo Santibáñez (2009) | Ambulatory care, Cancer centre | Single micro-system | none | RP, S |
| Vikram Venkatadri (2011) | Cath Lab | Multiple micro-systems | none | PM |
| Kidak Levent (2011) | Surgery | Multiple micro-systems | none | RP |
| Aaron E. Bair (2010) | ED | Single micro-system | acuity/ priority level | RP |
| Christopher Brasted (2008) | Diagnostic service | Single micro-system | none | S |
| James E. Stahl (2004) | Surgery | Single micro-system | complications | RP |
| Bo Kim (2013) | Mental health clinic | Single micro-system | none | RP |
| S G Elkhuizen (2007) | Outpatient clinic | Single micro-system | none | RP |
| Chi-Lun Rau (2013) | Physical therapy | Single micro-system | none | RP |
| Mathew Reynolds (2011) | Pharmacy service | Single micro-system | none | PM, RP |
| Allyson M. Best (2014) | ED | Single micro-system | none | RP |
| Brian J. Masterson (2004) | ICU | Multiple micro-systems | none | RP |
| Riitta A. Marjamaa (2009) | Surgery | Single micro-system | none | RP, PM |
| Lloyd G. Connelly (2004) | ED | Single micro-system | none | PM, RP |
| Stuart Brenner (2010) | ED | Single micro-system | acuity/ priority level | PM |
| A. Sciomachen (2005) | Surgery/ OR | Single micro-system | none | S |
| Theodore Eugene Day (2012) | ED | Single micro-system | none | RP |
| **ED**: Emergency Department, **OR**: Operating Room, **Cath Lab**: cardiac catheterisation laboratory, **RP**: resource planning, **S**: scheduling, **DM**: demand management, **PM**: process modification | | | | |

### 2.5.1 Objectives and scope of simulation studies

I broadly divided objectives of simulation studies into four categories based on the proposed intervention strategy of each simulation model (Table 2-1). The categories and their use in the reviewed articles were as follow: 1) resource planning, 2) demand management, 3) process modification, and 4) scheduling. Many papers included more than one of these categories. In this section I will discuss the objectives of the simulation studies and how they relate to the models' level of detail.

Some of the reviewed studies utilised DES for evaluating policy at strategic level,[73] addressing tactical level issues such as waiting time management,[14, 15] or evaluating logistical issues at the operational level.[74-76] The popularity of DES can be attributed to the ever-increasing sophistication of DES simulation software packages.[77]

### 2.5.2 Resource planning

Most studies in my review were motivated by the desire to plan resources more effectively to overcome system issues such as waiting times and bottlenecks. Resource planning in this review entails modification of capacity either by adding more resources or downsizing existing ones to achieve an optimum operational level as defined by some performance measures.

There are substantial waiting times involved in many healthcare facilities. Perhaps it is because of this single problem, simulation in healthcare has been predominately focused on tackling waiting times.[63] Several simulation studies were motivated by sources of inefficiencies leading to extended waiting times. This has been the case in studies assessing patient flow in emergency departments where overcrowding and prolonged waiting times have been a source of concern to healthcare planners.[78-87] Zhen Zeng et al,[79] for example, constructed DES models to evaluate how changes in the number of nurses, physicians and computerised tomography scanners can impact waiting times and patient walking away from ED. Similarly, the policies explored by Brenner et al[88] to improve throughput of an ED involved selecting optimal configuration of nurses at different type of care as well as the number of doctors, radiograph machines and a CT scanners.

The use of DES for planning and managing resources in other healthcare departments has also been driven by similar issues such as long waiting times to access healthcare services (e.g. a surgery). However, such models are more oriented toward tactical rather than operational level. In this case, individual processes and tasks are non-relevant to the simulation as long as they are represented by a high level process with related parameters. For example, Tako et al[89] developed a simulation model of patient flow in an obesity service to determine the best decision to allocate resources in order to reduce waiting times and achieve 18 week target. A fixed number of patients are allocated to each clinic (e.g. pharmacotherapy clinic) per week instead of sampling a service time for each patient from a probability distribution. The only uncertain event that is considered in the model is the failure of patients to attend surgery.

Kim et al[90] found that extending daily operating hours of a mental health clinic by two and including an additional psychiatrist will result in a decrease in patients seen outside clinic hours. Elkhuizen et al[91] calculated the number of consultants needed to keep appointment time within two weeks for outpatient clinics. A daily operational routine at a physiotherapy unit was simulated in order to evaluate the effect of varying patient arrivals, human resource availability, patient scheduling, and the number of beds on patient throughputs.[92] Among the findings of this study is the opportunity to increase throughputs when the number of treatment rooms is decreased. Likewise, Wullink et al[93] found that having a dedicated operating room for emergency is unnecessary and that an effective option would be to spread capacity for emergency surgeries to all elective operating rooms.

Berg et al[75] used DES to simulate workflow of a colonoscopy suite with performance measure that included patient volume and utilisation of key resources. Utilisation of intake and recovery resources becomes more efficient as the number of procedures rooms increases, indicating the potential benefits of large colonoscopy suite. A similar study[94] assessed patient flow, equipment utilisation, and staff needs for a mammography clinic to reduce waiting times.

The dynamic interdependency between healthcare resources are not adequately captured in some of the reviewed studies. Gupta et al[95] found that allocating extra capacity to the highest urgency patients waiting for cardiac Cath Lab procedure has reduced waiting times. However, the authors fail to consider bed capacity required after each catheterisation procedure and the fact that Cath Lab productivity can be reduced by patients blocking beds for reason such as unanticipated additional LOS. Comparably, the study by Storrow et al[83] only considered lab turnaround as the only measure to improve ED throughput and decrease emergency diversion. In reality, capacity can be restricted by other factors such as availability of admission beds.

Another issue can be identified when DES are used for human resource planning such as defining staffing levels. Generally, clinical staff in DES models are only seized for a single task at a time. This practice disregards real life situations where staff are engaged in multiple tasks and their workflow might consist of working with several patients. Nevertheless, one study has included some aspects of human resource management in DES to understand the effect of punctuality of staff members on patient waiting times.[96]

### 2.5.3 Demand management

There is an opportunity in healthcare to manage admissions, transfers or discharges. Ignoring such management responses in simulation projects can overestimate the capacity requirement.[73] Many simulation studies don't explicitly incorporate demand management strategies. In many instances, managing demand can be seen as a way to ease pressure on a valuable resource when the option considered is convenient for patients.

Shahani et al[97] tested the impact of discharging patients with LOS of over 15 days from a critical care unit to another (notional) unit capable of looking after them. Although the long stay patients represent only 3.6% of all admissions in the study, moving patients elsewhere reduced the transfer rate by approximately 60%, the deferral rate by 50% and bed occupancy by 10%. Tako et al[89] examined the policy of reducing patient referral to an obesity service in the UK to half of the baseline figure. As a result, the proportion of patients waiting for more than 18 weeks was reduced. The rationale behind this policy is that certain patients can be seen by general practitioners in primary care clinics rather than treated at the obesity centre. Another study examined the effect of managing demand by smoothing arrivals of patients uniformly throughout the course of the day.[98] Rau et al[99] simulated patient flow in a physiotherapy outpatient clinic to investigate the potential effect of changing the number of returning patients. Five incremental demand levels were defined (e.g. 10% less, 30% more). Impact on waiting time and LOS was quantified for each level.

### 2.5.4 Process modification

I define process modification as alteration of the rules of existing practice or workflow to improve processes without necessarily modifying the quantity of resources. For example, Lehtonen et al[100] suggested some process interventions such as induction of anaesthesia outside the operating room, shorter slack time (i.e. the time margin used when accepting a second surgery to avoid overtime work), and shorter setup time between surgeries to increase output and productivity for open-heart surgery. Similarly, several workflow models of parallel induction of anaesthesia were assessed to select the optimal alternative that increase patient volumes.[101] A centralised multiple-bed induction room serving several operating rooms was found to positively improve performance compared to traditional model having induction in the OR.

Storrow et al[83] have provided evidence on how a decrease in lab turnaround (through alternative use of point-of-care testing) can positively affect ED efficiency. The study has not considered, however, the reliability of these tests (assuming they cover a wide range of tests) and their acceptance among physicians. Tan et al[102] designed a DES model to estimate the impact of an automated dispensing device on patient waiting time. The simulation results showed that the automation system will not reduce waiting time. However, employing two additional pharmacists can meet the waiting time target of 30 minutes without the need to invest in a new system. In a similar study, an incremental increase in the utilisation of an automated dispensing machine was found to decrease mean turnaround times of medicine dispensed.[103]

Maull et al[80] claim that an ED (fast-track) strategy can provide significant reductions in patient wait time for patients with minor conditions. Connelly and Bair[104] compared two patient triage methods in ED. A fast track approach and a novel triage concept called acuity ratio triage. In the new approach patients were assigned to staff on an acuity ratio basis. The authors suggest that their model has shown reduction in imaging bottlenecks and average treatment times for high acuity patients when the new approach is used. However, their sample size was based only on five-day period which might not be representative of the actual ED population. Santos et al[105] used DES to evaluate patient journey of patient with spinal cord injury. Their model suggested that providing early surgeries to patients with tetraplegia has direct impact on their neurological recovery and also indirectly impact on cost reduction.

Non-value added time spent by patients at a catheterisation laboratory centre was examined by Venkatadri.[106] To achieve a lower patient turnaround time, four process improvement scenarios were tested. First, assuming patients are available immediately after every procedure without any delays so that inter-procedure delays can be eliminated. Second, reduce inpatient transfer delays (from inpatient ward to the Cath Lab room). The third scenario involved reducing outpatient waiting time and finally testing the effect of reducing procedure room turnaround time.

### 2.5.5 Scheduling

When solutions are based on altering scheduling practices, simulation studies reported no immediate requirement for more resources or financial investment. This should be an important option for decision makers seeking to maximise resource utilisation while controlling expenses. A DES model was used to test the impact of two scheduling methods.[107] In this model, pooled-appointment list and individual-surgeon appointment list were compared based on their impact on the number of patients on waiting lists. The model provides evidence that a pool list increases the chances of getting an appointment within a given time after referral (e.g. within 12 weeks). However, this method led to an increase in the time that non-urgent patients had to wait and thus had no profound impact on total post-referral times. Hung et al[82] constructed a DES model to manipulate physicians schedule to reflect patient arrival rates at a paediatric ED. An extra physician shift to the staff schedule was found to reduce waiting times. Even though the suggested interventions have positive effect on overcrowding, the study doesn’t suggest whether downstream inpatient beds have direct effect on patient waiting times as the model doesn’t interface with inpatient wards.

Solmaz Azari-Rad et al[108] simulated patient flow in perioperative care to reduce the number of surgical cancellations. One tested scenario was altering the weekly schedule of surgeons according to expected LOS. Patients with higher LOS are scheduled at the end of week to take advantage of weekend when no surgery are scheduled. The second scenario examined the effect of sequencing surgical procedures by their length and variance. The two suggested scheduling alternatives were shown to reduce the number of surgical cancellations. Similarly, Sciomchen et al[109] evaluated the impact of changing master surgical schedule and scheduling rules based on: the longest waiting time, the longest processing time, and the shortest processing time. Impact on throughputs, number of patients in the waiting list, number of delayed operations and overruns were the key performance indicators. One of the evaluated strategies in Ferreira et al[110] was to replace the existing rigid scheduling that require assigning a specific OR to a specific team by more flexible schedule that allocates surgical team to any free OR. The authors observed a significant improvement in the surgical centre. However, emergency cases are not included as the hospital has no emergency department.

In study by Baril and colleagues,[111] a DES model was used to allocate number of nurses and consulting rooms based on patient flow types and appointment scheduling rules in an outpatient orthopaedic clinic. This approach may offer an avenue for further investigation because it studies the relationship and interaction between resource capacity, patient flows, and appointment scheduling. Another model designed to improve workflow at outpatient clinics is discussed by Weerawat.[112] They tested a flexible working schedule which involved rearranging doctors' working hours according to patient demand. Under the new scheduling strategy, the average patient total times in the system were reduced. Another study[113] evaluated whether appointment scheduling order for three type of appointments: new patient, follow-up and inter-program consult will have any effect on the system. No significant improvement has been identified by any particular configuration. Brasted[114] used DES that incorporated a distinctive feature of a booking system for a general ultrasound. The model has the flexibility for allowing patients to reconcile their own time within the waiting list.

### 2.5.6 Inclusion of patient-related factors and complications in simulation studies

If we consider patient flow to consist of operational and clinical parts,[115] it would make sense to closely observe the interlink between the two components. Previous research established that patient clinical factors can affect resource utilisation, and hence influence operations as a whole. Such factors include severity of disease,[116] adverse events,[117] and variation in patient mix.[118] Models differ considerably in their inclusion of detail. As such, selecting a sufficient level of detail in a simulation model is a matter for the modeller's judgement, as this is more of an art than a science.[119, 120] In this section, I examine how simulation studies have incorporated patient-related factors. I define patient-related factors as any medical attribute that is unique to the individual patient such as a patient's acuity, age, and sex. I also consider patient complications and adverse events that can influence their care progression and resource use.

#### 2.5.6.1 Adverse events and complications

Only four studies can be identified as having considered or implied patient complications. Santos et al[105] proposed DES model of spinal cord injuries considering several patients attributes. Each patient was given a probability of getting one of five complications. The model revealed that a 10% reduction of pressure ulcers, one type of complications, would result in 9% reduction in total acute LOS. This effect will cascade to rehabilitation services which will experience 2.5% reduction in total rehabilitation LOS. Probabilities in this model are derived from published literature not from site-specific data. This is a drawback as using incidence rates more generically might not reflect the experience of the local practice under investigation.

The study by Troy and Rosenberg[121] incorporated the need for a second ICU stay after an intervention by assigning a probability of patient bouncing back to the ICU for each type of operative procedure. However, there is no indication of whether the second ICU stay is required because of patients developing complications, which is more likely the case. The model could be enhanced by specifying the type of complications and assigning a probability of their occurrence. Marmor et al[122] designed a model to predict minimum recovery bed needs after a cardiovascular surgery and to explore the effects of transferring long-stay patients from the ICU at Mayo Clinic. The model accounted for patients flow between OR, ICU and a step down unit. In the model, patients can bounce back from step down unit to ICU, or from ICU to OR. As the case with the previous study, no specific detail is provided for why patients are returning to previous treatment steps and only fixed percentages are used for their movements.

A DES model was constructed by Stahl et al[123] to determine the cost-effectiveness of a proposed change to surgical and anaesthesia care of laparoscopic cholecystectomy. Complication rate is incorporated into the model. In a case of a complication, patients will progress from laparoscopic to open cholecystectomy. In addition they will required more hospitalisation. The study doesn't explicitly discuss the effect of complication on the overall performance.

#### 2.5.6.2 Patient acuity

I found that the most common clinical representation among the reviewed papers was related to patient priority. In general, incorporating acuity levels in simulation models is a means to prioritise patients in receiving care or to define specific flow. In several ED models patient flows are influenced by patient priority. Triage categories were incorporated into a DES model[80] to assess the impact of a fast-track strategy on patient wait time. Patient acuity was also used to manage admission and the level of care in ED.[84] The model is intended to forecast several operating conditions in a single ED unit. The DES model constructed by Paul and Lin [85] included five severity levels. In the model, incoming ED patients were prioritised according to these levels and test turnaround times were also based on the severity levels. Similarly, in Duguay and Chetouane[86] three triage codes with their standard wait times were used to evaluate patient wait in an emergency department. However, the study lacked a proper representation of different pathways experienced by patients.

Beate Jahn et al[124] considered in their DES model the type of stent (bare-metal vs. drug-eluting stents) and the associated need for repeated intervention if a bare-metal stent is used. In the model, patients were split into four subgroups to account for the higher risks of revascularisation. These groups were based on whether a patient is diabetic or non-diabetic. Patients are further subdivided into whether they are having short or long lesions and a narrow or wide vessels. The implication of using such detail is the ability to determine the type of first (stenting), second (re-stenting) and third line treatments (CABG surgery). Chemweno et al[67] used DES model to achieve lower LOS and improve performance in a stroke unit. In their model, patients are initially given priority status which can change as they advance in the model. Accordingly, priority rules in the model are set to govern patient interaction with resources. Zhen Zeng et al[79] incorporated five patient acuity levels in an ED simulation model. Improvement in waiting times was collected for different acuity levels. A similar study[78] attempted to determine the optimal operating room team composition during the night shift to minimise cost while providing adequate resources for safe operation. The model assigns safety interval for emergency patients from which a decision on postponing night shift surgery can be made.

#### 2.5.6.3 Patient categories

Most simulation models of emergency departments classified their patients by level of triage[86, 87, 104, 125] or trauma level (e.g. minor or major).[80] When the application involves shared resources such as operating theatres, it is common to group patients by speciality[78] or by type of surgery.[74] Despite the evident need to distinguish between patients, some studies have aggregated patients into a single type.[126, 127] Such practice ignores variation known to be associated with patient mix and therefore results can be misrepresentative of the actual resource utilisation.

Swisher et al[128] designed a generic model that is intended to be used as a template within a physician network setting. Patients attending clinics are divided into 10 categories (e.g. patients visiting for tests only, immunisation, diabetes, etc.) Subsequently, data related to resource use, routings, and other behaviours were collected for each category. Data collection was acknowledged to be a formidable task by the authors. Therefore, expert opinions had to be elicited for some unavailable data. Patient categories provided a greater insights and extended the range of possible decisions that can be derived from the model. The DRG groups were used in a simulation study to evaluate changes to improve ICU performance.[129] These groups were used only to distinguish between patient diagnosis and not as a mean to evaluate resource consumption.

Unlike the study done by Levent and Mehmet to improve process in a general surgery services,[126] VanBerkel and Blake[74] assigned 8 diagnosis categories to their patients flow. OR time and LOS were fitted according to the analysis of historical data of each diagnosis category. In the study performed by Kumar[130] to optimise number of beds for surgical patients, heterogeneity among simulated patients is not considered nor their surgery types. The inherent heterogeneity of surgical patients can affect resource use and thus should be treated as an integral element for resource allocation models. Classifying patients based on surgery type would have augmented the model utility and provided an insight into resources and waiting list of different types of patients.

Identification of clinically meaningful patient groups is a way to predict demand and resources more accurately. In Shahani et al,[97] a Classification And Regression Tree Analysis (CART) was used to create patient groups. Statistical distribution of the LOS for each patient category was then fitted. By doing so, the model accounted for patient variability in a higher level of detail.

## 2.6 DISCUSSION

Unlike previous reviews by Fone et al,[131] Gunal and Pidd,[63] and Katsaliaki and Mustafee,[132] my review sought to identify DES applied only to delivery of care within healthcare facilities. It also highlighted some important aspects related to patient variation such as incorporation of patient-related factors, patient acuity, and complications that were not been addressed previously in any review.

I found that objectives of simulation studies tend to be quite varied and broad. A wide range of healthcare issues have been approached by simulation modellers. They have touched almost every part of hospital operations such as bed allocation, OR productivity, ED performance, and patient flow improvement in units such as outpatients and diagnostic services. Despite their usefulness in supporting local management, most of these studies were context-specific and extrapolating their results into the context of other practices is problematic. That is, rules and operational characteristics of the local practice are reflected in the models. In this respect, generic models would require substantial modification if they were to be applied to other settings.

Among the reviewed studies, there was only one study that has considered patient flow beyond the hospital setting. Bayer et al[133] simulated stroke patient journey in the acute and the community care using DES. They tested the effect of changing capacity, availability of resources, the size of community rehabilitation team, and telecare on costs at the acute and community sector. However, for such large system, several parameters were only derived from published literature and national datasets which might not reflect local practices. Respectively, incorporating several microsystems (i.e. multiple hospital departments) in a model, as in studies attempting whole-hospital modelling such as the one done by Moren et al[134] and Gunal and Pidd[135] for the purpose of gaining operational insights is challenging. First, large data are needed from disparate sources. Even with the widespread use of hospital information systems, data are still not readily amenable to simulation.[136] Second, as models increase in size and complexity they are more likely to be susceptible to errors and become difficult to validate.[120] A broad focus on the system is rarely productive.

### 2.6.1 Patient grouping based on resource utilisation

One of the most difficult aspects of using simulation models for healthcare capacity studies is the creation of a manageable set of patient types to include in the model.[137] Categorising patients is a way to provide greater insights on resource utilisations and other variables in the system. Patients are having fundamentally different resource needs and thus modellers should take this into consideration. Patients are differentiated by new or return patients, by acuity, by disease type, or by some other features which ultimately affect service time, routings, and resource utilisation. Having different patient classes in a simulation model is seen as a way to identify specific improvements in patient subgroups that otherwise may be undetectable if patients were lumped together.[98]

Despite the wide use of risk scoring systems among healthcare providers, there is no utilisation of these systems in simulation models to indicate level of acuity. Moreover, many of the reviewed simulation studies have not considered grouping patients based on common resource consumption. Ridley et al[138] attempted to address this limitation through the use of CART technique. Models that consider individual-level patient heterogeneity account for patient characteristics. In such models, values are estimated by sampling from distribution. Patients are split into segments that are as homogenous as possible to provide quantitative information about demand from specific patient group.[139]

### 2.6.2 The value of incorporating patient characteristics in DES

The capability of DES is undermined by failure to incorporate complex system elements such as uncertainty and detail related to patient clinical factors. Thus, the potential benefits of DES as an aid to decision makers are reduced. This is not to suggest, however, that substantial detail is required in all situations. Instead, the inclusion of essential detail should be evaluated in agreement with the overall objectives of the study. Reflecting variation among patients in terms of resource use should enable evaluation of resource allocation strategies. It would be possible to optimise resources based on patient mix and to accommodate existing level of complications into resource planning. Additionally, hospital capacity is influenced by patient mix, thus identifying patient subgroups (e.g. patient with prolonged LOS) permits more focused understanding on how to manage patients to facilitate better patient flow.

The reviewed articles differ in their level of detail. Many models have considered patient flows at a high abstraction level, overlooking significant determinants of resource utilisation such as patient characteristics and occurrence of adverse events. No study, in my review, has attempted to incorporate elements of care pathways (i.e. medical guidelines). Care pathways have been shown to positively affect resource consumption.[140] Their use in simulation modelling can improve inclusion of essential patient details such as progression and complications. However, it might be the case that several features of care pathways can't be numerically captured and the amount of detail that should be collected is a prohibiting factor. Likewise, patient variables can significantly affect system behaviours, throughputs, and cost.[141-143] Yet, there is a paucity of research about the impact of these variables beyond a single resource.

The minimum representation of patient detail can be attributed to: 1) the hurdle with obtaining data. This might be complicated if manual extraction is required, 2) assumption of low significance of certain parameters or variables to the study, and 3) lack of sufficient knowledge about patient-resource interdependency due to low stakeholders engagement. Regardless of the reason, lacking the right detail undermines significant elements of a system and reduces the capability of the model to evaluate important scenarios. The ability of modellers to integrate patient details into simulation models enables more predictive power and may provide greater detail about the patient-resource utilisation relationship.

### 2.6.3 General comment on the quality of the reviewed articles

The reviewed studies considerably varied in their transparency and validation. Transparency involves disclosure of important detail about the model structure such as parameter values, equation and assumptions. While validation is concerned with judging a model's accuracy in making relevant predictions.[144] Validation includes face validity of a model's structure, problem formulation, evidence, and results. A proper description of data source and sensitivity analysis are also important parts of model validation. It was difficult to evaluate individual studies as discussion of these elements are not fully clarified. Data sources are commonly discussed. However, issues with limited sample size, reliability of data obtained from expert opinions, or the applicability of data from published literature are not often discussed.

### 2.6.4 Research gap analysis

The common theme among the reviewed simulation studies is that patients are treated as a homogenous population, overlooking their differences in resource utilisation. Different patient factors not only affect resource use, but can also alter patient care process and hence impact overall operational performance. The same thing can be said about complications which have been found to significantly impact resources.[145, 146] The reviewed studies didn't appropriately address complications and adverse events as factors that impact upon resource utilisation. There is a research opportunity to examine how factors related to patients and complications can affect operational performance. To data, DES has been used to manage artificial variation related to process and structure and not much been done to apply this successful technique in understanding natural variation.

## 2.7 CONCLUSION

The review highlighted that DES is a commonly used tool for addressing capacity and resource issues in healthcare facilities including hospitals. However, while considerable efforts have been made toward understanding healthcare operations through simulation models, there still remains a knowledge gap of incorporating elements related to patient characteristics, patient severity, and complications into simulation modelling. I argue that these elements should be an integral part in resource planning. Despite the well-documented effects of patient complications on resource utilisation, there have been very few attempts to include them in simulation models to assess their impact on the operational performance. This leaves a void in healthcare simulation field that must be addressed.

There is a need for more research to exploit routinely collected data on patient and complications into simulation models to gain insights on operational performance. Such models can not only improve credibility of the models but also open the door to evaluate several strategies related to patient mix and resource utilisation.

When modelling patient-resource relationships in healthcare facilities, sufficient operational and process detail should be incorporated to minimise the risk of oversimplifying this relationship. To improve the current practice: 1) patient level detail should be explicitly included into models aiming to improve resource performance, and 2) determinants of patient resource utilisation should be incorporated into simulation to gain better insight into patient-resource relationship.

# Chapter 3

# LITERATURE REVIEW: THE IMPACT OF VARIATION AROUND PATIENTS, TREATMENT AND COMPLICATION ON RESOURCE UTILISATION IN CARDIAC CARE

## 3.1 CHAPTER OVERVIEW

In this chapter, I review several published articles to highlight factors that impact upon resource utilisation among patients undergoing cardiac interventions. The effect of patient mix on resource utilisation is very complex. A good understanding of this complicated relationship should facilitate resource planning and assist analysis. This chapter forms the basis for subsequent chapters, acting as evidence base for the types of factors that impact resource utilisation and that should be considered for further analysis within the Omani healthcare context.

## 3.2 INTRODUCTION

The provision of cardiac care services is associated with costly and often scarce resources such as intensive care and surgical services. Patients receiving cardiac care differ significantly in their use of resources. A range of clinical and non-clinical factors induce this variation. Moreover, the complexity of patients treated by cardiac units and the invasive nature of heart procedures are associated with risk and complications. Understanding factors related to patient resource consumption is a prerequisite for good capacity planning in hospitals. The benefit can expand beyond hospitals to include payers who often adjust their reimbursements based on patient mix.[147]

Researchers have examined variation in resource utilisation through several preoperative, intraoperative and postoperative factors. From a healthcare planning perspective, understanding variation should help improve patient flow.[19] However, integrating patient and treatment-related factors (i.e. natural variation) into a resource planning process requires profound understanding of these factors and their specific impact on resources.

The reviewed articles highlight resource utilisation among patients who underwent cardiac procedures such as PTCA, CABG, and valve surgeries. In this review, I gather evidences on the type of factors affecting resource utilisation and whether any recommendations that are of an interest to healthcare planners were presented.

### 3.2.1 Aims and objectives

The overall aim of this chapter was to comprehensively review the available literature to explore factors affecting hospital resource use among hospitalised patients undergoing cardiac interventions such as PTCA and heart surgeries. The review was guided by the following three questions: 1) what type of factors are associated with resource utilisation among patients undergoing cardiac interventions? 2) Do the reviewed articles relate these factors to patient flow or resource management? and 3) Can preoperative risk stratification systems be reliably used to estimate postoperative resource utilisation?

## 3.3 METHOD

### 3.3.1 Selection and exclusion criteria

**Selection criteria:** Studies were included if they met the following criteria: 1) reported association between patient characteristics, complications and hospital resource utilisation, 2) were concerned with resource utilisation among patients who underwent cardiac interventions such as heart surgery or PTCA, 3) were written in English language, and 4) were published between 1990 and 2014.

**Exclusion criteria:** I excluded studies based on the following criteria: 1) studies with no reference to specific resource use as a measure of outcome, 2) studies that have investigated resource utilisation among medical patients (e.g. heart failure) and not patients who underwent a specific heart procedure, and 3) Studies that have reported cost as the only measure of outcome.

### 3.3.2 Search strategy

Electronic searches of PubMed, Web of Science, Embase and Google Scholar were conducted using the following subject headings and free text terms: ‘adverse events’, OR ‘cardiac complications’, OR ‘post-operative complications’, OR ‘heart surgery’, OR ‘surgery’, OR ‘percutaneous coronary intervention’ OR ‘percutaneous transluminal coronary intervention’, OR ‘Perioperative’, OR ‘operation’ OR ‘coronary’ combined with terms for ‘resource utilisation’, ‘cost’, and ‘service utilisation’. References contained in the included papers were checked for additional papers that were not identified in the electronic search.

The word “resource” constitutes a wide range of tangible and nontangible assets. Therefore, individual terms such as: length of stay, reoperation, staffing level, readmission and intensive care unit were also searched in conjunction with previous search terms to maximise articles retrieval. This has assisted in identification of articles that were not retrieved in the initial search.

#### 3.3.2.1 Data extraction

Using a standardised data collection form, I extracted data related to study type, patient sample size, identified significant factors, outcome measures, and number of institutions in the study.

## 3.4 RESULTS

Sixty-two papers met the inclusion criteria Figure 3-1. The majority of the papers 53 (85%) were conducted in developed countries. Several studies have specifically addressed a single resource utilisation predictor such as EuroSCORE, Atrial Fibrillation (AF), or the use of Cardiopulmonary Bypass (CPB) (Table 3-1). On the other hand, 21 (34%) studies evaluated resource utilisation against several preoperative, intraoperative and postoperative variables. LOS was commonly used as a proxy of hospital resource utilisation. Few studies have included other resources such as investigations, blood units, and intubation time. Factors associated with cost were investigated in 15 studies. The majority of the studies collected their data from a single institution 50 (81%), while the remaining studies have utilised data from regional or national databases.

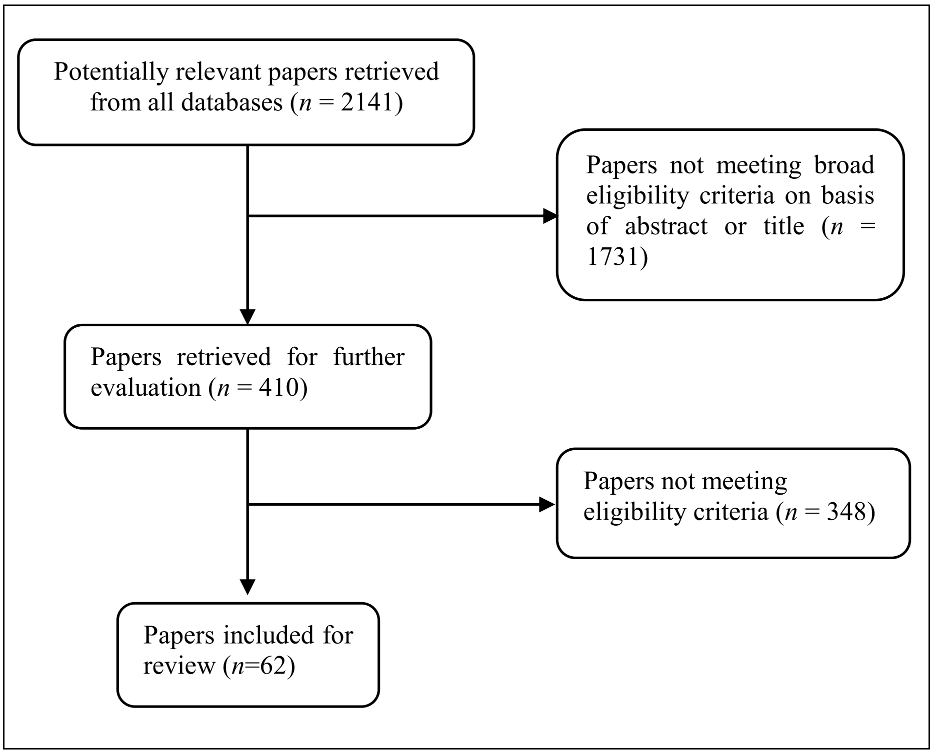



Figure 3-1 Search process flow for articles included in the review

**Table 3-1 Summary of the articles included in the review**

| First author and year | Number of hospitals | country | total patients | Outcome measures | Intervention type |
|---|---|---|---|---|---|
| Dento (1998) | 1 | USA | 882 | Cost & LOS | CABG |
| Speir (2009) | Regional | USA | 14,780 | Cost & LOS | CABG |
| Sokolovic (2002) | 1 | Switzerland | 201 | Cost & LOS | Cardiac surgeries |
| Shirzad (2010) | National | Iran | 15,580 | Postoperative AF | Cardiac surgeries |
| Nilsson (2004) | 1 | Sweden | 3,404 | ICU LOS & Cost | Cardiac surgeries |
| Brown (2008) | National | USA | 114,233 | Cost & total LOS | CABG |
| Pasquali (2013) | National | USA | 32,856 | Mortality, PLOS, cost | Cardiac surgeries |
| Avery II (2001) | 1 | USA | 455 | Cost | Cardiac surgeries |
| Scott (2005) | 1 | USA | 1,746 | Time to extubation, blood units, ICU LOS, PLOS | CABG |
| Boyd (1999) | 1 | USA | 90 | Ventilation time, ICU LOS, PLOS | CABG |
| LaPar (2014) | National | USA | 49,264 | ICU LOS, PLOS & cost | |
| Osnabrugge (2014) | Regional | USA | 42,839 | PLOS & cost | CABG |
| Mangano (1998) | 24 | USA | 2,222 | Renal dysfunction | CABG |
| Scott (2005) | 1 | USA | 1,746 | PLOS & Blood transfusion | CABG |
| Harvnak (2002) | 1 | USA | 720 | LOS, ventilation time, readmission to ICU & cost | CABG |
| Ehsani (2007) | National | Australia | 16,766 | Cost, LOS & mortality | Cardiac surgeries |
| Ngaage (2011) | 1 | USA | 6,971 | Blood transfusion, interventions, medicine | CABG |
| Scott (2003) | 1 | USA | 371 | Intubation time, blood transfusion, ICU LOS, PLOS, LOS | CABG (OPCAB) |

| First author and year | Number of hospitals | country | total patients | Outcome measures | Intervention type |
|---|---|---|---|---|---|
| Kurki (2001) | 1 | Finland | 2,104 | LOS, PLOS & cost | CABG |
| MaWhinney (2000) | 1 | USA | 2,481 | Cost, charges & LOS | Cardiac surgeries & PCI |
| Riodan (2000) | 1 | USA | 628 | LOS & cost | CABG |
| Aranki (1996) | 1 | USA | 570 | LOS & AF | CABG |
| Kugelmass (2006) | National | USA | 335,477 | Cost & LOS | PCI |
| Doering (2001) | 1 | USA | 109 | ICU LOS | CABG |
| Abrahamyan (2006) | 1 | Armenia | 391 | Morbidity & ICU LOS | CABG |
| Mounsey (1995) | 1 | UK | 431 | ICU LOS & PLOS | CABG |
| Azarfarian (2014) | 1 | Iran | 280 | ICU LOS | Cardiac surgeries |
| Zenati (1997) | 1 | USA | 50 | Cost, LOS, ICU LOS & transfusion | CABG |
| Unsworth-white (1995) | 1 | USA | 2,221 | ICU LOS | Cardiac surgeries |
| welsby (2002) | 1 | USA | 2,609 | LOS | Cardiac surgeries |
| Puskas (2001) | 1 | USA | 1,200 | LOS & re-exploration for bleeding | CABG |
| Scott (2008) | 1 | USA | 1,746 | ICU LOS & PLOS | CABG |
| Murphy (2007) | 1 | UK | 8,724 | Cost & infection | Cardiac surgeries |
| Wolfe (1995) | 9 | USA | 591 | LOS | PCI |
| Vamvakas (2000) | 1 | USA | 421 | LOS & ICU LOS | CABG |
| Lazar (1995) | 1 | USA | 194 | LOS > 7 d | CABG |
| Batterworth (2000) | 51 | USA | 1,974 | intubation time, LOS | CABG |
| Williams (1998) | 1 | USA | 2,589 | PLOS & cost | Cardiac surgeries |
| Gruberg (2001) | National | USA | 7,741 | Dialysis | PCI |
| Michalopoulos (1996) | 1 | Greece | 652 | ICU LOS | CABG |
| Najafi (2012) | 1 | Iran | 570 | ward LOS> 3 d ICU LOS>48 h | CABG |
| Lazar (2001) | 1 | USA | 786 | Readmission | CABG |
| El Naggar (2012) | 1 | Egypt | 40 | Complications & LOS | CABG |
| Salmon (2003) | 1 | USA | 2,569 | AF | CABG |
| Lawrence (2000) | 1 | UK | 5,591 | ICU LOS < 24 h | Cardiac surgeries |
| Utriyaprasit (2011) | 1 | Thailand | 109 | PLOS | CABG |
| Hollenbeak (2000) | 1 | USA | 201 | Cost, LOS & surgical site infection | CABG |
| Toor (2009) | 1 | UK | 2,936 | Complication rates, ICU LOS & total LOS | CABG |
| Toumpoulis (2005) | 1 | USA | 5,051 | LOS > 12 d | CABG |
| Herman (2009) | 1 | Canada | 3,483 | ICU LOS > 72 h | CABG |
| Eltheni (2012) | 1 | Greece | 150 | ICU LOS> 2 d | Cardiac surgeries |
| Kurki (1996) | 1 | Finland | 386 | PLOS > 12 d | CABG |
| Oliveira (2013) | 1 | Brazil | 104 | ICU LOS >3 d & ward LOS 7 d | CABG |
| Katz (1997) | 1 | USA | 853 | Mortality, complications, LOS, hospital charges | Cardiac surgeries |
| Tribuddharat (2014) | 1 | Thailand | 202 | ICU LOS | Cardiac surgeries |
| Atoui (2008) | 1 | Canada | 426 | ICU LOS ≥ 2 d & ward LOS > 7 d | Cardiac surgeries |
| Giakoumidakis (2011) | 1 | Greece | 313 | LOS | Cardiac surgeries |
| Wang (2012) | 1 | China | 3,925 | ICU LOS ≥ 2 d | Valve |
| Christakis (1996) | 1 | Canada | 889 | ICU LOS > 3 d | Cardiac surgeries |

| First author and year | Number of hospitals | country | total patients | Outcome measures | Intervention type |
|---|---|---|---|---|---|
| Rosenfeld (2006) | 1 | USA | 9,869 | ICU LOS ≥ 7 d | CABG |
| Bucerius (2003) | 1 | Germany | 10,759 | ICU LOS ≥ 3 d | CABG (on vs off pump) |
| Ghotkar (2006) | 1 | UK | 5,186 | ICU LOS >3 d | CABG |

Abbreviations: AF=Atrial Fibrillation, LOS= length of stay, PLOS= postoperative length of stay, ICU= intensive care unit.

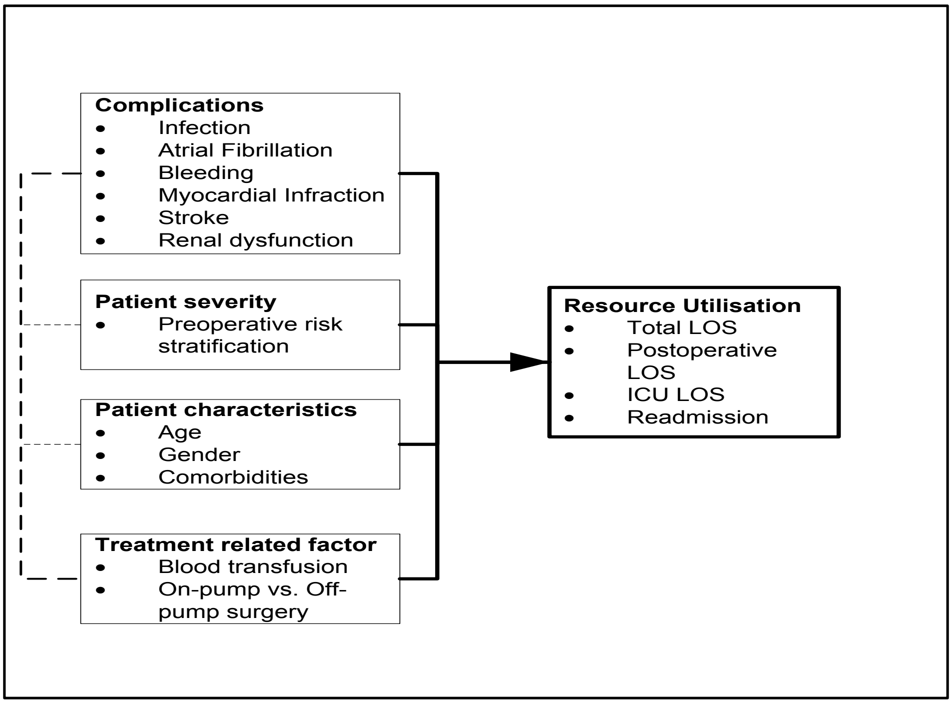



**Figure 3-2 Relationship between different factors and resource utilisation**

### 3.4.1 Assessment of resource utilisation through cardiac risk stratification systems

Risk stratification algorithms reflect the clinical risk of patients.[33] LOS and cost have been suggested to correlate with clinical risk.[148] 15 studies have included preoperative risk algorithms either alone or with other variables for predicting resource utilisation. These scores were adopted to predict association between patient clinical variable and resource utilisation, namely total LOS, ICU LOS, and cost.

Several types of risk scoring systems were evaluated in the reviewed articles including EuroSCORE,[149-151] Cleveland Clinic preoperative model,[152] Parsonnet,[153-156] MedisGroups,[142] and the Society of Thoracic Surgeons (STS)[24, 148]. Risk scores, in these studies, were either grouped (e.g. low risk EuroSCORE <3) or used individually for correlation with resource utilisation. As risk scoring systems differ in their structures and the type of variables, I will discuss how different scoring systems were used to investigate resource utilisation.

**EuroSCORE**: This preoperative risk scoring was introduced in 1999 as a simple 17 variable system.[157] Data from 128 cardio-surgical units all around Europe were used to construct EuroSCORE. Geissler and colleagues found that EuroSCORE had the best mortality predictive value among six risk stratification systems.[33] Nillsson et al[149] found 15 out of 17 variables in the EuroSCORE to be significantly associated with cost of open heart surgery. Higher risk patients as indicated by EuroSCORE had higher cardiovascular events and longer LOS.[150] The EuroSCORE was found to be a weak predictor of LOS when individual scores from every patient were used. However, strong association was observed when patients are grouped into similar risk cohort groups.[149]

**Cleveland Clinic preoperative model**: A total of 13 variables are collected for the Cleveland Clinic score that include age, reoperation, renal failure, cerebrovascular disease, emergency, anaemia, prior vascular surgery, and weight. This score algorithm was evaluated in a study by Kurki et al[152] for its prediction of total LOS, postoperative LOS, and total costs among CABG patients. In the study, risk scores were grouped into six classes. Comparison were made to a reference value (risk score=0) where patient assumed to have no risk. LOS and costs were found to increase exponentially to the increase in risk score. The effect of risk score remained stable even after controlling for variables related to age and complications.

**The Society of Thoracic Surgeons (STS) predicted risk of mortality**: Riordan et al[148] evaluated the ability of STS risk to predict cost of CABG. Analysis was performed using both individual patient score and patients grouped into similar risk cohorts. The STS risk score was a poor predictor of both LOS and cost for individual patients even when outliers were excluded. However, when patients were grouped into cohorts of similar risks, the mean cost and mean LOS were highly correlated to the mean STS risk. Using the same risk scoring system, Osnabrugge and colleagues[24] observed that LOS and costs incrementally increased as the STS score increased.

**Parsonnet**: This scoring system was the most commonly discussed. Lawrence et al[155] investigated the value of the Parsonnet score in predicting ICU LOS following cardiac surgery. This risk score was found to be an objective method for predicting postoperative ICU LOS as well as complications. Patients in their study were stratified into two groups: those with score of 0 to 9 and those with scores of 10 and above. A Receiver Operating Characteristics Curve (ROC) was used for assessing Parsonnet score as a predictor of postoperative ICU LOS of < 24 hours. In addition, Parsonnet scores positively correlated with several complications such as stroke, intra-aortic balloon pump, haemofiliteration, resternotomy and tracheostomy. Contrary to Lawrence et al findings, Doering et al[154] assert that Parsonnet score may be helpful in identifying patients who need prolonged ICU LOS but fails to identify patients in need of a short ICU stay. Only high score (score 20: extremely high risk) yielded a predictive value of 84% for ICU > 1 day.

In another study, additive Parsonnet risk scores of 2,589 patients were compiled into five categories.[153] The mean postoperative LOS was then obtained for each risk category. The LOS was compared with the mean risk for each Parsonnet risk group. The study concluded that postoperative LOS was highly correlated with the risk score. The authors devised a formula for marginal cost considering patient risk. Formulas of this nature can be highly applicable in estimating cost for different risk groups.

#### 3.4.1.1 Cardiac risk scoring systems as predictors of complications

It was noted that in a group of patients with serious complications, the mean EuroSCORE was nearly double that in patients without complications.[158] EuroSCORE was found to be an independent predictor of Myocardial Infarction (MI) after unprotected left main coronary stenting.[159] Other complications were predicted by EuroSCORE include postoperative renal failure, sepsis or endocarditis, and respiratory failure.[151] One study found that patients who underwent reoperation had higher preoperative Parsonnet risk scores.[160] Similarly, patients with moderate or severe Parsonnet scores accounted for three fourth of all Atrial Fibrillation (AF) patients.[161] Finally, high score of Global Registry of Acute Coronary Events (GRACE) was an independent predictor of contrast induced nephropathy in patients who underwent angiography.[162]

### 3.4.2 Studies examining the effect of complications on resource utilisation

In the reviewed studies, researchers were interested in revealing factors contributing to complications as well as the variation in resource use introduced by adverse events. Complications were found to be associated with prolonged LOS,[156] reoperation,[160] and readmissions.[163] In a large study[24] designed to predict costs and LOS in CABG, adverse events explained the largest portion of the variation in LOS and total hospital costs. In terms of the economic burden, postoperative complications after CABG were reported to increase cost by 6700 Euros per complication.[152]

#### 3.4.2.1 Complications related to heart surgeries

In the reviewed articles, the most common complications investigated for heart surgery were renal failure, stroke, sternal wound infection, septicaemia, pneumonia, bleeding, prolonged ventilation, AF, and MI. Cardiac surgery adverse events are among the most significant contributors to the morbidity, mortality, and cost associated with hospitalisation.[164] In general, postoperative complications result in an increased resource use and greater financial burdens.[40] Hospital costs for patients with complications such as stroke, arrhythmia and infections are significantly higher than for patients with uncomplicated recovery.[152]

There were six studies that attempted to identify multiple complications and quantify their impact on different resources. Welsby et al[156] evaluated the differences among complications types in mortality and prolonged LOS (>10 days) after cardiac surgery. Complications were divided into four groups (no complications, cardiac complications only, non-cardiac complications only, and both cardiac and non-cardiac complications). Patients who had "non-cardiac complications only" had higher LOS and mortality compared with patients exhibiting "cardiac complications only". In a study that collected data from multiple hospitals in Australia, the leading types of adverse events were haemorrhage, haematoma and AF.[164] In another study, Medicare beneficiaries who experienced complications (13.64%) after CABG had significantly longer LOS (average incremental stay was 5.3 days) and higher cost after adjusting for patient demographics and comorbid conditions.[39] The most costly complications were found to be septicemia, postoperative infection, adult respiratory distress syndrome, reoperation, and stroke. Another study found that the most costly complications associated with isolated CABG were prolonged ventilation, renal failure, and mediastinitis.[40]

**Studies investigating a single complication**

**Atrial Fibrillation:** New-onset of postoperative AF is the most common complications following cardiac surgery.[163] Consequently, AF was a subject of several studies designed to determine its impact on resources.[161, 163, 165] LaPar et al[163] found that postoperative AF incidence rate was 18.8% and that it was associated with greater hospital resource utilisation and increased costs after adjusting for confounding factors. Specifically, postoperative AF was associated with 48 additional ICU hours and 3 additional hospital days. A unique aspect of this study was the adjustment of individual surgeon influence as well as changes in practice patterns over the study period. Another study examined the incidence of postoperative AF among 15,580 patients in Iran who underwent a cardiac surgery.[165] AF was found to occur in 7.2% of the patients. Readmission was significantly higher in patients with AF, as well as the total LOS and postoperative LOS. Hravnak et al[166] revealed that patients with new-onset AF had longer LOS, more days in mechanical ventilation, and higher rate of readmission to the ICU. The study also examined the effects of AF on the utilisation of laboratory tests, cardiac drugs prescriptions and cost which were all found to be associated with AF.

A study which examined data from the year 1994 found that postoperative AF had occurred in 33% of the patients.[161] A more recent study found the rate to be 28%.[167] These figures indicate that despite advances in standard medications, the rate of this common complication seems to persist over time. It should be noted, however, that the reported incidence rate of AF among different studies can be influenced by the selected definition, criteria for diagnosis, and mode of postoperative monitoring (intermittent or continuous).[161] Moreover, the association between the types of heart surgery and the occurrence of AF was not emphasised in the reviewed articles. One exception is the study by LaPar et al[163] who found that AF was significantly associated with the type of surgical procedures.

**Renal dysfunction or failure:** Patients who develop renal dysfunction or failure after a heart procedures are more likely to require extended hospital stay.[117, 146, 168] This is the case because of need for dialysis and critical care. For patients with dialysis dependency, their stay was twice as long as the stay for patients with renal dysfunction and was five times as long as the stay for patients without the complication.[117] Mangano et al[117] found that postoperative renal dysfunction was reported in 7.7% of the patients, while renal failure that required dialysis was reported in 1.4% of the patients.

**Resternotomy for bleeding:** Reoperation due to excessive bleeding was found to be a major determinant of resource utilisation and cost.[152] Valve surgical cases were more than three times as likely to experience reoperation to control bleeding.[160]

**Wound infection (i.e. surgical site infection):** Wound infection was found to significantly prolong LOS,[169, 170] and increase hospital costs.[171] In one study, infected patients after CABG were found to incurred an average of 20 additional hospital days and $20,012 in additional costs.[172]

#### 3.4.2.2 Complications associated with PCI

Among the selected studies for this review, three papers investigated association between complications and resources among PCI patients. In one study, major and minor complications occurred in 15.4% of the patients who underwent angioplasty.[173] Major complications were defined as death, MI, emergency CABG (within 24 hours of PCI) while minor complications were defined as the need for blood transfusion and abrupt closure. Complications were the strongest predictors of LOS. Kugelmass et al[146] found that a total of 9.5% of the patients in the study population developed acute PCI complication. Regression analysis and propensity-matched samples were used to estimate cost of complications. Analysis revealed large difference in average cost and LOS between complicated and uncomplicated patients. For example, septicemia, adult respiratory distress syndrome, and emergency CABG increased LOS by >7 days.

Contrast induced nephropathy is a potentially serious complication of coronary angiography with significant consequences.[174] The radiographic contrast agent was considered to be responsible for the majority of the acute renal failure cases that required dialysis after PCI.[168] However, only 0.7% of the patients who underwent PCI developed such complication.

### 3.4.3 Patient related characteristics and resource utilisation

Some of the natural variation in resource utilisation in hospitals are attributed to several types of patient characteristics. The commonly discussed types of patient attributes that impact resources were age[175, 176] and gender[177 178]. In general, patient characteristics have smaller impact on LOS and costs compared to other factors such as adverse events.[24]

#### 3.4.3.1 Age

Advances in medicine have led to people living longer. As a results, more patients with advanced age are undergoing cardiac surgery.[179] Age has been considered an important risk factor for heart operations and is a major component in risk stratification systems. It is commonly acknowledged that younger patients are expected to recover faster than older patients. Moreover, treatment complexity is associated with older age (e.g. ≥85) as elderly patients, for example, are more likely to undergo multivessel procedure than younger patients.[180]

Most of the reviewed articles have discussed age as an important determinant of resource utilisation. Age alone has a major impact on costs in CABG surgery.[152] It was also found to be a significant predictor of hospital stay after CABG.[181] Elderly patients (≥ 70 years) undergoing cardiac surgery tend to have slower progression through care.[182] This is evident by more needs for intensive care management, intensive care readmission, and total LOS. Katz and Chase[183] found no differences, however, in the frequencies of complications between patients who are ≥70 years old and patients younger than 70 years who underwent cardiac operations. In the study conducted by Toor et al[184], patients who were ≥75 years old had significantly higher postoperative complications and incurred longer intensive care and postoperative stays. Herman et al[185] developed a predictive model to identify CABG patients at risk of prolonged

LOS in ICU (stay exceeding 72 hours) based on preoperative factors. Age was found to be an independent predictor.

Scott et al[175] found that octogenarians who underwent CABG had a significantly higher incidence of preoperative stroke, peripheral vascular disease, chronic obstructive lung disease, congestive heart failure, and left main disease. In terms of resource consumption, this group of patients had longer time from end of surgery to endotracheal extubation (9.3 hours vs 6.3 for their younger cohorts). Blood transfusion was required in 88.4% of octogenarians compared with 58.6% of younger patients. Their ICU LOS was slightly higher, however the mean postoperative LOS was 8.7 days for octogenarians and 5.8 days for non-octogenarians. Octogenarians had higher incidence of postoperative renal failure and neurologic complications. The study concluded that age (80 years or older) was independent predictor of increased resource utilisation.

A similar study[176] documented complications occurring more frequently in octogenarians. However, unlike previous study by Scott et al[175], this study included several types of heart surgeries (e.g. aortic valve repair, CABG, double valve replacement, and mitral valve repair). The type of complications associated with this group were severe low output state, reintubation, and atrial fibrillation. Postoperative intubation times in the octogenarians averaged 29.8 hours vs. 16.7 hours in younger patients. The average ICU was 69.9 hours for octogenarians, versus 43.3 hours in younger patients. Postoperative LOS was also higher (10.09 days vs. 7.45 days respectively). Total direct costs were 26.8% higher in the elderly than the younger cohort. It is worth mentioning that the hospital under investigation implemented fast track program for cardiac patients which was designed to reduce intubation times and length of stay for all age groups. The study, however, didn’t report whether implementation of this protocol had an effect on their results.

#### 3.4.3.2 Gender

Gender is another important risk factor in cardiovascular disease. A retrospective study examined whether gender had an influence on the duration of tracheal intubation, blood transfusion needs, ICU stay, postoperative LOS, and total LOS in patient undergoing off-pump CABG.[177] The authors affirmed that female sex was a predictor of increased blood transfusion and longer postoperative LOS and total LOS. In a similar study,[178] female gender was associated with significantly longer ICU LOS and postoperative LOS even after adjusting for preoperative covariates. The authors noted that these effects could be attributed to the ways in which men and women respond to anaesthesia, CABG surgery or to bias on the part of healthcare workers.

#### 3.4.3.3 Comorbidities

Comorbidities are diseases that are not directly related to the principle surgical diagnosis, but can influence the outcome of operations. Several diseases were found to coexist with heart surgery patients such as diabetes, obstructive pulmonary disease, hypertension, and renal failure. Hypertension was identified as an independent predictors of prolonged ICU stay after a cardiac surgery.[158] The LOS was increased significantly in PCI patients with unstable angina and multiple coronary artery disease,  complex lesions, and filling defects.[173]

### 3.4.4 Treatment and system related factors

Several factors independent of patient characteristics affect resource utilisation. In this section, I discuss factors related to treatment strategies and system settings.

#### 3.4.4.1 Use of cardiopulmonary bypass machine to support heart surgery

Difference in postoperative complications between cardiac surgical patients has been attributed to the use of CPB technique. The use of CPB in conventional CABG surgeries is associated with a systemic vascular inflammatory response.[186] Consequently, patients operated with the support of the cardiopulmonary machine (i.e. on pump) were found to have increased rate of complications such as reoperation for bleeding[187], and an increased rate of AF[188]. Moreover, patients who have longer CPB times are more likely to have longer hospitalisation.[156, 189]

Even elderly patients (age >70) who underwent off-pump coronary artery bypass have less resource utilisation compared to patients in the same age group who were operated under the conventional CABG surgery (on pump).[188] Off-pump patients had lower ICU stay, shorter ventilation time, and lower postoperative LOS. They also had lower complication rates for AF, stroke, and respiratory complications. In the same study, Off-pump and conventional CABG patients were matched only to similarity in risk score (Parsonnet and Ontario provincial acuity index). Another study,[190] however, matched patients according to age, sex, pre-existing disease (renal failure, diabetes, pulmonary disease, previous MI, and primary or redo status). Similar findings were reported which confirmed that off-pump CABG reduces hospital costs and postoperative LOS compared with the conventional CABG surgery. In a study by El Naggar,[191] on pump CABG was found to be associated with higher incidence of postoperative complications such as AF, prolonged mechanical ventilation, acute renal complications, MI, and wound infection. Higher incidence of complications has corresponded to higher LOS. However, the study has not adjusted for factors independently known to increase these complications.

There is, however, conflicting evidence on the effect of off-pump CABG surgery on the incidence of AF.[186] This is also supported by Salamon et al[192] who concluded that avoiding cardiopulmonary bypass didn’t aid in reducing atrial fibrillation at their institution.

#### 3.4.4.2 Blood transfusion

Another factor that was examined is the effect of blood transfusion on resources. In a study by Murphy et al,[193] blood transfusion was found to be associated with increased LOS, infection, and hospital costs. A similar study found blood transfusion in patients undergoing CABG surgery (on-and off-pump) to be an independent contributor to increased resource utilisation.[194] For example, the postoperative LOS was found to increase with the number of packed red blood cells transfused. Additionally, the transfused patients had significantly higher postoperative complication rates and longer time for tracheal extubation than their non-transfused counterparts. This study, however, has not incorporated several variables that are independently known to be associated with higher resource utilisation, and thus it would be inaccurate to arrive at a conclusion without reference to these variables. A more comprehensive set of confounding factors were incorporated by Vamvakas and Carven[195] to control for the effect of blood transfusion on LOS. In this study, a regression model was used to adjust for 20 variables that pertained to risks and difficulty of operation. These factors accounted for 60% of the variation in the postoperative hospital LOS. The number of transfused blood units was then entered into this model. A small but significant effect on postoperative LOS was noted. However, the authors concluded that this independent association may be due to a relationship between blood transfusion and a higher incidence of septic complication or may reflect the function of blood transfusion as a marker for severity.

#### 3.4.4.3 Fast track cardiac pathways

Fast track pathways enable selection of patients for early extubation which allow patients to be transferred to the ward in a shorter time. Some patients might be transferred to a post-anaesthesia care unit instead of ICU after surgery to minimise working load on the ICU. Hospitals implementing fast track protocols for CABG patients are expected to reduce ICU and hospital stays in low-risk patients.[196] Bed days gained from earlier discharge, however, might be offset by hospital readmission.[197] Consequently, resource consumed during subsequent admissions may outweigh the potential benefits.

#### 3.4.4.4 Type of surgery

While CABG was the most researched type of open heart surgery in the selected papers, 18 studies have included other types of cardiac surgeries (referred to as cardiac surgeries in Table 3-1).

With respect to resource consumption, the frequency of prolonged ICU LOS was higher among patients who underwent CABG in combination with valve surgery than those who underwent each surgery separately.[141] A similar finding was reported by Lazar et al[169] Minimally Invasive Direct Coronary Artery Bypass Grafting which requires a smaller incision to separate the sternum is done as an alternative to conventional CABG for patients with suitable coronary anatomy. This procedure was found to be associated with significant reduction of resource utilisation and morbidity.[198]

#### 3.4.4.5 Hospital ownership and reimbursement system

Factors that are related to the delivery of care such as type of reimbursement, hospital ownership, and local practice structure are not discussed. No paper was found that analysed the effect of the hospital ownership or the type of reimbursement system on resource utilisation.

### 3.4.5 The effect of other contextual factors

Several factors unrelated to treatment or patient conditions have a strong influence on resource utilisation. Cultural, physician judgements, hospital policy or type of reimbursement system can influence LOS decisions. Variability unexplained by the models in several studies may be attributable to these factors. However, these factors were rarely mentioned in the reviewed articles.

## 3.5 DISCUSSION

The reviewed studies have addressed sources of variation in resource utilisation among patients with cardiac care procedures. Findings from these studies can be utilised to support clinical and managerial decisions especially when some influencing factors can be modified. However, no paper has suggested how this should be put in practical use. While most papers addressed the aspect of variation in resource utilisation, there was a lack of discussion on how this variation impacts patient flow and hospital operational performance in general such as productivity and waiting times. The reviewed papers didn't report specific real-world applications that might be realised from understanding influential predictors. Conversely, I found that hospital management literature lacks a defined methodology on how to incorporate patient related factors, severity, and complications into resource planning strategies despite the number of studies that have examined capacity planning in healthcare.[5, 37, 95]

Most of the reviewed studies investigated several predictors of resource utilisation among surgical patients with few papers attempting to assess their impact on patients undergoing revascularisation procedures that involve PCI. The majority of the studies have included a single type of surgery. However, other cardiac surgical patients share the same resources such as operating theatre, staff time, and beds. Exclusion of these patients undermines analysis around resource utilisation. The collective impact of these different type of patients on resource utilisation performance are often ignored. Furthermore, most of the studies were conducted in western countries where the availability of resources such as hospital beds (e.g. critical care beds) and trained personnel are relatively high.[199] Availability of sufficient resources can impact patient outcome and ultimately improve productivity.

Several studies[143, 191, 192, 194] in my review did not adjust for important confounding factors. Isolating the effect of factors on hospital resource utilisation is challenging due to the large number of variables that should be controlled for confounding. This is especially the case when assessing the effect of complications on patient resource use. Some other studies[39, 147, 166] have not considered patients who died during their hospitalisations when assessing the effect of complications on resource use. Moreover, none of the reviewed papers attempted to predict surgery duration as an outcome. This might be due in part to the need to manage scarce resources such as hospital beds which are usually seen as common bottlenecks. Lehtonen et al[100] suggest that there is a high variability in cardiac surgery length and this imposes a challenge in managing productivity.

LOS was widely used as a proxy measure for resource utilisation in the majority of the studies. It is important, when analysing factors affecting resources, to distinguish between patient stays at different stages of hospitalisation (e.g. ICU LOS and postoperative LOS) especially when research involves assessing the effect of complications. The use of *total* LOS alone is more likely to overstate the true time a patient takes to recover from complications.[39]

### 3.5.1 The value of cardiac risk scoring models for resource utilisation measurement and prediction of complications

Risk scoring systems such as EuroSCORE are not specifically designed for predicting resource needs rather they are intended to predict morbidity or mortality.[33] However, their applicability to such analysis has been proven to be feasible as indicated in this review. Risk stratifications systems were also used in predicting complications after surgery. The concept of stratifying patients into different groups based on their risk can be incorporated into operational research methods to investigate resource utilisation under varying patient severities. High risk can influence the timing of the operation, the type of anaesthesia (fast track vs. non fast track), the planning of surgical procedures, and resource allocation after surgery.[200] Hospital costs can also be closely related to patient severity.[171]

Many of the reviewed papers argued in favour of using risk stratification in predicting resource utilisation for different patient groups. However, some authors cautioned that risk factors predictive of resource consumption were generally not the same as those factors predicting mortality for cardiac patients. For example, MaWhinney and colleagues[142] suggest that risk models can't be confidently used for the purpose of predicting resource utilisation unless another extensive set of clinical and socioeconomic risk factors are included.

### 3.5.2 Sources of data

Data collection was assisted in several studies[24, 39, 40, 163-165] by availability of data from regional or national registries or databases. However, the majority of the studies collected data through review of patient medical charts from a single institution. An intuitive question would be whether results from single centres are generalisable across diverse populations and countries. Studies that have used routinely collected data from national databases have not accounted for differences between hospitals and how they might affect resource utilisation patterns.

### 3.5.3 Implication for hospital management and health policy

The majority of the studies have identified factors predicting LOS without reference to a particular use in operational or clinical application. Understanding patient variability around resource consumption is an important task that should be often undertaken by hospital managers. Continuous surveillance of factors affecting cardiac ICU LOS will allow better design of services and streamline patients more efficiently. However, there is a paucity of literature on whether hospitals are integrating these risk factors into resource planning. As stated previously, the majority of the reviewed studies have not demonstrated the applicability of their findings in improving the clinical or operational performance. Hospital managers might not put as much time and effort into understanding data related to patients and resource utilisation.

Factors contributing to patient resource use variability can be potentially integrated into resource management practices. Broadly speaking, the utility of such knowledge can be applicable to patient management (e.g. aggressive treatment of comorbidities, fast track triage) and resource management (e.g. scheduling surgery, bed allocations, or determining staffing level). At the operational level, all flows in a hospital are interconnected and a system-wide attention is required to facilitate smooth patient journey. While identifying factors responsible for resource variation can be advantageous in prioritising resources, managers need to further understand the relationship between factors affecting resource variation and system performance such as delay, cancellations, and throughput. Several factors discussed in this review can affect patient flow and thus affect multiple areas of care such as operating rooms and critical care.

Costs associated with complications can be presented as a business case for quality improvement initiatives.[39] Decision makers can benefit from studies discussed in this review by redirecting resources toward preventing complications and thus reducing the average cost of care. They should target high-cost and high-frequency complications especially if their hospitals operate under a reimbursement system because payers can reduce payment for the care of individual patients who develop preventable complications.[201] Natural variation is largely ignored in hospital resource planning.[3] Variation related to patients is impossible to eliminate. However, it can be managed. Several of the factors discussed in this chapter should be known to care providers in advance (i.e. preoperatively). For example, targeting risk factors through aggressive treatment regimens prior to surgery may reduce the proportion of patients who require lengthy ICU LOS which can result in several medical, operational and financial benefits. This is the case because many of the risk factors are potentially modifiable. Consequently, aggressive preoperative treatments and workups prior to surgery can mitigate the need for extended LOS.[202] Similarly, decisions regarding patients scheduling can be enhanced by understanding variations.

### 3.5.4 Which factors should be evaluated for resource planning?

Based on the findings from this review, several factors should be considered in hospital planning in order to optimise resources for cardiac care patients. A possible reason why these factors are not incorporated in hospital planning processes is the difficulty in determining which variables are relevant. However, simply collecting these data will not provide hospital administrators with enough information to sufficiently plan resources. More sophisticated techniques should be used.

To facilitate data collection and analysis, factors affecting hospital resources can be divided into three categories:

1. Factors related to patient characteristics.
2. Treatment and system related factors.
3. Factors related to adverse events.

The above mentioned categories belong to either one of the two types of variation: natural or artificial that were previously discussed. A distinction should be made as to whether these factors are preventable. For example, several comorbidities can’t be prevented and thus patients can only be managed to minimize any negative consequences that might affect patient flow.

There are some non-medical factors that can influence resource utilisation. These are related to system characteristics (e.g. fewer transfers from ICU or surgical wards in weekends or holidays), social consideration (e.g. patient occupying a hospital bed as there is no bed available in a nursing home), availability of downstream services in the same hospital, type of hospital (academic vs non-academic) and payment mix. Other factors might not be easily quantifiable such as surgeon skills and physicians' judgement.

### 3.6 CONCLUSION

Patient and treatment factors are valuable information for predicting resource utilisation in cardiac care. However, the extent at which these factors are utilised in managing patients is unclear. Studies vary on the type of predictors being selected. A few variables were more common than others. For example, atrial fibrillation/ arrhythmia, increased age, surgery type renal failure/ dysfunction and non-elective surgery status were common predictors.

Identifying risk factors for high resource utilisation (i.e. prolonged LOS) should not be treated in isolation of the intended use. That is, the utility of identifying risk factors should be clearly defined. This will facilitate integrating influential factors into the resource allocation decision making process, which I believe is currently an underrepresented activity. This may also allow hospital stakeholders (e.g. bed managers) to engage in patient mix evaluation and thus empirically assess resource needs. More research is needed to link variation around hospital resource use and management strategies designed to optimise patients flow.

# Chapter 4

# RESEARCH METHODOLOGY

## 4.1 CHAPTER OVERVIEW

This chapter describes the research methodology which was mainly informed by the previous literature reviews. It includes a description of the data collection and statistical methods used in this research.

## 4.2 ETHICAL APPROVAL

Permission to carry out my research using data from the two Omani hospitals was approved by ethical committees. To acquire the SQUH data, I submitted an application to the main ethics committee of the Sultan Qaboos University which has granted permission to conduct the research. The director general of the hospital as well as the head of the cardiology and cardiothoracic departments have also approved my research protocol. For the Royal Hospital, I submitted an ethical application to the hospital ethics committee as this hospital has its own local committee independent from the Ministry of Health national ethics committee. Ethical approval letters from both institutions are included in appendix B. There was no patient involvement in the study.

## 4.3 DATA COLLECTION

### 4.3.1 Study sample and data collection

Data were collected from the hospitals' information systems. The type and availability of data vary between the two hospitals. Due to the complexity of care, patient data are scattered in many tables inside the hospital electronic systems. I approached the hospitals' Information Technology (IT) departments for assistance in data retrieval. Several datasets related to patients surgery, admissions, A&E visits, cath lab procedures, CICU admissions, and outpatients' visits were retrieved. A unique visit identification was provided for each patient encounter with the hospitals. I was able to derive several parameters by linking different datasets using Microsoft Access. These include number of previous outpatient visits, number of complications, and previous cardiac interventions and their types. I determined inter-arrival distributions as well as other process timings by analysing timestamps provided in the datasets.

**Data related to cardiothoracic surgery:** Details for all patients who underwent cardiac operations during the 4-year period from 2009 to 2013 (for SQUH hospital) and from 2009 to 2014 (for RH hospital) were entered into a customised Microsoft Access database. For each patient, the database included several variables. However, the type of variables were not the same for both hospitals. Table 4-1 lists the variables that were available for retrieval. This difference is due to the fact that the SQUH is an academic hospital that collects data prospectively for research purposes. Hence, more variables were available. Children (age <18 years) were excluded for two reasons. First, resources used to treat paediatric patients differ than those allocated for adults (e.g. different CICU beds, and operating rooms). Second, the type of complications associated with paediatric cardiac patients are different.

Some other information was obtained from informal interviews with medical staff. These interviews were useful in refining scenarios explored in improving performance (discussed in respective chapters). Moreover, it was necessary to understand the rules regarding hospital services and patients flow in order to construct the conceptual model.

**Data related to cardiology interventions:** For this analysis, data were collected from the RH only. Unlike Cath Lab data at the SQUH, the data from the RH are managed within a single information system which was easier to retrieve. Two analyses concerned optimising Cath Lab services were carried out in the research. The first is related to the factors associated with patient admission following outpatient catheterisation and the second is related to the best configuration of resources incorporating influential factors.

Disease presence and diagnostic history are based on International Classification of Disease (ICD-10) codes. The hospital has well-qualified coders with several years of experience and formal training. All ICD coding is done in the medical records department and is carried out by medical records specialists. The data for this part of the research were retrieved with the help of a senior coder. The types of variables are discussed in chapter 6.

### 4.3.2 Data definitions

The resource utilisation components were defined as LOS and hospital charges associated with: 1) investigations (laboratory and radiology tests)[2], 2) surgery, and 3) hospital stay. LOS was subdivided into three categories: preoperative LOS, CICU LOS, and postoperative LOS. Preoperative LOS was defined as the time between the date of admission and the day of surgery. Postoperative LOS was defined as the time between the day of surgery and discharge from the hospital while CICU LOS was defined as the time in days between the admission and

[2] Tests were obtained by linking the datasets using the unique patient admission ID. For the RH charges were already assigned to each test. However, for SQUH hospital costs were assigned to each test as per the fee schedule.

discharge from CICU. LOS was recorded as a continuous outcome (despite its discrete nature). Charges are based on the administrative fee schedule of 2014.[203] Healthcare services in Oman are highly subsidised and charges specified in the fee schedule might not reflect the actual cost incurred for services. For calculating total cost one would expect to include the hospital cost for all services such as medications, direct supply, and labour cost. Unfortunately, such detail are not routinely collected by public hospitals in Oman. However, it is still fairly accurate to include charges of services for surgery, investigations, as well as per diem bed charges as they constitute the majority of any hospital cost. The Omani Riyal was fixed to the US dollar (USD). Thus, the total costs were converted to US dollars by a multiplication factor of 2.56, which was the existing exchange rate at the start of the study (June 2013).

The type of surgery encompassed in this thesis include several types of open heart operations including isolated valve, isolated CABG, combined surgery, and other type of cardiothoracic surgeries. Under the latter category, there are several complex procedures such as aortic aneurysm and aortic dissection surgery or congenital defect repair. I included them because patients who had these surgeries typically share the same resources (operating theatre, wards, etc.) as other patients. From the perspective of hospital operation management, all these types of patients compete for resources and disregarding a specific patient type will jeopardise the analysis. Respectively, postoperative outcomes include several complications all of which are defined according to the Society of Thoracic Surgeons database definitions.[204-206] Surgeons at the SQUH agreed to adopt these definitions for constructing their own database (some important definitions are listed in appendix C). Complication data were only collected from the Sultan Qaboos University Hospital.

For the RH hospital, comorbidities were selected based on ICD-10 codes, incorporating a look-back period of two years prior to the cardiac surgery admission to capture more conditions per patient.[207] An experienced coder was consulted to provide the corresponding codes for common comorbidities. The risk of misclassifying comorbidities with complications was minimised by only selecting primary diagnoses.

**Table 4-1 The type of variables that were retrieved from both hospitals**

| | SQUH | RH |
|---|---|---|
| **Pre-operative** | Age, gender, height, weight, BMI, BSA, urgency status, number of previous heart surgeries, EuroSCORE, STS, Parsonnet scores, and NYHA Score.<br><br>**Risk factors/ comorbid diseases (binary Yes or No):** smoking, diabetes, insulin dependent, hypercholesterolemia, renal failure, dialysis, hypertension, cerebrovascular disease, peripheral vascular disease, pulmonary hypertension, infective endocarditis, gastrointestinal, endocrine, myocardial Infraction, angina, Unstable Angina, Congestive Heart Failure, Congestive Heart Failure on Admission, cardiogenic shock, resuscitation, arrhythmia, previous CV intervention, and previous PCI. | Age, gender, weight, BMI, urgency status, number of previous heart surgeries, ASA classification.<br><br>**Risk factor/ comorbid diseases (binary Yes or No):** diabetes, insulin dependency |
| **Intraoperative** | Type of surgery, cross clamp time, CPB use, number of vein grafts, perfusion time (min), cardiopulmonary Bypass time, and operative mortality. | Type of surgery, cross clamp time, CPB use, number of vein grafts, perfusion time (min), and cardiopulmonary Bypass time. |
| **Post-operative** | **Complications (Yes or No):** experienced complication, Number of Complications, mortality, operative Mortality, ventricular Arrhythmia, heart block requiring PPM, Cardiac Arrest, New Atrial Arrhythmia ,Cardiac tamponade, Stroke Permanent, Stroke Transient, Continuous Coma > 24hrs, Neuropsychiatric, Prolonged ventilation > 24hrs, Pulmonary Embolism, Pneumonia, Reintubation and ventilation, Thoracotomy, Septicaemia, Leg wound comps, Sternal Dehiscence, Sternal Superficial, Sternal Deep, Aortic Dissection, Acute Limb Ischemia, Anticoagulant comps, GI complications, Multisystem failure, Postoperative AMI, New Renal Failure.<br><br>Readmission 30 days, reoperation, death. | Readmission 30 days, reoperation, death. |
| **Catheterisation procedure** | Data were not collected. It was not possible to collect data as there was no integration between the Cath Lab system and the main HIS. | Age, gender, angina, hypertension, diabetes, coronary artery disease, cardiomyopathy, congestive heart failure, hyperlipidaemia, arrhythmia, obesity, previous CABG, previous PTCA, chest pain and myocardial infarction. |

As can be seen in Table 4-1, postoperative complications were not included in the RH dataset. There are two main reasons for this. The first is related to the coding and availability of data (i.e. technical). The hospital management and the Ministry of Health, which the hospital comes under, do not mandate reporting of adverse events. Furthermore, some incidences of major complications are entered into medical notes in unstructured format. Hence, in most situations, these complications are not coded by the medical record staff. Retrieving complications would have required a tremendous manual work and thus contradicts the purpose of this thesis which is based on the use of routinely collected data. The second reason has to do with the methodological definition of complications. That is, even when complications were provided in the medical notes, the hospital does not maintain uniform definitions. A typical example would be on how to define bleeding (minor vs. major) after surgery or when to consider an arrhythmia as a complication. This a common problem faced by researchers as there is a lack of consensus on how to define and grade postoperative complications.[208]

To verify the above claim, I requested help from the cardiothoracic department at the RH to retrieve detail from a sample of 300 patient records. The department allocated a medical student and a senior nurse for this task. We found difficulty retrieving details regarding complications as they are not appropriately recorded. In most cases, details were vague with no explicit indication for whether patients had experienced complication. The task was formidably difficult as manual search was needed.

I defined prolonged LOS in this thesis as LOS greater than or equal to the 75$^{th}$ percentile (in days). The use of this cut-off value is common.[209-211] It is worth mentioning that there is no appropriate definition for prolonged LOS in the literature. A definition of a prolonged stay varies according to the type of disease and the type of hospital.[212] For reimbursement evaluation, payers of health services only consider extreme LOS which is usually equal to three times the average of the DRG group.[213] This definition is not suitable for my research because roughly less than 3% of the patients would be classified as long-stay outliers according to this definition.

## 4.4 ANALYSIS OF FACTORS ASSOCIATED WITH RESOURCE UTILISATION

With so many factors that were identified by researchers as predictors of resource utilisation, there was a need for conducting a study that is tailored to the Omani hospitals. The analysis on factors provides a preliminary evaluation of the patient mix and the impact they impose on hospital resources. I hypothesised that patient and treatment characteristics drive variation in resource use and thus policies regarding resource allocations can be augmented by better understanding of this variation. As such, it would be possible to select appropriate policies for managing natural variation.

In this section I will discuss methods used to achieve the objectives of this research. However, specific detail about individual method will be provided in the respective chapters.

**(1) Factors associated with prolonged LOS in ward and CICU:** Two types of regression models are used in this thesis for identifying factors associated with utilisation of resources. First, the logistic regression was used to identify factors associated with prolonged LOS in the ward as well as in the CICU. Second, I used survival analysis (Cox proportional hazard) to compare survival (i.e. discharge) between patients. Factors influential to high resource utilisation are incorporated into prediction models. I evaluated the predictive performance of the models through bootstrapping or through external validation in the case of the CICU model.

**(2) Admissions following outpatient catheterisation**: Unanticipated admissions following a routine angiography constitutes a source of uncertainty similar to that of emergency admissions which can complicate patient flow. However, it has not been adequately addressed. The goal is to provide a mechanism to flag patients who have a high probability of admission. Patients at high risk of admission could be targeted for some interventions.[214] Cardiac Cath Lab services are limited in Oman and the existing facilities are operating under limited resource environment. Logistic regression modelling was conducted to identify which variables are independently predicting admissions. Records of 840 patients were used to build the model. 15 explanatory variables were selected based on the recommendations of the cardiologists.

## 4.5 ANALYSIS OF COMPLICATIONS ASSOCIATED WITH RESOURCE USE

I carried out an analysis to assess the incremental LOS associated with postoperative complications. I used Poisson regression to identify complications most influential to LOS. Excess LOS was assessed through the marginal effect of each complication.

## 4.6 SIMULATION MODELLING

### 4.6.1 Conceptual model

Robinson defines a conceptual model as "*a non-software specific description of the computer simulation model, describing objectives, inputs, output, content, assumptions and simplification of the model*".[119] Pidd [215] suggests that only after thinking about the model can the analyst know what type of data to collect. However, it was also necessary to understand the system and to have a sense of its complexity in order to develop a representative DES model. During the phase of my data collection, I met with several people, in both hospitals, including physicians, nurses, Cath Lab technicians, and IT specialists. I discussed system structure, patient flow, and availability of data. Accordingly, I created a conceptual model of patient flow that is universal to both hospitals (depicted in chapter 7, Figure 7-3).

**(1) Optimising resources based on influential factors to LOS:** Two DES models were created in order to identify the optimum strategies that can improve patient flow. The first model evaluates potential strategies that can improve operational performance incorporating factors that I found to be influential to LOS. The second model assesses the optimum capacity required to minimise waiting time for Cath Lab procedures, considering emergency cases and unexpected admissions following angiography.

**(2) Quantifying the effect of complications on operational performance:** I used DES to estimate the effect complications on operational performance. The marginal effects associated with postoperative complications were used to investigate their roles in operational performance.

## 4.7 PATIENTS GROUPS PREDICTIVE OF RESOURCE USE

Variability can be captured more realistically by dividing patients into some homogenous groups. Patient groupings are a means to understand the effect of heterogeneity on resource use. Hospital managers should be interested in evaluating resource use based on patient case mix. As stated in the introduction chapter, the DRGs, which defines medically meaningful groups that are predictive of hospital resource consumption,[216] are not adequate for defining resource consumption among patients with cardiac interventions. Failure to identify patient characteristics that may potentially influence resource use (i.e. LOS) may lead hospital managers to underestimate patient variations. Determining which set of characteristics can be used to obtain homogenous groups is a complex process. In Table 4-2, I discuss some existing methods and systems that are commonly available to classify patients based on their potential hospital resource use.

**Table 4-2 Methods and systems that can be used to predict hospital resource utilisation**

| Type | Example | Strengths (+) and limitations (-) | |
|---|---|---|---|
| Reimbursement systems | • Diagnosis Related Groups (DRG) and its variants. | + | Well-established mechanisms. |
| | | - | Too broad for a single speciality |
| | | - | Not in use in many countries including Oman |
| Cardiac risk stratification systems | • EuroSCORE<br>• Parsonnet<br>• STS | + | Derived from several medical variables |
| | | - | Not specifically designed for resource utilisation assessment |
| | | - | Not in use in many hospitals |
| Medical status assessment | • ASA,<br>• APACHE | + | Usually derived from few variables |
| | | - | Can be highly subjective |
| | | - | Not specifically designed for resource utilisation assessment |
| Statistical methods | • Regression modelling<br>• Data mining techniques | + | Can be derived and validated for a specific population |
| | | + | Can have higher calibration than previous systems |
| | | - | Outputs from data mining can be too complex to be easily understood |
| | | - | Availability and quality of data are common issues |

APACHE: Acute Physiology and Chronic Health Evaluation

### 4.7.1 Decision trees

Decision trees based on Classification and Regression Tree or C5.0 algorithm are commonly used in medicine.[217, 218] Few studies have extended their use for hospital resource utilisation predictions. Both CART and C5.0 use the statistical calculation of information gain from a single attribute to build a decision tree.[217, 219] CART starts out with the best univariate split. It then iteratively searches for perturbations in attribute values (one attribute at a time) which maximize some goodness metric.[220] C4.5, the predecessor of C5.0, introduced an alternative formalism consisting of a list rules (if A and B … then class =X).[219] The two methods will be discussed in more detail in chapter 6.

## 4.8 METHODS FOR DES MODEL VALIDATION

Five main types of validation are commonly described: face validity, verification (or internal validity), cross validity, external validity, and predictive validity.[144] Sargent[221] discussed several methods of verification and validation techniques. He defines verification as a process of assuring that the software design and the specifications for translating the conceptual model is satisfactory, while validation includes graphical representation (e.g. animation), event validity, extreme condition test, face validity, sensitivity analysis and historical data validation to name a few.[222, 223]

In general, it can be said that verification of the model involves ensuring that the underlying logic of the model reflects the actual process, while validation is concerned with determining whether the conceptual simulation model is an accurate representation of the system under study.[224] Verification and validation processes have been developed in order to minimize errors involved in building a model and to make models trustworthy for decision making.[144, 223, 225]

Once the conceptual model is validated, it is then translated into a simulation model. The simulation model can either be built with the common programming language, or with the use of simulation software package, which are designed to overcome the limitations of general programming languages.[226] The procedure is often referred as model translation. The process of building and validation DES models in this thesis was iterative as can be generally depicted in Figure 4-1.

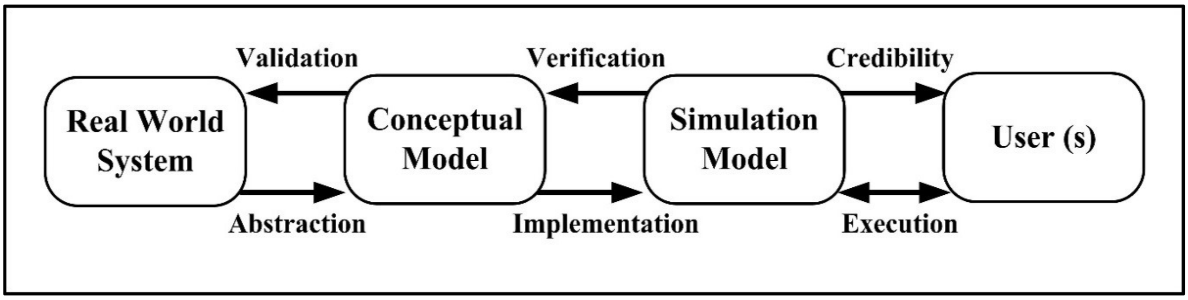



**Figure 4-1 Model abstraction in the simulation process**
Source: Frantz, Frederick K[227]

First, I created a conceptual model by documenting the number of resources, patient flow rules, type of available data, and type of patients. I then created a schematic representation of patient flow which is one part of the conceptual model understanding. I discussed different elements of the conceptual model with key staff to validate its accuracy (face validation) and I made changes accordingly. Based on this understanding, I created the computer simulation models. The inputs (which will be discussed in further detail in the perspective chapters) are mostly derived from the Hospital Information System (HIS). However, some other parameters were derived from experts due to unavailability of data. At least two opinions were obtained and when opinions tend to be in disagreement, I validated the data with other experts to reach consensus. I made some assumptions to simplify model building owing to unavailability of data (will be discussed in chapters 7 & 8).

In this thesis, I emphasised validation by historical data. Several statistical techniques for validating DES models using historical data have been discussed in literature. Chung[228] highlights some statistical tests such as the F test. He suggested that only one version of the test is required for simulation validation which is represented by the following equation:

$$F = \frac{S^2{}_M}{S^2{}_m} \qquad 4\text{-}1$$

Where:

$s^2{}_M$ is the variance of the data set with the larger variance.
$S^2{}_m$ is the variance of the data set with the smaller variance.

The null hypothesis for this test states that the variances of both sets of data (real and simulated) are similar. The null hypothesis is rejected if the F value exceeds the critical value. Another commonly used test is the t-test applicable for normally distributed data. The test determines whether averages from two groups are statistically different, given a significance level α. The null hypothesis for this test states that the averages of both sets are equal. When data are not normally distributed, non-parametric methods are used. Mann-Whitney U tests is the nonparametric alternative to the t-test for two independent samples. Once the simulation model is verified and validated, it can be used to investigate a number of what if scenarios. The validation of the models in this thesis was applied by comparing results from the model against data obtained from operations.

Table 4-3 summaries the major types of analysis that will be discussed throughout the thesis.

Table 4-3 Summary of major analysis discussed throughout the thesis

| | **Independent factors affecting resource utilisation** | | **Patient stratifications for resource utilisation prediction** | | **Resource planning based on patient factors** | **The effect of complications on resource use and patient flow** |
|---|---|---|---|---|---|---|
| **Analysis** | Prolonged postoperative LOS | Admission following outpatient cardiac angiography | Evaluation of the existing risk stratification systems for predicting prolonged LOS | Rule-based resource allocation | The effect of allocating resource by using patients factors | The effect of complications on LOS |
| **Patient type** | Adult patients undergoing cardiac procedures | Adult patients undergoing cardiac angiography (day case patients) | Adult patients undergoing cardiac procedures | Adult patients undergoing cardiac procedures | Adult patients undergoing cardiac procedures | Adult patients undergoing cardiac surgery. |
| **Hospital** | SQUH | RH | SQUH and RH (for ASA) | RH | SQUH and RH | SQUH |
| **Data source** | Prospectively collected data | Linked medical records | Prospectively collected data (SQUH) and linked medical records (RH) | Linked medical records | Prospectively collected data | Prospectively collected data (SQUH). |
| **Method type** | Statistical- logistic regression, Cox proportional hazard regression. | Statistical- logistic regression | Discriminative power assessment through ROC curve | Regression trees: CART and C.5 | Discrete event simulation | Statistical- Poisson regression, Discrete event simulation |
| **Purpose** | Scoring system for predicting patients at risk of prolonged LOS. | Understand factors that can affect patient flow for better scheduling of patients. | To assess whether risk stratification system would provide an objective method for predicting resource utilisation | examine whether rules can be extracted to meaningfully predict LOS category | Optimise resource use based on patient factors | To understand the effect of complications on resource use |

# Chapter 5

# EXAMINING VARIATION IN RESOURCE UTILISATION AMONG CARDIAC CARE PATIENTS: A DESCRIPTIVE ANALYSIS

## 5.1 CHAPTER OVERVIEW AND GENERAL IMPORTANCE

In this chapter I sought to characterise variation in hospital resource utilisation for cardiac care patients. I investigated whether variation in resource use exists amongst cardiac patients. Little is known about factors influencing hospital resource use in patients admitted for cardiac interventions in Oman as there is no previously published report revealing patterns of resource utilisation. The analysis in this chapter should be viewed as the first step toward understanding natural variation and its effect on resource use and how such knowledge can be translated into practical application for resource planning.

An objective of this thesis was to understand how variation in patient mix and surgical procedures influence LOS and costs. Therefore, the chapter is geared toward investigating patient casemix in the two hospitals and their relationship with resource use. A substantial variability should warrant the need to consider these variations in hospital resource planning. For example, knowledge on patient variation can be used to assess future bed usage, control preventable complications, and plan admissions and surgeries. It also allows hospital managers to narrow the focus on ways to reduce LOS. This is especially important for allocating scarce resources such as critical beds.

## 5.2 INTRODUCTION

It is widely agreed that before undertaking more complex analysis, it is important to understand the empirical features of the data and patterns of association between different variables.[229] In the literature, several variables were used to stratify patients for their resource use. When LOS is used as proxy for resource utilisation, it is usually common to divide patients into two or more groups based on a specific cut-off value (e.g. less than or greater than 7 days). The characteristics of patients in these groups are then compared. For achieving the objectives of this research, it was important to understand the characteristics of patients who can be identified as high users of resources. From a resource planning perspective, patients with prolonged LOS are a very crucial segment that proportionately consume more resources and might impact patient flow. For example, very long-stay (i.e. outlier) patients group was found to be a major contributor to hospital congestion, and that congestion was a major factor driving increased waiting times.[213]

## 5.3 METHODOLOGY

Data collected from both hospitals were used for analysis in this chapter. Descriptive statistics are presented as percentages and frequencies for discrete variables and means and standard deviations for continuous variables. Several bivariate analyses were performed to compare LOS between groups (e.g. gender, types of surgery, complications). I used *Mann-Whitney U test* and *Kruskal Wallis test* (to accommodate for more than two groups in the dependent variable) when the data do not meet the requirement for parametric tests. *Chi square test* was also used for categorical variables. The 75$^{th}$ percentile was used to separate prolonged LOS in a similar manner to other analyses in the rest of this thesis. Associations between continuous variables were assessed by Pearson correlation with 95% confidence intervals.

The variation that is attributable to patient characteristics, rather than practice style differences, was evaluated through *Poisson regression*. This type of regression is suitable for count data (i.e. discrete LOS) that don't assume normality. The main purpose of this analysis was to examine whether differences in LOS can be explained by the hospital type when other factors related to patients and treatment are accounted for. For constructing the Poisson model, the dependent variable of interest was LOS and hospital type was the independent variable. The model adjusts for five covariates: ages, sex, BMI, urgency level, and type of surgery. I hypothesised that LOS among cardiac care patients in Oman is influenced, in part, by the local organisational practices. The implications of this to the research and to the hospital resource management will be discussed subsequently.

## 5.4 RESULTS

### 5.4.1 The normality of the LOS distribution

The normality of the distribution for the collected hospitals cost and LOS was tested by use of the Shapiro-Wilk test for normality as well as through inspecting graphs such as Q-Q plot.[230] To illustrate the normality assumption, I present data from 1000 patients from both hospitals. I performed linear regression by regressing postoperative LOS against common variables such as age, sex, BMI, surgery type and urgency status. It was evident that there is a large spread of residuals (error terms) against the regressed variables due to the skewed nature of the data, shown in Figure 5-1. Furthermore, I attempted to apply different types of transformations such as log, cube, square root, and reciprocal root (assessed using *gladder* command in Stata).[231] However, the shape of the distribution did not improve and failed to even approximate normality. Moreover, removing outliers is not appropriate as patients with extreme LOS may have characteristics that are relevant to the level of resource use. Consequently, I was inclined toward using models and methods which do not assume normality of data.

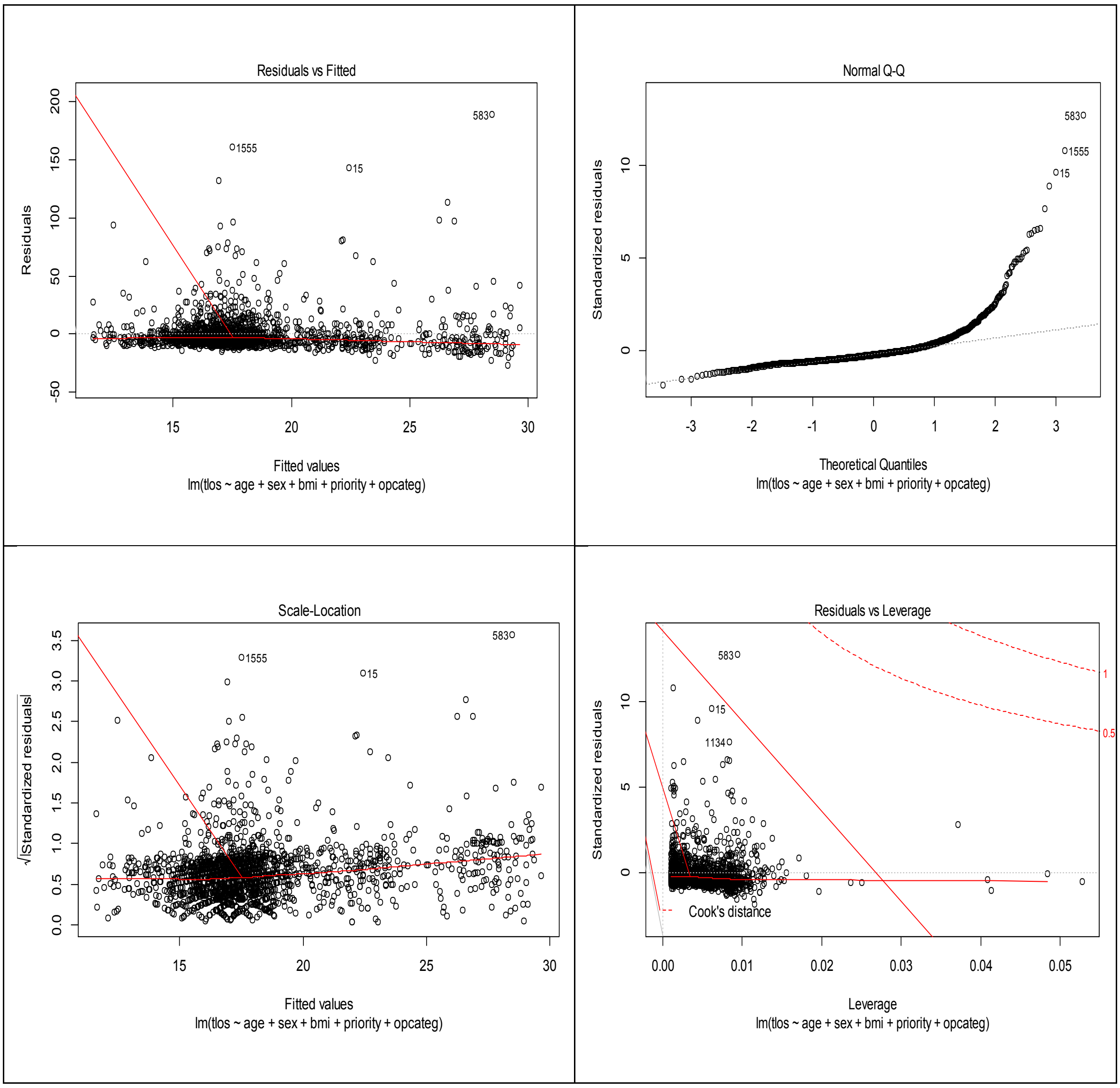



**Figure 5-1 Regression model residual plots**

### 5.4.2 Demographic and clinical characteristics

This section presents overall descriptive statistics for both hospitals. These statistics reflect the unique characteristics of patients who underwent cardiac interventions in Oman.

#### 5.4.2.1 Baseline and surgical characteristics

2241 patient records were included in the analysis. Table 5-1 presents patient, surgery, and length of stay characteristics for both hospitals. Of all patients (the two hospitals combined) there were much higher number of males (69%) than females (31%) and their proportion was similar in both hospitals. 10% of the patients being older than 70 years. There were 35 octogenarians in the dataset. The mean age of cardiac surgical patients (i.e. all types) was 56 years (CABG = 60, valve = 49, combined surgery= 63 and other types= 43). Patients with an age of 40 years or younger constituted 3.1% of CABG, 32% of valve surgery, and only two patients (1.2%) of combined CABG and valve and slightly more than half (51%) for other types of surgery. This indicates that it is unlikely for younger people to undergo combined surgery in Oman. It also shows that cardiac patients undergoing heart surgery in Oman are relatively younger than what has been revealed in the literature.[202, 232]

**Table 5-1 Patient's baseline characteristics using common variables to both hospitals**

| variable | All patients | Results | |
|---|---|---|---|
| | | SQUH | RH |
| **TOTAL** | 2241 | 600 | 1641 |
| **Patient characteristics** | | | |
| Gender | | | |
| Female, n (%) | 689 (31) | 182 (30) | 507 (31) |
| Male, n (%) | 1552 (69) | 418 (70) | 1134 (69) |
| Age, average ± SD | 56 ± 13 | 59 ± 12 | 55 ± 14 |
| Weight, average ± SD | 68 ± 15 | 68 ± 15 | 68 ± 16 |
| Height, average ± SD | 159 ± 9 | 159 ± 9 | 159 ± 9 |
| BMI, average ± SD | 26 ± 5 | 26 ± 5 | 27 ± 5 |
| Ejection Fraction | 49 ± 14 | 50 ± 13 | 45 ± 14 |
| **Comorbidities,** n (%) | | | |
| Hypertension | 1108 (49) | 403 (67) | 705 (43) |
| Diabetes | 828 (37) | 270 (45) | 558 (34) |
| Hyperlipidaemia | 884 (39) | 375 (63) | 509 (31) |
| Heart failure | 311 (14) | 229 (38) | 82 (5) |
| Renal failure | 139 (6) | 73 (12) | 65.6 (4) |
| Atrial fibrillation/ arrhythmia | 118 (5) | 36 (6) | 82 (5) |
| Myocardial infarction | 425 (19) | 277 (46) | 148 (9) |
| Unstable Angina | 403 (18) | 157 (26) | 246 (15) |
| **Surgery** | | | |
| Elective procedure, n (%) | 1864 (83) | 502 (85) | 1356 (83) |
| Non-elective procedure, n (%) | 377 (17) | 92 (15) | 285 (17) |

| variable | All patients | Results | |
|---|---|---|---|
| | | SQUH | RH |
| Bypass time (min), average ± SD | 105 ± 43 | 118 ± 47 | 98 ± 39 |
| Cross clamp time (min), average ± SD | 60 ± 29 | 71 ± 29 | 56 ± 28 |
| **LOS,** median with range | | | |
| Total LOS | 15 ( 1-217 ) | 14 (1-217) | 15 (1 -178 ) |
| Preoperative LOS | 6 ( 0-123 ) | 6 ( 0-123 ) | 7 ( 0-48 ) |
| CICU LOS | 2 ( 0-134 ) | 4 (0 -134 ) | 2 ( 0-76 ) |
| Postoperative LOS | 7 ( 0-212 ) | 8 (0 -212 ) | 7 ( 0-176 ) |

Approximately half of the patients in the study had two or more comorbid diseases. Diabetes affected 37% of the patients undergoing heart surgery. This rate was 44% for CABG, 10% for valve, 34% for combined surgery, and 14% for other surgery. Hypertension was present in almost half of the patients. There were 311 patients who had congestive heart failure. 18% of the total patients had unstable angina. Approximately 6% of the patients had renal failure or renal dysfunction preoperatively, but among these patients only 1.4% were on dialysis. Based on the BMI as used by the World Health Organisation,[233] patients were either of underweight (<18.50)= 3%, normal weight (18.50 - 24.99) = 35%, overweight (25.00 - 29.99) = 37% or obese (≥30) = 46%. Male and female patients had statistically different distributions of BMI $P$ ($t \leq 3.20$) = 0.001. The high number of obese patients reflects the obesity epidemic in this group.

4% of the patients died after surgery and during their hospitalisation (2.8% of CABG patients, 4.8% of valve, 12% of combined surgery, and 4.3% of other surgeries). Thus, mortality was highest in patients who underwent combined surgery. LOS of patients who died in the hospitals were similar to those who were discharged alive. The level of urgency in the RH hospital was only coded as elective or emergency despite three types of urgency levels used among the cardiac surgeons. It was difficult to estimate the urgent cases. Therefore, I labelled cases in both hospitals as either elective or non-elective. In total, 16.82% of the cases were non-elective.

The proportion of non-elective patients admitted to the RH was higher than their counterparts in the SQUH (15% vs.17%).

#### 5.4.2.2 Surgical characteristics

According to Table 5-2, the most frequently performed surgery was CABG (71%) followed by valve surgery (16.5%), and combined valve and CABG (10.2%). The RH hospital performed higher number of other types of cardiothoracic surgeries (18.5% vs. 2.6% for the SQUH). Most patients who underwent *valve* surgeries had operations on a single valve (SQUH: 96%, RH: 83%). Out of the patients who had valve surgery, the proportion of patients who had *double* valves was higher in the RH (15%) vs (4%) for the SQUH. In total there were only four cases with *triple* valve operations. A significantly greater proportion of men than women had CABG surgeries (75% vs. 25% respectively). In total, 83% of the surgeries were elective.

**Table 5-2 Type of surgeries and their percentages calculated based on the total cardiothoracic surgeries for both hospitals**

| Cardiac surgery type | Patients (%) | |
|---|---|---|
| | SQUH | RH |
| | n = 600 | n = 1641 |
| Isolated CABG | 70.71 | 65.50 |
| Isolated valve | 16.50 | 8.30 |
| Combined CABG + valve | 10.15 | 5.90 |
| Aortic valve surgery | 9.56 | 4.00 |
| Mitral valve surgery | 12.74 | 4.10 |
| Tricuspid valve surgery | 0.79 | 0.20 |
| Double valve surgery | 3.18 | 1.60 |
| Triple valve surgery | 0.39 | 0.30 |
| CABG + Aortic valve surgery | 3.18 | 2.10 |
| CABG + Mitral valve surgery | 6.77 | 3.50 |
| CABG + Double valve surgery | 0.19 | 0.20 |
| CABG + Triple valve surgery | 0 | 0 |
| Others | 2.58 | 18.6 |

The majority of the CABG procedures were performed on the CPB (96.5 % vs. 3.5%). The median bypass time was 91 minutes and the cross clamp time was 50 minutes with a maximum of 198 minutes. The average surgery duration was four and half hours. The combined operation group had the highest surgery mean duration in hours (CABG: 4.25, valve: 4.28, combined surgery: 5.23, and other procedures: 2.37).[3]

For the Royal Hospital patients, the isolated CABG was the most common operation (65.5%), followed by other type of surgeries (18.6%). Combined CABG and valve was performed in 6% of the patients. While only 2.6% of the surgeries performed at the SQUH were labelled as “non CABG or valve”, 18.6% of the surgeries at the RH fell in this category which includes several procedures such as aortic aneurysm, aortic dissection surgery and congenital defect repair.

### 5.4.3 Hospital resource use

#### 5.4.3.1 Length of stay

At the SQUH, only 5% of the patients who underwent cardiac procedures were discharged by the 5$^{th}$ postoperative day. The majority (61%) were discharged between 6 and 10 postoperative days. The mean postoperative LOS was 12 days and the median was 8 days. The 75$^{th}$ percentile corresponding to postoperative LOS and CICU were 10 and 5 days respectively. The median preoperative LOS was 4 days with a mean of 6 days. On the other hand, these figures were lower for the RH hospital. For example, patients had lower mean postoperative LOS of 10 days (vs.12 for SQUH hospital). Moreover, the proportion of patients who were discharged by the 5$^{th}$ postoperative day was higher (16%). The CICU part of postoperative LOS accounted for 22% of the overall postoperative LOS for the RH and 38% for the SQUH. Table 5-3 presents median LOS for both hospitals in relation to demographic and surgery characteristics.

[3] Surgery duration was obtained from only one hospital (RH), as surgery durations in SQUH were manually recorded in paper-based format which was difficult to retrieve. Surgery duration could have been used as an outcome for operating room utilisation, however, the accuracy of this measure was low as many surgeons didn’t entered the duration in the system.

**Table 5-3 Median length of stay for some selected clinical and operative variables**

| | Length of stay (median ) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | SQUH | | | | RH | | | |
| | Total LOS | Pre-op | CICU | PLOS | Total LOS | Pre-op | CICU | PLOS |
| **All patients** | 14 | 4 | 4 | 8 | 15 | 7 | 2 | 7 |
| **Surgery type** | | | | | | | | |
| CABG | 13 | 5 | 4 | 8 | 15 | 7 | 2 | 7 |
| Valve | 16 | 4 | 4 | 10 | 20 | 9 | 2 | 9 |
| Combined | 18 | 5 | 4 | 11 | 24 | 12.5 | 2 | 11 |
| Other | 14.5 | 4 | 4 | 8 | 11 | 4 | 1 | 6 |
| Male | 15 | 5 | 4 | 8 | 13 | 4 | 4 | 8 |
| Female | 13 | 4 | 4 | 8 | 16 | 7 | 2 | 8 |
| **Age groups** | | | | | | | | |
| <49 | 12 | 4 | 4 | 8 | 13 | 6 | 1 | 7 |
| 50-59 | 13 | 4 | 4 | 8 | 14 | 6 | 2 | 7 |
| 60-69 | 15 | 5 | 4 | 9 | 17 | 7 | 2 | 8 |
| 70-79 | 13 | 5 | 4 | 8 | 16 | 7 | 2 | 8 |
| 80 + | 13 | 5 | 3 | 7 | 19 | 8 | 2 | 8 |
| **Urgency** | | | | | | | | |
| Elective | 14 | 4 | 4 | 8 | 15 | 7 | 2 | 7 |
| Non-elective | 14.5 | 4 | 4 | 9 | 14 | 5 | 2 | 7 |
| **ASA class** § | | | | | | | | |
| I | - | - | - | - | 8 | 4.5 | 1 | 3 |
| II | - | - | - | - | 12 | 3 | 1 | 6 |
| III | - | - | - | - | 17 | 8 | 2 | 8 |
| IV | - | - | - | - | 17 | 6 | 2 | 8 |
| V | - | - | - | - | 31 | 1 | 5 | 21 |
| **EuroSCORE**† | | | | | | | | |
| < 6 | 13 | 4 | 4 | 8 | - | - | - | - |
| ≥ 6 | 14 | 5 | 4 | 8 | - | - | - | - |

§ ASA scores were only available from the RH hospital.

† EuroSCORE was only available from the SQUH hospital.

There was a positive correlation between LOS and charges related to diagnostic services (lab tests and radiology). Figure 5-2 shows a scatter plot which suggests a positive correlation between LOS and charges for diagnostic services. The correlation was very strong 0.80, $p<0.001$, 95% CI= 0.76-0.82. The total hospital charges were also strongly correlated with the postoperative LOS, $r=0.84$, $p<0.001$, 95% CI= 0.82-0.87. These results support the use of LOS as proxy for hospital resource utilisation.

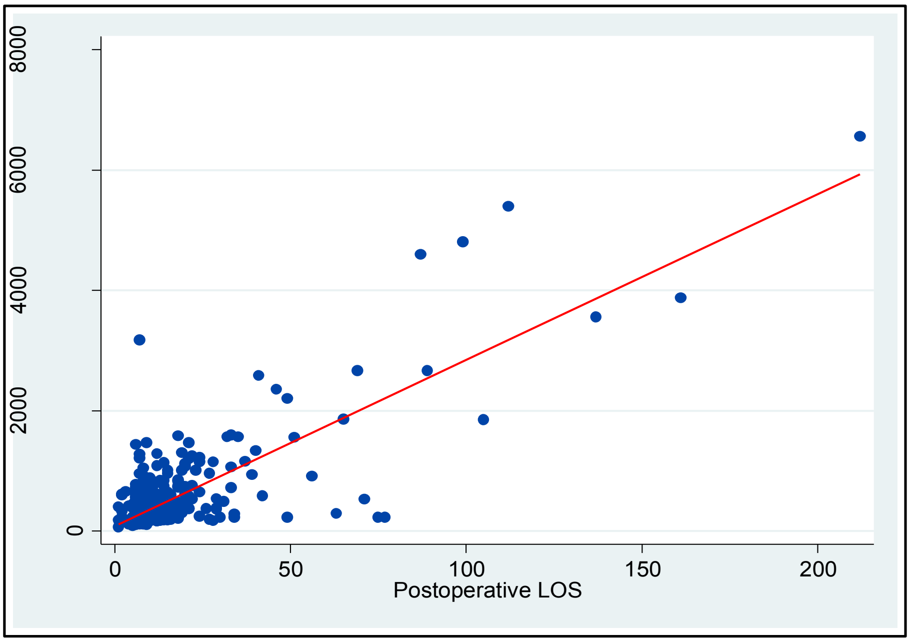



**Figure 5-2 Scatter graph of total charges for investigation services against postoperative LOS**

Surprisingly there was a high length of *preoperative* stay in both hospitals. The Median for the SQUH was 4 days and one week for the RH. As can be seen from Table 5-3, preoperative LOS was closely associated with the type of surgery and patient age. Lengthy preoperative stay could signal inefficiency in the system. According to some staff at the RH hospital, there were many patients who were admitted long time before surgery simply to hold a bed and thus avoid waiting times.

### 5.4.3.2 Resource utilisation among high LOS patients

A notable difference between the two hospitals was on the percentage of patients who had prolonged LOS at a cut-off period that is equal to the $75^{th}$ percentile or more (Table 5-4). The RH patients were discharged faster, on average, than SQUH patients. In terms of patient flow, this is a remarkable difference which intuitively supports the notion that hospital factors can impact LOS decisions.

**Table 5-4 The proportion of patients who had extended LOS (≥ 75th percentile) at the three types of hospital stays**

| | LOS ≥ 75 percentile | | | |
|---|---|---|---|---|
| | SQUH | | RH | |
| LOS type | cut-off in days | % of patients | cut-off in days | % of patients |
| Preoperative LOS | 7 | 29 | 11 | 27 |
| CICU LOS | 5 | 18 | 3 | 35 |
| Postoperative | 11 | 30 | 10 | 30 |
| Total (overall) LOS | 19 | 25.5 | 21 | 27 |

Table 5-4 shows there were considerable differences between the two hospitals in terms of LOS. For example, the 75th percentile for cardiac intensive care unit LOS was lower for RH (3 days) than that of SQUH (5 days). However, the period corresponding to the total LOS was higher for the RH than that of the SQUH. The percentage of patients who would be classified as high resource users was around 30%. Prolonged LOS amounts to 50% of total hospital stays in the SQUH and 48.6% in the RH. Among the prolonged LOS patients, the average hospital charges were higher by 38%. Moreover, patients with prolonged postoperative LOS received more number of packed red blood cells units (3.4 units) than patients with normal stay (2 units).

Another important segment of patients, not specifically the focus of my thesis, is the group of patients with extreme hospital stay, defined as 3 *times* above the mean LOS at each stage of patient stay.[213] Both hospitals have long-stay outliers (Table 5-5). Extreme LOS (total LOS) constitutes about (2.6%) of the patient population in both hospitals. Even though the median *preoperative* LOS was higher for the RH, there were no patients with extreme preoperative LOS.

**Table 5-5 Extreme LOS (outliers) in both hospitals**

| **Hospitalisation stage** | **Percentage of patients** | |
|---|---|---|
| | **RH** | **SQUH** |
| **Pre LOS** | **0%** | **3.1%** |
| **CICU LOS** | **3.7%** | **1.7%** |
| **Total postoperative** | **3.9%** | **3.8%** |
| **Total LOS** | **2.0%** | **3.3%** |

I hypothesised that the waiting times tend to increase as the number of admitted patients with prolonged stay increases. To test this hypothesis, I performed a Pearson correlation between the average monthly waiting times (in days) and the monthly number of patients with prolonged LOS. There was a moderate correlation (r=0.61, n=72, 95% CI= 0.48- 0.76). Waiting times are a product of several factors including availability of human resources, patients preferences, work practice, etc. that were not accounted for in my research. However, the positive correlation still signifies a positive relationship between waiting times and the number of patients with prolonged LOS.

#### 5.4.3.3 Association between throughputs, cancellations and bed-occupancy rates

The average number of monthly Cath Lab procedures at the RH was 205. On average the SQUH performed 13 heart operations per month. The operating theatre was only operating 4-days a week. On the other hand, an average of 34 procedures were performed per month at the RH. For the same hospital there were an average of 7 surgery cancellations per month (causes of cancellation are not clear from the data provided by the hospital). These could be related to medical or non-medical reasons. Since I was interested in system-related cancellations (e.g. unavailability of beds), I carried out a Pearson’s correlation coefficients test to assess the strength and significance of relationships between bed occupancy, number of cancellations and procedure throughputs. There was strong positive correlation between the monthly admission rates and the number of Cath Lab procedures, r=0.964, n=78, p< 0.001. Likewise, there was a strong relationship between the reported monthly cancellations and the number of admissions to the cardiology unit, r=0.72, n=78, p<0.001. The relationship is graphically depicted in Figure 5-3.

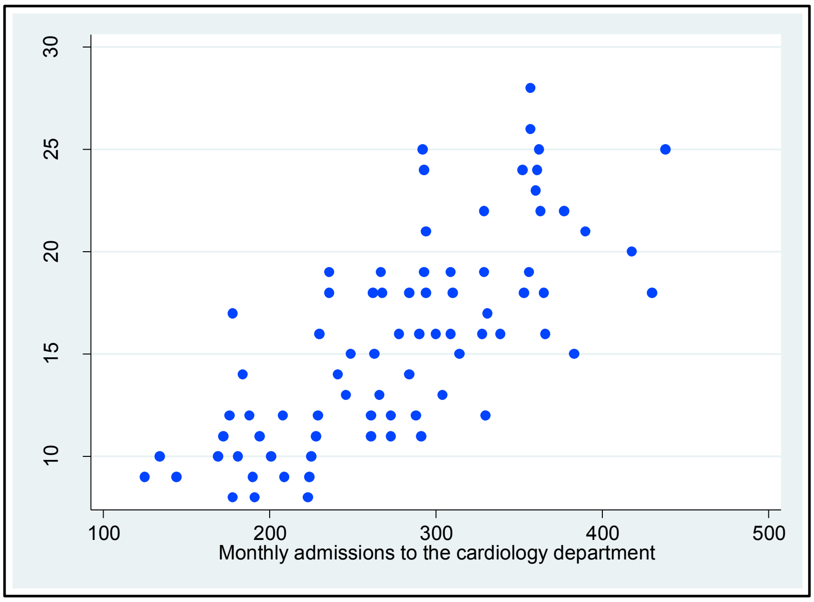
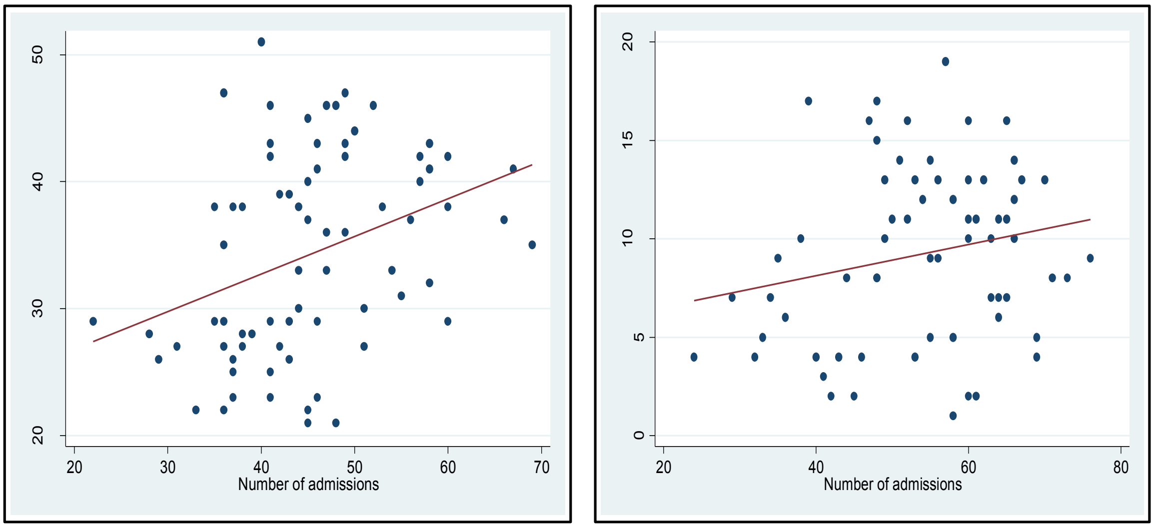



**Figure 5-3 The association between the monthly admissions to the cardiology unit and the number of Cath Lab cancellations**

Since the CICU unit was the main bottleneck in both hospitals, I assessed the association between the number of monthly admissions and the number of procedures in both hospitals (Figure 5-4).




RH hospital, r= 0.35 (b) SQUH hospital, r= 0.21

**Figure 5-4 The association between the monthly admissions to the cardiothoracic unit and the number of surgeries**

There was a weak positive relationship between the number of admissions and the number of operations. This could be because there were many non-surgical patients admitted to the CICU.

The average CICU bed turnover was 11.0 for the RH (calculated as the number of monthly discharges from the CICU over the available beds). The rate indicates that on a monthly average each bed in the CICU served 11 occupants. The bed turnover rate for the SQUH was only 4.0, much lower than the RH.

#### 5.4.3.4 LOS difference between groups: univariate analysis

The purpose of the univariate analysis was to identify unadjusted differences between variables of interest and LOS. Differences between groups were analysed using LOS as continuous variable (rather than dichotomous). Results are summarised in Table 5-6.

**Types of surgery:** A Kruskal-Wallis H test showed a significant difference in postoperative LOS between the type of surgeries, with a mean rank score of 820 for CABG, 1049 for valve, 1117 for combined surgery and 608 for other types. The type of surgeries also had significant differences in CICU and total length of stay (*p*<.001). Figure 5-5 shows a boxplot of postoperative LOS distribution by the type of surgery in both hospitals.

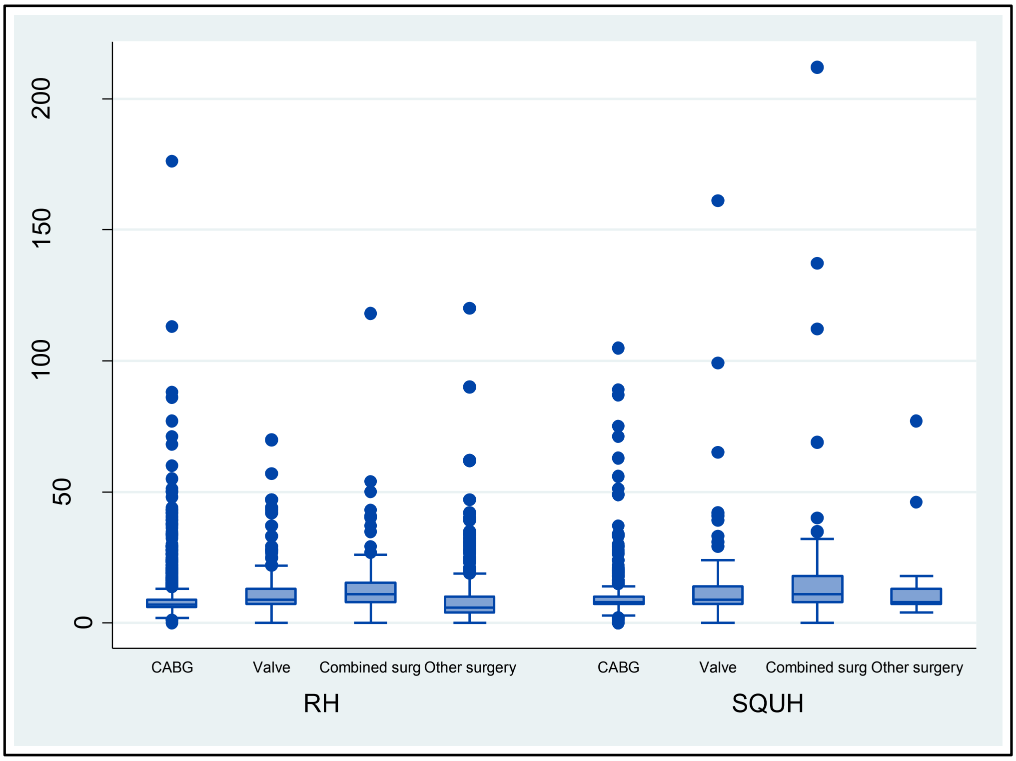
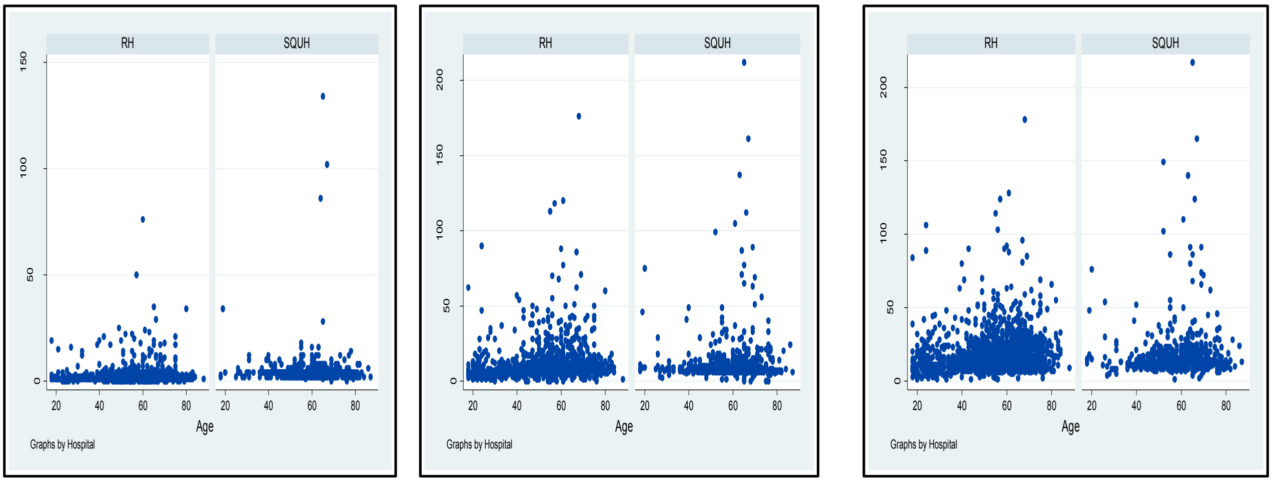



**Figure 5-5 Postoperative LOS distribution by type of surgery**

**Age groups:** Using the Kruskal-Wallis test, I assessed the difference between age groups and total LOS which was significant (*p* <.001). Post hoc test revealed that the difference was mainly significant between the younger patients <49 and other older patients' groups indicating that the effect was projected because of the presence of these younger patients who usually spend less time in hospitals (t= 4.32, p<0.001). The scatter plot in Figure 5-6 shows the relationship between age and LOS for CICU, PLOS, and total LOS. By visually inspecting the scatterplots, it seems that patient ages were closely associated to the total LOS (Figure 5-6 (c)), than to the CICU LOS (a) and postoperative LOS (b).




(a) association between age and CICU LOS

(b) association between age and postoperative LOS

(c) association between age and total LOS

**Figure 5-6 Association between patient age and LOS**

**Gender:** The difference between male and female patients across different types of hospital stays was assessed using Mann-Whitney test. I found no significant difference between genders in respect to CICU LOS (z=0.28, *p*=0.782). However, there was statistically significant difference when the overall postoperative LOS was considered (z= 2.54, *p*= 0.011). On average, female patients tended to stay longer in hospital after surgery.

**Urgency level:** The Wilcoxon rank-sum (Mann-Whitney) test suggests there is a statistically significant difference between the underlying distributions of the PLOS of elective and non-elective patients (z=-2.597, *p* =0.0094). However, there is no significant difference between the two priority groups in relation to CICU LOS (z= -1.189, *p*= 0.2344).

**Number of comorbidities:** Patients were divided into five groups based on the number of comorbidities at admission: a) no comorbidities (n=702), b) 1 comorbid disease (n= 466), c) 2 comorbid diseases (n=489), d) 3 comorbid diseases (n=333), and e) 4 or more comorbid diseases (n=251). The non-parametric Kruskal-Wallis equality rank test revealed that there was a statistically significant difference between the five groups, $\chi^2$ (4) = 86.12, $p$ = 0.0001. The test also revealed a statistically significant difference between the comorbidities groups when CICU LOS was entered as the dependent variable, $\chi^2$ (4) = 242.42, $p$ = 0.0001

**Preoperative risk stratification:** To test the difference between the patients' ASA status scores in terms of their PLOS, the Kruskal- Wallis rank test was used since the independent variable was ordinal consisting of more than two levels and the dependent variable was non-normal.[230] The difference between classes was statistically significant for both postoperative LOS, $\chi^2$ (4) = 30.15, $p$ = 0.0001 and CICU LOS, $\chi^2$ (4) = 17.59, $p$ = 0.0015. The other risk stratification system I tested was the EuroSCORE. A Spearman rank correlation was used to determine the relationship between the patients' EuroSCORE and their LOS. The Spearman correlation revealed evidence against the null hypothesis. However, there was a positive association, $r_S$ =0.30, p<0.001. A similar positive relationship was noted between CICU LOS and these scores ($r_S$ =.20, $p$ < 0.001). Further detail will be provided in the next chapter about the association between risk stratifications and LOS.

**Table 5-6 Summary of univeriately significant variables †**

| Variable | Statistical test type | Test value | p-value |
|---|---|---|---|
| **Type of surgery** | Kruskal-Wallis | χ2= 180.50 | <.001 |
| **Age groups** | Kruskal-Wallis | χ2= 60.322 | <.001 |
| **Gender** | Mann-Whitney | Z=0.28 | 0.782 |
| **Urgency level** | Mann-Whitney | Z=-2.59 | 0.009 |
| **Number of comorbidities** | Kruskal-Wallis | χ2=86.12 | <.001 |
| **EuroSCORE** | Spearman's | 0.30 | <.001 |
| **ASA** | Kruskal-Wallis | χ2=30.15 | <.001 |

† using total LOS

### 5.4.3.5 The effect of local practice and hospital settings on LOS

Previous results indicate that there were significant differences between several demographic and clinical variables and LOS. However, there was a need to understand whether these differences are due to patients and treatment factors or to the specific characteristics of the treating hospital. Therefore, I hypothesised that the type of hospital can significantly affect LOS, reflecting local practice differences related to LOS decisions. To support or refute this hypothesis, I first tested whether there is a difference in LOS between the two hospitals using the Mann-Whitney nonparametric test with a null hypothesis that states the two samples come from the same population. The results suggest that there was a statistically significant difference between the underlying *total* LOS distributions of both hospitals ($z=2.65$, $p=0.008$) and in *postoperative* LOS between the two hospitals ($z=-6.73$, $p<0.001$). Second, I accounted for some factors including age, sex, urgency level, and type of surgery using Poisson regression (Table 5.7). Instead of interpreting the Poisson regression coefficients as a difference between the logs of expected counts, it is more plausible to interpret the model coefficients in terms of Incidence Rate Ratio (IRR), obtained by exponentiating the Poisson regression coefficients.[234]

**Table 5-7 The effect of hospital type on Postoperative LOS**

| variable | IRR | 95% CI |
|---|---|---|
| **Hospital type†** | 1.144*** | 1.110-1.180 |
| **sex‡** | 0.945*** | 0.917-0.976 |
| **age** | 1.006*** | 1.005-1.006 |
| **BMI** | 1.007*** | 1.004-1.009 |
| **urgency level§** | 1.129*** | 1.087-1.171 |
| **Surgery type** | | |
| **Valve** | 1.299*** | 1.245-1.354 |
| **Combined surgery** | 1.696*** | 1.622-1.772 |
| **Other heart surgery** | 0.968 | 0.914-1.023 |
| **Intercept** | 5.819*** | |
| **Observations** | 1,843 | |

*** p<0.01, ** p<0.05, * p<0.1

† RH is the reference category, ‡ Male is the reference category, § elective surgery is the base category

From Table 5-7, we can see that the estimated rate ratio for type of hospital was 1.14. Accordingly, SQUH patients are expected to have an incidence rate for postoperative LOS 1.14 times that of RH (a 14.4% increase) after adjusting for some covariates. These results reveal that some of the variation in postoperative LOS can be accounted for by the type of hospital. It should be noted that the 14% increase in the incidence rate might further diminish if more covariates representing the severity of disease are added to the model. Figure 5-7 exhibits the difference in LOS between the two hospitals.

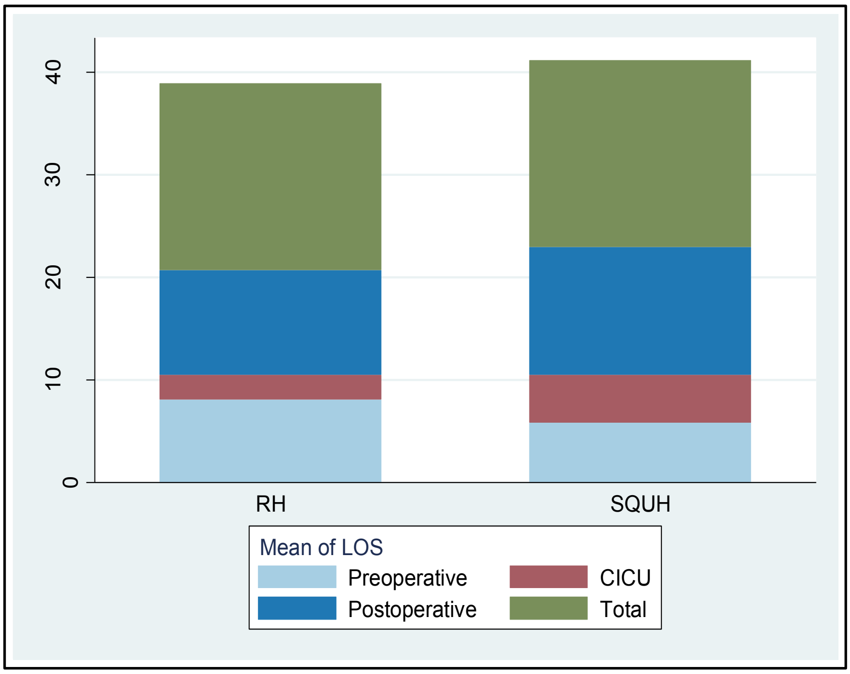



**Figure 5-7 Mean LOS differences between the two hospitals**

#### 5.4.3.6 Charges for surgery, room and diagnostic services

There are several tests that are performed to evaluate patient fitness for surgery (see[235] for some examples). In Oman, most of these tests are done after patient admission for surgery. Following operations, the standard patient care includes two chest x-rays and several lab tests. The most performed radiological test was x-ray while the full blood count was the most requested lab investigation.

The majority of hospital charges are related to performing surgery (average surgery charges: 2144 Riyals (5488.64 USD), room charges: 373 Riyals (954.88 USD) and lab investigations: 257 Riyals (657.92 USD) and radiological investigations: 170 Riyals (435.20 USD). Charges for room services were associated with LOS. Thus, patients staying longer in hospital incurred higher charges. Patients with combined surgery had the highest average hospital charges 3923 Riyals (10042.88 USD), followed by valve 3497 Riyals (8952.32 USD), CABG 2689 Riyals (6883.84 USD), and other surgery 2456 Riyals (6287.36 USD).

### 5.4.4 Postsurgical complications: what factors are associated with complications?

The analysis in this section uses available data from the SQUH hospital where data about complications were prospectively collected. The number of patients who experienced complications after surgery was relatively high (48%). A possible reason is that the type of complications reported by the hospital included arrhythmia which is widely common after cardiac surgery.[236, 237] For example, on admission 21 patients had ventricular arrhythmia and 38 patients had atrial arrhythmia. However, the number of patients who developed new ventricular arrhythmia after surgery was 66 and the number patients who developed new atrial arrhythmia was 62. Another reason for high reported complications could be related to the definitions used and the prospective nature of the data collection. Table 5-8 summarises differences between patients *with* and *without* complications in respect to different characteristics. Variables in the left represent preoperative and intraoperative factors. Patients are further segmented based on their type of complications.

There was significant difference at α level =0.05 between the mean ages of patients who did not develop complications and patient who did. This unadjusted result indicates that elderly patients were more likely to develop complications during their stay. However, sex was not significant between the two groups suggesting that there is no difference between genders in the probability of experiencing complications despite that female patients had higher postoperative LOS than men for this hospital which in turn could be subject to complications as a result of hospital-acquired infection. There was also significant difference between the two groups in terms of their EuroSCORE.

**Table 5-8 Baseline demographic, risk factors and characteristics of patients with and without complications**

| Variable | All Patients (n= 600) | Complications | | |
|---|---|---|---|---|
| | | Without | With | P value |
| **Patient attributes** | | | | |
| Female | 182 (30.3) | 103 (31.9) | 79 (28.5) | **0.371** § |
| Male | 418 (69.7) | 220 (68.1) | 198 (71.5) | |
| Age [a] | 59 ± 12 | 58 ± 12 | 60 ± 12 | **0.026**‡ |
| BMI [a] | 27 ± 5.40 | 27 ± 5.36 | 27 ± 5.45 | **0.908**‡ |
| BSA [a] | 1.71 ± .21 | 1.71 ± .21 | 1.71 ± .21 | **0.884**‡ |
| **Length of stay** | | | | |
| Pre-LOS [a] | 6 ± 7 | 6 ± 5 | 6 ± 9 | **0.999** † |
| CICU LOS [a] | 5 ± 8 | 4 ± 3 | 6 ± 11 | **0.0001**† |
| Post- LOS [a] | 12 ± 17 | 9 ± 5 | 17 ± 23 | **< 0.001**† |
| Total LOS [a] | 18 ± 18 | 14 ± 8 | 23 ± 25 | **< 0.001**† |
| Hospital charges [a] | 2945 ± 1043 | 2724 ± 427 | 3203 ± 1423 | **< 0.001**† |
| **Surgery characteristics** | | | | |
| CPB Use | 461 (76.8) | 240 (74.3) | 221 (79.8) | **0.113** § |
| CABG | 478 (79.7) | 252 (78) | 226 (81.6) | **0.279** § |
| CABG + Valve | 63 (10.5) | 21 (6.5) | 42 (15.2) | **0.001** § |
| Valve | 165 (27.5) | 82 (25.4) | 83 (30) | **0.211** § |
| Other surgery | 20 (3.3) | 11 (3.4) | 9 (3.2) | **0.915** § |
| Non-elective | 92 (15.3) | 44 (13.6) | 48 (17.3) | **0.209** § |
| Cross clamp time (min) [a] | 71 ± 29 | 66 ± 25 | 77 ±33 | **< 0.001**† |
| Bypass time (min) [a] | 118 ± 47 | 109 ± 43 | 129 ±49 | **< 0.001**† |
| Ejection fraction [a] | 59.22 ± 13.19 | 62.03 ± 11.95 | 56.15 ±13.84 | **0.003** † |
| Blood transfusion | | | | |
| Preoperative troponin level | 36.54 ± 16.86 | 33.98 ± 16.23 | 39.87 ± 17.34 | **0.111** ‡ |
| Inotropes support (after surgery) | 411 (74.6) | 204 (69.4) | 207 (80.5) | **0.003** § |
| EuroSCORE [a] | 6.37 ± 11.93 | 4.79 ± 8.40 | 8.29 ± 14.95 | **0.0026** † |
| NYHA Score | | | | **0.015** § |
| 1 | 9 (3.7) | 5 (4) | 4 (3.3) | |
| 2 | 36 (14.8) | 23 (18.5) | 13 (10.8) | |
| 3 | 137 (56.1) | 75 (60.5) | 62 (51.7) | |
| 4 | 62 (25.4) | 21 (16.9) | 41 (34.2) | |
| Current smoker | 62 (10.3) | 30 (9.3) | 32 (11.6) | **0.364** § |
| Diabetes | 270 (45) | 138 (42.7) | 132 (47.7) | **0.226** § |
| Hypercholesterolemia | 375 (37.5) | 183 (56.7) | 192 (69.3) | **0.001** § |
| Renal failure | 73 (12.2) | 28 (8.7) | 45 (16.2) | **0.005** § |
| Dialysis | 8 (1.3) | 2 (0.6) | 6 (2.2) | **0.100** § |
| Hypertension | 403 (67.2) | 207 (64.1) | 196 (70.8) | **0.083** § |
| Cerebrovascular disease | 44 (7.3) | 17 (5.3) | 27 (9.7) | **0.036** § |
| Peripheral vascular disease | 29 (4.8) | 11 (3.4) | 18 (6.5) | **0.078** § |
| Pulmonary hypertension | 74 (12.3) | 29 (9) | 45 (16.2) | **0.007** § |
| Myocardial Infraction | 279 (46.5) | 140 (43.3) | 139 (50.2) | **0.094** § |
| Unstable Angina | 160 (26.7) | 77 (23.8) | 83 (30) | **0.091** § |
| CHF | 229 (38.2) | 109 (33.7) | 120 (43.3) | **0.016** § |
| CHF on admission | 153 (26.3) | 70 (22.4) | 83 (30.7) | **0.023** § |
| Arrhythmia | 72 (12) | 36 (11.1) | 36 (13) | **0.487** § |
| Previous CV intervention | 44 (4.2) | 27 (8.4) | 17 (6.2) | **0.299** § |
| Number of diseased vessels | | | | **0.346** § |
| None | 75 (13) | 46 (14.9) | 29 (10.9) | |
| One | 51 (8.9) | 28 (9.1) | 23 (8.6) | |
| Two | 71 (12.3) | 41 (13.3) | 30 (11.2) | |
| Three | 378 (65.7) | 193 (62.7) | 185 (69.3) | |
| Left main disease >50% stenosis | 65 (11.4) | 31 (10.1) | 34 (12.8) | **0.311** § |

For categorical variables, values are expressed as count and (%). a: Values are expressed as mean ± SD.
§ Based on chi-squared test. † Based on Wilcoxon rank-sum (Mann-Whitney) test. ‡ Based on t-test.

#### 5.4.4.1 Difference in LOS and hospital charges between patients with and without complications

The two-sample Wilcoxon rank-sum (Mann-Whitney) test supported the overall hypothesis that there were differences between complicated and non-complicated cases in terms of resource use. There was statistically significant difference between the two groups in respect to the CICU LOS, postoperative LOS, and the total LOS (as can be seen in Table 5-6). Patients with complications spent more days in hospital ($p<0.001$) and had higher costs ($p<0.001$).

## 5.5 DISCUSSION

This study was the first national estimate of hospital resource utilisation for patients with cardiac interventions in Oman. The population can be characterised by the high prevalence of diabetes, hypertension and obesity compared to other countries.[238] Treated patients differed significantly in their casemix and resource utilisation. A substantial number of patients developed complications and had higher hospital resource utilisation.

### 5.5.1 Patient mix and variation in resource utilisation

Even in relatively similar group such as cardiac surgery, there was wide variation in resource use between patients. The relevance of this finding to hospital resource planning can be viewed from two perspectives. First, hospitals should understand resource use relative to their patient casemix which will allow them to identify factors that explain variation in resource across their patient population. A potential implication is that any changes in the patient mix over time can substantially affect hospital use of resources and operational performance. The level at which hospital management adopt to these changes will determine the effectiveness of the resource management. Second, resource allocation based on diagnosis rather than patient characteristics can be misleading.

Many patients were diagnosed with life style diseases that are common in the Middle East.[239] The high prevalence of these diseases among the Omani population has been previously discussed.[10] This was reflected in the collected data. Diabetes and obesity, in particular, were high among cardiothoracic patients. There was association between the number of comorbidities and patients LOS. Therefore, variation in resources in both hospitals could be explained by differences in patients' casemix (the concept is further discussed in next chapter). Comorbidities such as obesity were also found to increase the level of complications after cardiac surgery.[240, 241] On average cardiac care patients in Oman had higher LOS compared to findings from other studies.[242]

Researchers choose to account for patient complexity and severity in different ways such as by assessing the presence of comorbidities and risk factors.[243] In the patient classification scheme, DRG, complications and comorbidities are used as indicators of case severity. However, the DRG is too broad to define resource consumption among cardiac surgical patients. It was suggested that the DRG can be improved for resource use prediction by adding clinical, demographic and discharge data.[244]

The average rate of bed occupancy may vary as a consequence of case mix and differences in social and demographic characteristics of the patients.[245] My findings revealed that patients' case mix as well as patients experiencing complications afterward had an effect on LOS and hospital charges. The extent at which these individual factors (i.e. natural variation) impact throughput or constrain some other resources will depend largely on the level of available resources. For most hospitals, however, shortages in resources are the norm. A management strategy that accounts for patient difference should be implemented when planning important resources such as beds and operating rooms capacity.

### 5.5.2 The relationship between type of hospital and LOS

The Royal Hospital operates under the umbrella of the Ministry of Health which had successfully minimised hospital LOS over several years. The LOS for this hospital was considerably shorter than that of the SQUH (an academic hospital) which may have not received the same pressure to reduce LOS. LOS decisions can be influenced by the prevailing "organisational culture". For example, physicians were found to adapt their LOS decisions to their colleagues or to the managerial demands of the hospitals in which they work.[246] The literature suggests that variables related to practice style and environmental constraints are some sources of practice variations.[247] The term "small area variations" is used in the literature to refer to the difference in the care an individual receives contingent on where and by who the care is provided.[248]

As the results of this chapter revealed, preoperative LOS was exceptionally high, contradicting best practices in surgery admission. In many countries such as the UK, patients are admitted for cardiac procedures relatively near to the date of the surgery.[249] It has also been found that there is no difference in outcomes between patients admitted on the day of cardiac surgery and those admitted before the day of surgery.[250] It is difficult to speculate on why a similar policy has not been implemented in Oman. Indeed, inefficient use of hospital beds is a persisting problem, and in many countries inappropriate hospital bed use was found to be greater than 20%.[251] Inefficient practices have been targeted in many hospitals through various interventions to reduce unnecessary LOS, including periodical audits to identify reasons for delay, proper discharge planning favouring transfer to community services, standardizing and simplifying processes, the use of care pathways, and reminders to sensitise clinicians.[251, 252] A reduction in preoperative LOS can be a significant single measure that can be considered by the two hospitals to improve efficiency.

The observed difference in postoperative LOS between the two hospitals might be because of the RH hospital is the main hospital in Oman with many patients referred from all over the country. This is also coupled with a substantially large demand for cardiac surgery coming from internal referral through other departments. The high demand adds pressure on the hospital to improve beds turnover and reduce LOS. This leads us to the importance of considering the contextual factors influencing resource allocation along other factors discussed in this chapter.[28]

## 5.6 CONCLUSION

It is apparent from the results of this chapter, and from the literature review in chapter 3, that there are many sources of variation related to hospital resource use. I found that much of the variation in resource use was related to patients and surgical factors. Therefore, the findings justify my early hypothesis that resource allocation in hospitals could benefit from planning practices around the unique characteristics of individual patients. In a subsequent chapter, I will demonstrate how hospital managers can optimise hospital resources using some objective measure of patient and treatment characteristics.

LOS was closely related to the type of hospital. Therefore, resource utilisation should be treated as context-specific phenomenon and comparison might not be possible without controlling for several organisational factors.

# Chapter 6

# FACTORS PREDICTING RESOURCE UTILISATION

## 6.1 CHAPTER OVERVIEW AND GENERAL IMPORTANCE

As I found in the previous chapter, there was variation among patients in terms of resource utilisation which suggests that patients' casemix had a direct effect on the level of resource utilisation. In particular, patients with prolonged LOS had considerably higher resource utilisation. While there have been several studies investigating factors prolonging LOS among cardiac care patients, there has been no study conducted among the Omani population, taking into consideration the unique characteristics of the population. Once the factors are known, appropriate policies can be implemented to maximise operational performance. Thus, the objectives of this chapter are: 1) to identify factors that independently affect hospital resource utilisation, 2) to provide evidence on the utility of existing cardiac risk stratification systems for predicting patients' resource use, and 3) to create and validate models that can predict LOS based on data available from hospital information system.

## 6.2 INTRODUCTION

Variation in the intensity of care among patients and the subsequent mix of resources that is needed limit the usefulness of deterministic metrics for effective resource planning. Hospital planners can improve efficiency by predicting LOS more accurately.[31, 253] An effective hospital resource management policy should account for patient characteristics, comorbidities and adverse events. In surgical care, this means linking resource utilisation to several preoperative and postoperative factors (Figure 6-1). Building a model to predict LOS based on these factors can potentially be a useful decision tool. This essentially can enable resource planners to distinguish between patients' needs and design hospital services to accommodate these needs. Moreover, identifying factors influencing high resource utilisation can pave the way to quantify resource savings if a certain strategy involving the management of these factors was implemented.

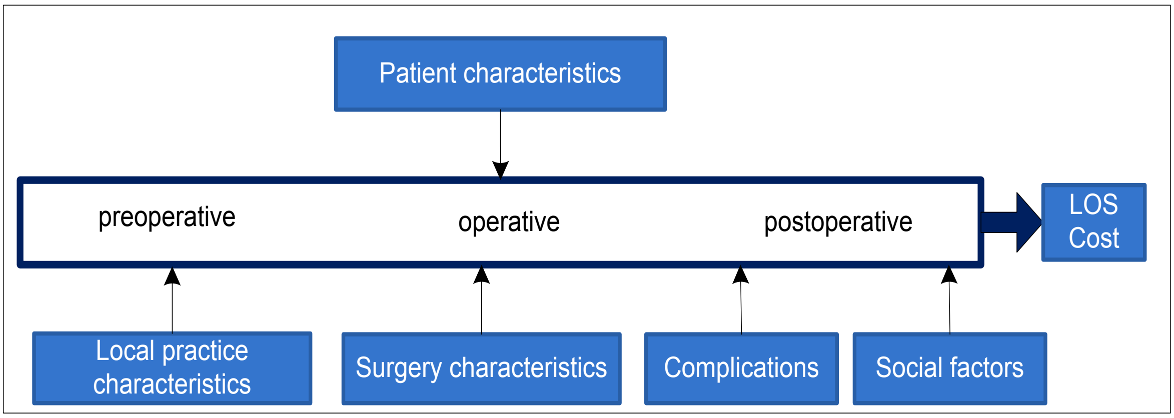



**Figure 6-1 Factors that influence resource utilisation**

An initial examination of LOS data from both hospitals under study revealed that patients had higher hospital stays compared to other reported LOS statistics for cardiac surgical patients in other countries.[232, 254] This should stimulate a further inquiry about the factors contributing to patients' prolonged stay.

As discussed in the introduction chapter, models that predicts LOS should, in theory, aid resource planners to optimise resources by selecting the best casemix management strategy that will produce the greatest impact. For example, patients with expected high LOS consume disproportionately greater resources and may reduce the bed turnover rate. Knowing this in advance can provide hospitals with the leverage to gain some control over the management of resources and hence LOS. This is especially important in hospitals with a constrained bed environment. Currently, LOS is the single most used measure of resource utilisation as it is easily accessible and relatively more reliable than several other indicators.[138] It is also an important metric for planning capacity within a hospital.[253]

### 6.2.1 Predicting resource utilisation for patients with cardiac interventions

Patients' medical needs and their resource utilisation differ during their preoperative, CICU, and ward stay. Much of the focus of this research would be on predicting postoperative LOS, but, a model with total LOS will also be evaluated to gain insight on whether preoperative LOS was clinically justified.

**Patient classification based on length of hospital stay:** gaining better understanding of factors affecting LOS provides an opportunity to reduce patients stay in hospital and to release capacity in the system.[255] In this chapter, I investigate factors affecting LOS and attempt to produce scoring systems which can be used as stand-alone models or incorporated into simulation modelling, which will be discussed in the next chapter.

**The use of existing cardiac risk stratification systems to predict resource use:** Cardiac risk stratification systems have been used to assess risk of death for many years[33, 256] (readers are referred to chapter 3 for more detail). At least 19 risk-stratification models exist for open-heart surgery.[256] Cardiac risk stratification systems such as the EuroSCORE are widely used around the world. However, they are not utilised for allocating hospital resources. I hypothesised that existing cardiac risk stratification systems can be useful in predicting resource utilisation among the Omani population and hence they may preclude the need for devising local prediction models. If this hypothesis holds true, I argue that these systems can potentially be used in resource optimisation initiatives and resource planning in general. In this chapter, I will evaluate and compare the predictive performance of three existing cardiac risk scoring systems (EuroSCORE, Parsonnet, and STS). In addition, I will assess the applicability of ASA classes (not solely related to cardiac risk stratification) in predicting LOS.

**Predicting admission requirement for Cath Lab patients:** Cardiac care services provided in Oman are expensive and often under short supply. The demand for catheterisation is much greater than for cardiothoracic services. While there is a limited number of Cath Labs in the two hospitals, bed availability has been an issue affecting their productivity. Beds for Cath Labs are shared with other medical cardiac patients. Thus, a considerable bed planning is required to ensure efficient operation. Most patients scheduled for angiography will be discharged home after two hours of observation from the time of their procedure. The standard care for angiography patients in Oman is to admit patients if they require medical attention. Patients who are at risk of staying in hospital after a catheterisation procedure can limit patient intake. Uncertainty regarding hospital admission following Cath Lab procedure challenges efficient inpatient bed management.[257] Overestimating admissions from the Cath Lab put an unnecessary hold on beds that may be used for other patients.[257] Consequently, predicting admission following a Cath Lab is a critical component in optimising cardiac care patient flow. There is scarcity in research on the type of factors that are associated with hospital admission following an outpatient catheterisation. In the two hospitals, it is the physicians' responsibility to estimate the required LOS/ observation time which also can be subjective. The model suggested in this chapter is intended to aid resource allocation by profiling patients who might be at risk of admission. The pressure on Cath Labs has been very high in the past with many cancellations. One of the reasons, is that for any given day the hospital should predict patients who might require admission.

**Rules-based resource allocation:** Decision trees are commonly used for variable selection, handling missing values, assessing the relative importance of variables, and prediction.[258] The popularity of their use has increased greatly over the past years.[259] The purpose of using decision tree analysis in my study was to examine whether patients can be grouped based on similarity in resource consumption. Consequently, resources can be allocated based on clinically-relevant features. Rules produced by decision trees can be adopted into DES modelling allowing patient heterogeneity to be better represented.

## 6.3 METHOD

The forthcoming analysis seeks to identify factors predictive of resource use. The analysis examines the influence of a range of patient and treatment factors upon hospital stay. By including the variable of interest, it is possible to obtain the average independent incremental effect of each variable. The analysis in this study made use of several variables obtained from the two hospitals which are readily accessible from the hospitals' databases. Data analysis was performed separately on both hospitals datasets based on data availability (see Table 4-1 in the research methodology chapter).

#### 6.3.1.1 Evaluation of existing risk stratification systems for predicting resource use

Stratification based on cardiac risk using risk models is not commonly practiced in Oman. However, 300 patients who underwent cardiac surgery were previously scored using the EuroSCORE at the SQUH for research purpose. In addition, the Parsonnet and STS scores were available for 200 of those 300 patients. All patients were preoperatively scored before admission. I also obtained ASA classes for 439 patients who underwent cardiac surgery at the RH. The discriminatory power of the risk models was evaluated by calculating the area under the ROC curves. An area of 1.0 under the ROC curve indicates a perfect discrimination, whereas an area of 0.50 indicates complete absence of discrimination.[260] Values between 0.5 and 1.0 reflect a quantitative measure of the ability of the risk stratification system to distinguish between two groups (e.g. normal and prolonged LOS). The threshold used to distinguish high LOS from normal LOS is the same $75^{th}$ percentile used elsewhere in this thesis.

#### 6.3.1.2 Prediction of prolonged CICU LOS

Several variables were entered into multivariable logistic regression model to identify significant factors of patients at risk of prolonged CICU LOS. Data from the SQUH was used to build the model. A simplified scoring system was derived by rounding the odds ratio of each predictor to the nearest 0.5.[261] The model was first internally validated using bootstrapping of the coefficient.[262] However, since the aim of this prediction model was to inform resource allocation strategies for cardiac patients in Oman, it was necessary to externally validate the model using patient data from the other hospital. For a model to be transportable, it should produce accurate predictions among patients drawn from a set of different but plausibly related patients.[263] As stated previously, the two hospitals performed 95% of the cardiac invasive interventions in the country. Therefore, a generalizable model can be used across different hospitals. To this end, a sample of 600 patients from the RH were randomly selected. Patients then were scored using the regression formula obtained from the logistic model using the same preoperative factors. The scoring system can be used as a stand-alone system or incorporated into the DES model as will be discussed latter.

#### 6.3.1.3 Prediction of LOS in the hospital ward

The main interest of this analysis was to identify preoperative factors that may influence LOS in the ward. Cox proportional hazard (PH) regression was used for this purpose. Cox regression is similar to logistic regression, but it assesses the relationship between survival time (i.e. time to an event) and covariates. The hazard function in the Cox PH regression is the probability of observing a survival time greater than or equal to some stated value.[264] Cox PH model is not based on assumptions concerning the shape of the underlying survival distribution. It said that the model is *semi-parametric* because it doesn't assume that the baseline hazard function follows any particular parametric distribution (e.g. Weibull).[265] An important assumption of the Cox regression, however, is that the ratio of two hazards (i.e. hazard ratios) is a constant (i.e. does not depend on time).[266] This means that the hazard of the two groups (normal stay vs. prolonged stay) should remain proportional over time. The hazard proportionality assumption was examined graphically through smoothed plots of the scaled Schoenfeld residuals and Log-Minus-Log plots.[267]

The response of interest was the time from the postoperative ward admission to the time of discharge from the hospital. The outcome variable was labelled as 0 for patients who were not discharged by the 10$^{th}$ day and as 1 if they were discharged. A model was fitted for postoperative LOS to estimate the adjusted probability of discharge with 95% CI. The model was evaluated using a cut-off duration of ≥10 postoperative days which was based on the surgeons' recommendations.

The advantage of Cox PH is that it allows including deceased patients. In this model patients who died during their postoperative stay (n= 25) were included in the analysis and hence were censored in the model. The number of cases per predictor was reasonably good. There are at least 15 events per predictor in the dataset. Approximately 10 to 15 observations per predictor are required to produce stable estimates in survival models.[268] The coefficient of each variable was negatively exponentiatied to obtain the hazard ratio for LOS (instead of discharge) to ease interpretation of the risk variables.[269] A bootstrapping with 500 repetitions was used to internally validate the model. This approach has been shown to be superior in logistic regression validation to other techniques, such as splitting the data set into training and testing sets.[262]

#### 6.3.1.4 A model for predicting admission following Cath Lab procedure

The cardiology department manages 22 beds. Two beds are designated for outpatient angiography patients. These patients are admitted and discharged in the same day following their angiography procedure. Several datasets were extracted from the RH information system to construct the "cath lab" database. These datasets comprised of data pertaining to discharge diagnosis, date of admission and discharge, type of procedure, and whether the procedure was an inpatient or outpatient (i.e. day case). I only included elective cases that were referred as outpatient. A total of 875 unique patients were initially included. Out of these patients, I excluded 31 patients due to missing sex and age values.

Discharge diagnosis from the admission dataset as well as diagnosis from the cath laboratory were used to extract relevant variables. The predicted outcome was inpatient admission. The explanatory variables were selected based on the recommendation of the cardiologists, as well as literature review. 15 potentially relevant variables were selected, these were age, gender, and whether any of these clinical factors were present: angina, hypertension, diabetes, coronary artery disease, cardiomyopathy, congestive heart failure, hyperlipidaemia, arrhythmia, obesity, previous CABG, previous PTCA, chest pain and myocardial infarction. All of the clinical variables were categorical (two level) and coded as yes or no. Variables with less than 15 events were dropped from the final analysis. Significant predictors were identified through multivariable logistic regression. To obtain a parsimonious and stable model, I performed bootstrapping with 500 iterations. The discriminatory powers of the model was assessed by the area under the receiver operating curve.

#### 6.3.1.5 Rules-based resource allocation: decision tree prediction

The purpose of this analysis was to examine whether rules can be extracted to meaningfully predict LOS category.[270] The ensemble rules can be used to group patients according to specific LOS categories. The rules can also be combined with DES to allow prediction of the effect of existing patient casemix. I will compare two commonly used decision trees algorithms namely CART and C5.0. Rules-based prediction is underused in simulation modelling and resource allocation in hospitals.

**CART:** CART analysis, a nonparametric statistical procedure, employs recursive partitioning to define mutually exclusive population subgroups whose members share characteristics related to the outcome of interest.[271] CART is suited to highly skewed datasets and where there are a large proportion of categorical independent variables.[272] A CART tree begins with a single "node" which has the entire sample, called a parent node. According to splitting criterion, variables are further divided into binary groups in respect to relationship to the dependent variable. The resulting two groups are called child nodes. The CART algorithm recursively splits the data to increase the homogeneity of the subsets based on the response variable. The tree continues to grow by assessing each remaining independent variables for further possible split. During this process, a child node will become a parent node for other subgroups. The process stops when no further partitioning can improve the homogeneity of the nodes.[273] When no further split is possible (usually based on a stopping rules defined by the user), a terminal node is created. The introduction of stopping rules is necessary so that terminal nodes have sufficient number of patients. Stopping rules can be made when:[272] 1. Nodes contain a certain number of cases, 2. Reduction of variance is below a certain threshold. 3. A maximum number of terminal nodes have been produced. Even though regression trees tend to have lower prediction accuracy compared to other regression methods,[274] it is a viable option for LOS analysis which I found to be highly skewed.

**C5.0 algorithm:** is the updated version of C4.5 classification algorithm which employs an entropy-based measure of node impurity called gain ratio.[275] C5.0 trees are pruned with a heuristic formula instead of cross-validation. This data mining technique can be used to extract rules that can be interpreted as "If" (antecedent) and "Then" (consequence).[270] The rules can potentially be applied to real-world problem such as classification of chest pain diseases.[276] C5.0 algorithm code is free and is available in several common statistical software such as R. In this chapter I will investigate whether classification rules can be extracted from the datasets for application in simulation modelling. DES is an efficient environment to execute complex rules related to patients or system features. However, this has been largely neglected in the literature.

The RH dataset was used to create and extract the rules regarding resource use. The dataset contains 1641 patients who underwent cardiac surgery. Postoperative LOS was treated as a categorical variable. For the CART analysis, the tree growth was limited to a minimum of 100 cases for the parent nodes and 50 for the child nodes. To avoid overfitting, a maximum difference in standard errors was set to 1. The total postoperative LOS was split into three groups: Low (0-4 days), medium (5 to 9 days) and high (≥10 days). The following variables related to patient history were used: age, sex, BMI, urgency level, PTCA same admission, angiography same admission, number of angiography done in the past 365 days, number of PTCA performed, number of outpatient visits in the past 365 days, number of past admissions to the hospital, diabetes, hypertension, unstable angina, and operation type. To validate the models, I split the data into two sets. The first dataset was used to construct the model (training set) while the other was used to test its validity (testing set). 60% of the cases were used for training while the other 40% were used for validating the model. The cases in both sets were independent. The analysis was carried out using the IBM SPSS Statistics for Windows for the regression tree, version 22.0. Armonk, NY: IBM Corp and IBM Modeler - IBM Corporation, 2015.

## 6.4 RESULTS

### 6.4.1 Relevance of cardiac risk stratifications in LOS prediction

Table 6-1 provides the average scores as well as the minimum and maximum values for different risk stratifications. The number of patients who were scored using these stratification instruments are listed in the last column.

**Table 6-1 The minimum, maximum and means scores for the four stratification systems**

| Score | Minimum | Maximum | Mean | No. of patients |
|---|---|---|---|---|
| EuroSCORE | 0.88 | 79.64 | 6.58 | 300 |
| Parsonnet | 0 | 86 | 9.63 | 200 |
| STS mortality | 0.2 | 75 | 5 | 200 |
| ASA | 1 | 5 | 3.14 | 439 |

The ROC curves constructed using risk stratifications as predictors of prolonged LOS are shown in Figure 6-2. For the CICU, the EuroSCORE (AUC= 0.70) was the best model to predict prolonged LOS followed by the STS (AUC=0.67). For the postoperative stay in general, the STS had the highest area under the curve (0.70) while the area under the curve was slightly lower for the EuroSCORE (0.69). When I tested the EuroSCORE for *mortality* prediction, the model had very good discrimination (AUC=0.81). This not a surprising result because EuroSCORE was originally designed as a prognostic tool for mortality.

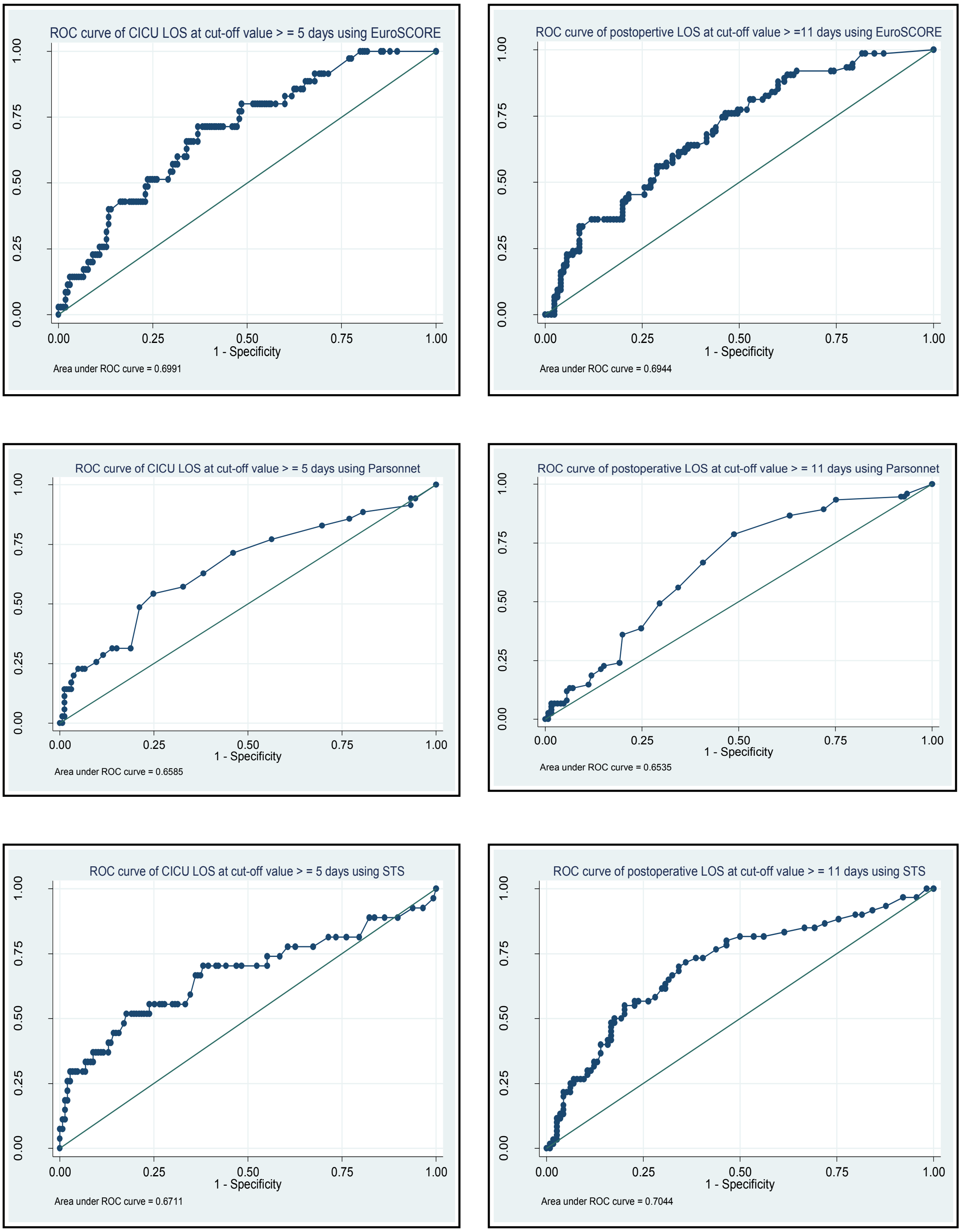



**Figure 6-2 The predictive power of risk for the three stratification systems**

ASA was evaluated using the chi-square test as it is composed of more than two levels of data. This test revealed a significant relationship between ASA classes and CICU LOS at ≥2 days ($\chi^2$ (4) = 25.77, p < 0.001), ≥ 3 days ($\chi^2$ (4) = 43.62, p < 0.001), and ≥ 4 days ($\chi^2$ (4) = 53.92, p

< 0.001). The same relationship was observed for postoperative LOS at ≥ 6 days ($\chi^2$ (4) = 50.10, p < 0.001) and ≥ 10 days ($\chi^2$ (4) = 11.61, p = 0.020).

### 6.4.2 A scoring system for prolonged CICU LOS using logistic regression

Several preoperative factors (i.e. known before surgery) were entered in the model simultaneously. The following variables emerged to be statistically significant (Table 6-2): non-elective surgery, current chronic heart failure, renal failure, combined surgery, and other none CABG-Valve surgery. The combined surgery was the strongest predictor of prolonged LOS (OR= 6, 95% CI= 3.3 – 10.0, P < 0.001). Age and sex were not significant in this model.

**Table 6-2 Preoperative variables predicting CICU LOS greater than or equal to the 75th LOS percentile (5 days)**

| Variables | *OR* | *SE* |
|---|---|---|
| **Non-elective surgery** | 1.779* | (0.545) |
| **Current CHF** | 1.894** | (0.482) |
| **Renal failure** | 4.015*** | (1.268) |
| **Combined Valve & CABG surgery** | 5.835*** | (1.610) |
| **Other surgery type** | 5.067*** | (2.760) |
| **Constant** | 0.079*** | (0.016) |

CHF: Chronic Heart Failure

*** p<0.01, ** p<0.05, * p<0.1

The scores for the prediction model were obtained based on the coefficients from the multivariate regression model (Table 6-2). The scores were then assigned to each patient in the dataset based on the significant factors. The highest total score was 14. Patients total scores were divided into three groups: 0-1, 2-4, and > 5. A Kruskal-Wallis test revealed a statistically significant difference in CICU stay among the three score groups $\chi^2$ (2) = 14.19, p < 0.001. The average CICU LOS was 4 days, 5 days, and 6.5 days for the first, the second and the third score groups respectively. The probabilities of prolonged CICU LOS were 11%, 26%, and 28% for group 1, 2, and 3 respectively. Table 6-3 presents the predictive scores for each significant predictor.

**Table 6-3 Predictive score for CICU stay**

| **Variables** | ***Score*** |
|---|---|
| **Surgery urgency level** | |
| Elective | **0** |
| Non-elective surgery | **2** |
| Current CHF | **2** |
| Renal failure | **4** |
| **Type of surgery** | |
| Isolated CABG or Isolated Valve | **0** |
| Combined Valve & CABG surgery | **6** |
| Other surgery types | **5** |

#### 6.4.2.1 Model validation

**Internal validation:** A test of the full model versus a model with intercept only was statistically significant ($\chi^2$ = 94.84, $p$ < 0.001 with $df$ = 18). The overall rate of correct classification is estimated to be 86%. The area under the ROC curve was 0.79 (95% CI 0.74-0.84). The Hosmer and Lemeshow $\chi^2$ (526) = 8.82; $p$ = 0.358 which suggests that the model fits the data well. In addition to this, I performed a bootstrapping on the model with 200 repetitions in order to examine those variables which appear to be consistently selected (at the significant level of 0.05). Figure 6-3 presents the number of times a variable was selected by the bootstrap method. A higher number of selection times indicates that the significant variables would be consistently selected.

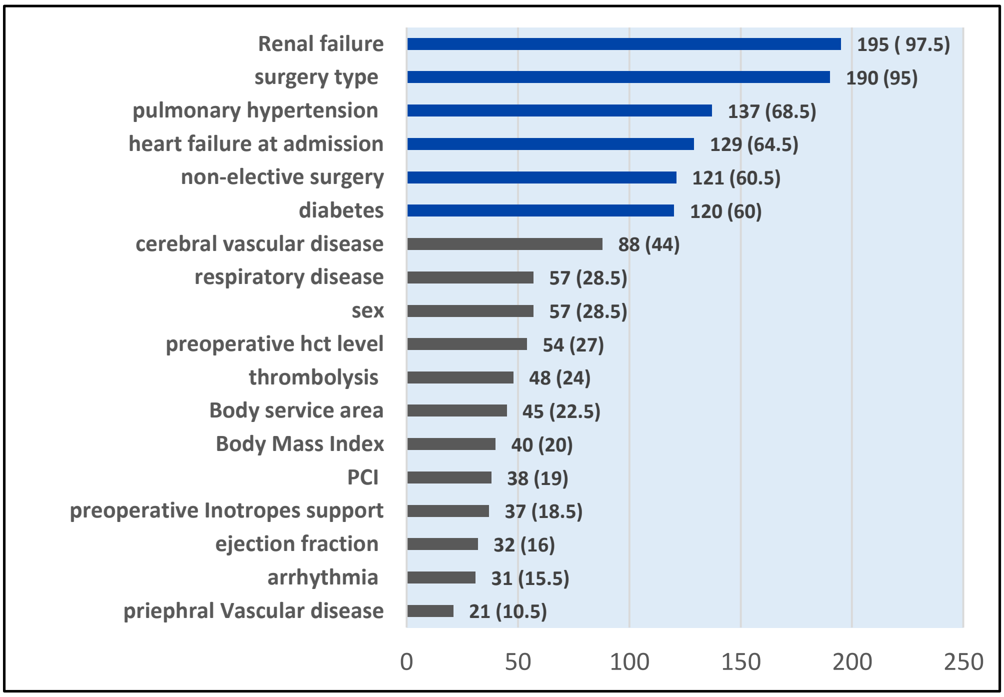



**Figure 6-3 The number of times and (%) a variable was significant based on bootstrapping the model for 200 repetitions.**

**External validation:** I evaluated the ability of the scoring system to identify patients deemed to be at high risk of experiencing prolonged CICU LOS using sample set of 600 randomly selected patients from the RH. The first step was to derive the risk equation from the SQUH logistic model. Patient risk of experiencing prolonged LOS can be generated using equation 6.1.

$$\textbf{Prolonged CICU LOS} = e^{(\beta o + \sum \beta i\, Xi)} / 1 + e^{(\beta o + \sum \beta i\, Xi)} \qquad 6\text{-}1$$

Where:

e is a mathematical constant that is the base of natural logarithm = 2.718281
βo is the constant of the logistic regression equation which is equal to -2.5314218
βi is the coefficient of variable Xi which are listed in table 6.2
Xi = 1 if a risk factor is present and 0 if it is not.

To obtain the scores based on the logistic regression from the model the following Stata code was used: **generate pr = invlogit([-2.53142181] + [1.390099]*renalfailure + [.63859785]*chfc + [.57585931]*nonelective + [1.76382241]*_Isurgtype_2 + [1.6227741]*_Isurgtype_4).** In this code, the first number between the brackets corresponds to the constant term of the equation while the rest of the numbers are the coefficients of the variables. The code *invologit* is the inverse of the logit function of x. I applied this equation to the RH dataset to obtain a score for each individual in the dataset. The model predicted patients having prolonged LOS reasonably well at LOS ≥ 3 days. The area under the ROC curve was (72%) as shown graphically in Figure 6-4. The 3 days was chosen because the 75th percentile (the definition used in this thesis for prolonged LOS) for the CICU LOS at the RH corresponded to this period.

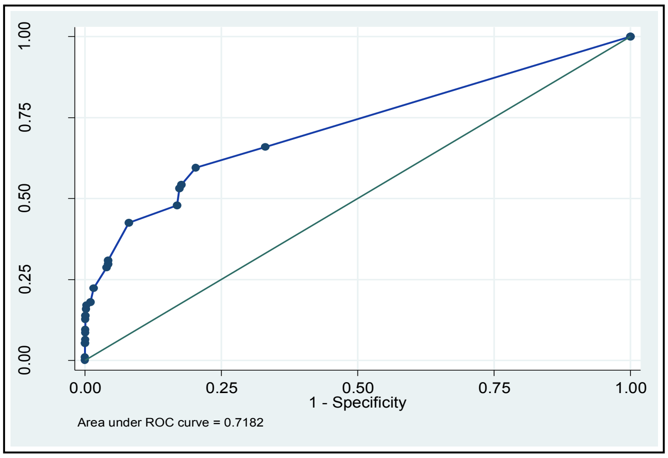



**Figure 6-4 Area under the ROC curve for CICU LOS at cut-off value ≥ 3 days for the validation dataset**

### 6.4.3 Factors predicting LOS in post critical care

In the previous section, I have examined the effect of some variables on prolonged patients stay in the CICU using logistic regression. In this section, the Cox PH model was used for the postoperative LOS in the ward. Unlike logistic regression, the LOS was handled as a continuous variable in the Cox PH.

The variables that were significant in the univariate analysis at α= 0.10 were included in the multivariate model. Of the 49 preoperative variables, the univariate survival analysis identified 19 potential predictors. These variables were entered simultaneously in the model. The independent predictors of extended LOS in the ward are shown in Table 6-4.

**Table 6-4 Preoperative variables that significantly influenced the probability of experiencing prolonged LOS (≥ 10 days) in the ward**

| Factors | Hazard ratio | Standard error | 95% CI | P value |
|---|---|---|---|---|
| **Renal failure** | 1.53 | 0.15 | 1.14 -2.04 | 0.004 |
| **Pulmonary hypertension** | 1.64 | 0.14 | 1.25 -2.15 | < .001 |
| **Non-elective surgery** | 1.47 | 0.14 | 1.13 -1.92 | 0.004 |
| **Combined surgery** | 1.73 | 0.16 | 1.27 -2.35 | < .001 |
| **CPB use** | 1.41 | 0.10 | 1.15 -1.73 | 0.001 |

From Table 6-4, it can be said that renal failure (a dichotomous variable) is associated with approximately 53%: (1.53-1) × 100) increase in the probability of experiencing an extended stay compared to patients without this comorbidity holding other variables constant. The same interpretation can be applied to other factors. Among the variables, combined surgery was associated with the highest increase in the probability of prolonged LOS in the ward. This means that patients who underwent concurrent surgery had 73% higher risk of prolonged LOS. Gender and age were not significant at the alpha level of 0.05. This model has a striking similarity with the CICU logistic model. However, pulmonary hypertension and the CPB use were not significant in the CICU model. The overall model was statistically significant with p-value less than .001. For the overall model, the hazard assumption test failed to reject the null hypothesis (states that the hazard is proportional) ($\chi^2$ =10.20, df= 8, p=0.251), and therefore I concluded that the proportionality of the hazard assumption was met in this model.

Probabilities for prolonged LOS were generated for every patient in the dataset based on the Cox regression formula obtained from the model. These probabilities can be divided into four groups. Table 6-5 summarises the average postoperative LOS for each group. The majority of the patients (the third group) had between 51% to 70% likelihood of being discharged by the 10th day in the ward. In contrast, patients in the first group had only 0% to 10% of being discharged from the ward by the 10th day. The average ward LOS of this group was 16 days. Patients in the fourth group had greater than 70% probability of being discharged from the ward by the 10th days. However, they constitute only 4% of the patients in the dataset.

**Table 6-5 Survival probabilities (being discharged by the 10th day in the ward)**

| Group | Survival probabilities | % of patients | Average ward LOS |
|---|---|---|---|
| **1** | 0 – 10 % | 12% | 16 |
| **2** | 11- 50% | 17% | 8 |
| **3** | 51-70% | 67% | 4 |
| **4** | > 70 % | 4% | 1 |

As can be seen from Figure 6-5 the probabilities of discharge before or at the 10th postoperative day differ significantly among patients with and without the statistically significant risk factors.

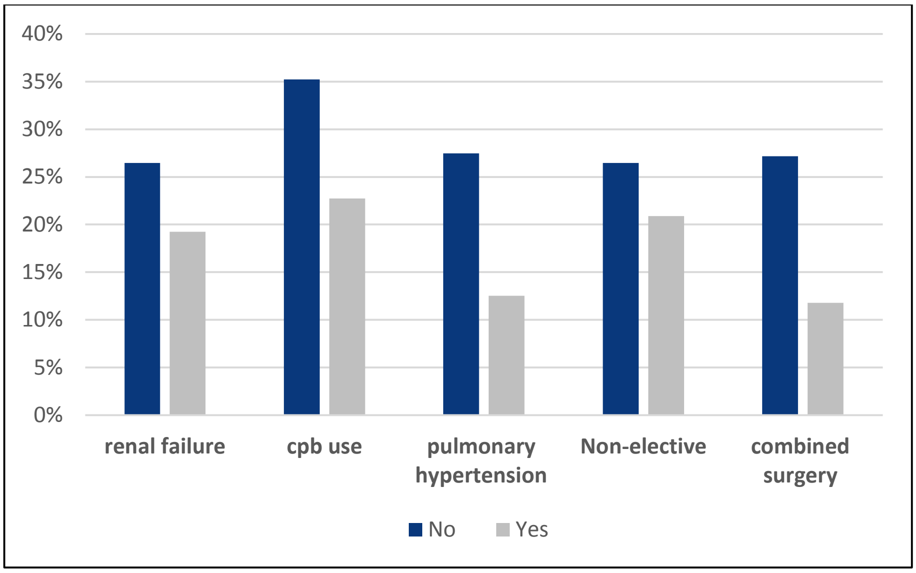



**Figure 6-5 Distribution of discharge probabilities among patients with the risk factors and without**

The applicability of the Cox proportional Hazard for planning patient flow in the ward can be illustrated by selecting four patients and comparing their likelihood of survival (i.e. discharge). Table 6-6 provides the predicted probability of discharge of four randomly selected patients. On average, patients would require 7 days of ward stay (average obtained from the sample). However, patients presenting with any of the identified variables are more likely to stay in the ward for longer time. Therefore, it would be expected that more beds will be occupied by high risk patients when these factors are present.

**Table 6-6 The probabilities of patients discharge from the hospital by the 10th day of ward stay based on preoperative predictors**

| Patient | Renal failure | Pulmonary hypertension | Non-elective surgery | Combined surgery | CPB use | Observed ward LOS (days) | Ward LOS category | Probability of discharge by the 10th day in the ward[4] |
|---|---|---|---|---|---|---|---|---|
| **A** | Ye | Yes | Ye | Ye | Ye | 25 | high | 20% |
| **B** | Ye | Yes | Ye | No | No | 14 | high | 40% |
| **C** | No | No | No | No | Ye | 6 | medium | 66% |
| **D** | No | No | No | No | No | 3 | Low | 73% |

The next step for a resource planner is to estimate bed requirements in a particular day using information related to the expected LOS and discharge probabilities. The template (Table 6-7) can be used by a resource manager to estimate bed requirement. Based on the scores provided by the Cox PH model, the expected LOS categories for patients in the waiting list can be determined for each day of the week. The template provides an overview of the future and existing state of the ward. It allows scheduling patients according to given capacity constraints.

**Table 6-7 Template for predicting bed requirement for patients**

| Day | Predicted admission LOS (count) | | | Number of Bed occupied | Predicted emergency | Predicted discharges | Predicted bed requirement | Predicted beds available | Predicted cancellations |
|---|---|---|---|---|---|---|---|---|---|
| | Low | Med | High | | | | | | |
| Saturday | | | | | | | | | |
| Sunday | | | | | | | | | |
| Monday | | | | | | | | | |
| Tuesday | | | | | | | | | |
| Wednesday | | | | | | | | | |
| Thursday | | | | | | | | | |
| Friday | | | | | | | | | |

[4] Based on the Cox PH equation: $h(t)=h_0(t) \times e\ (b_1x_1+b_2x_2+\cdots+b_px_p)$

#### 6.4.3.1 Factors predicting total LOS

The final regression model was designated for predicting *total* LOS which was divided into three groups: 1-6 days, 7-14 days, 15 and more. Results in Table 6-8 indicate that the two hospitals differ considerably in the type of significant variables. This is possibly due to: 1) different methodologies used for data collection (retrospective vs. prospective), 2) the arbitrary cut-off periods used to define LOS duration, and 3) the inclusion of preoperative LOS in the model which the researcher think was highly influenced by factors unrelated to patient conditions. Therefore, total LOS might not be reliable for studies involving resource utilisation based on patients' related factors.

**Table 6-8 Preoperative variables predictive of *total* LOS at different cut-off durations**

| | Odd ratios | | | | | |
|---|---|---|---|---|---|---|
| | SQUH hospital | | | RH hospital | | |
| **Variables** | **Short LOS (0-6 days)** | **Medium LOS (7-14 days)** | **Long LOS (15+)** | **Short LOS (0-6 days)** | **Medium LOS (7-14** | **Long LOS (15+)** |
| **Age** | | | | 1.12 ** | 1.10 | 1.03 *** |
| **Sex** | | 1.47 * | 0.68 * | | | |
| **BMI** | 1.02 *** | | 1.03 * | | | |
| **Surgery type** | | 0.44 * | 3.46 | 11.05 | 1.22 * | 9.20 *** |
| **Priority** | | | | | | |
| **Past myocardial infarction** | | 0.68 ** | 1.41 * | | | 2.34 *** |
| **Renal failure** | | | | | | |
| **Unstable angina** | | 0.52 ** | 2.03 | | | |
| **Heart failure** | | | | | | 1.83 * |
| **Diabetes** | | | 1.52 ** | | | |
| **Hypertension** | | | | | | |
| **Hyperlipidaemia** | | 1.43 * | | | | 1.66 ** |

*** p<0.01, ** p<0.05, * p<0.1

#### 6.4.3.2 Predictive factors of hospital admission following cardiac cath lab procedure

Data were available on 844 outpatient cases who were routinely referred for catheterisation. On average, outpatient referral constituted around 25% of all catheterisation patients. Among the angiography outpatient visits, 17% were admitted to the hospital. The model correctly classified 84% of the cases. The model also fits the data reasonably well according to the

Hosmer-Lemeshow test (group= 10): $\chi^2$ (8) =4.21, p=0.8374. The area under the curve was 68%. Table 6-9 shows the results of the model. In the logistic regression model only two predictors were identified as statistically significant. These were heart failure and previous PTCA.

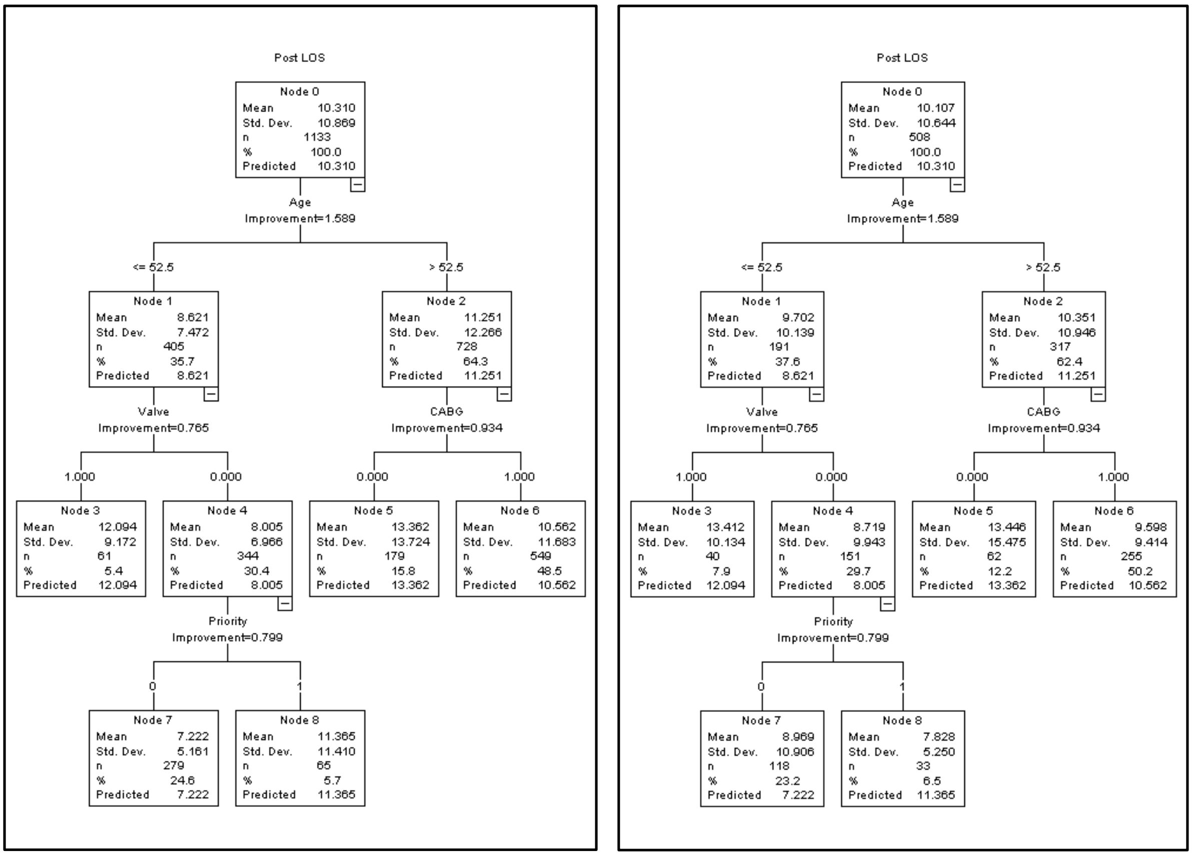
**Table 6-9 Significant factors for hospital admission following angiography**

| Variable | Coefficient | SE | 95% CI |
|---|---|---|---|
| **age** | 1.002 | (0.008) | 0.99 -1.02 |
| **sex** | 0.971 | (0.182) | 0.67 -1.40 |
| **hypertension** | 1.046 | (0.234) | 0.68 -1.62 |
| **Diabetes** | 0.904 | (0.207) | 0.58 -1.42 |
| **Coronary artery disease** | 0.926 | (0.214) | 0.59 -1.46 |
| **Heart failure** | 7.379*** | (3.247) | 3.11 -17.48 |
| **Previous PTCA** | 1.978*** | (0.471) | 1.24 -3.16 |
| **CABG** | 1.118 | (0.489) | 0.47 -2.64 |
| **Chest pain** | 1.197 | (0.337) | 0.69 -2.08 |
| **Myocardial infarction** | 1.090 | (0.716) | 0.30 -3.95 |
| **Angina** | 1.285 | (0.599) | 0.52 -3.21 |
| **Arrhythmia** | 0.587 | (0.409) | 0.15 -2.30 |
| **hypothyroidism** | 0.510 | (0.326) | 0.15 -1.79 |
| **cardiomyopathy** | 0.504 | (0.290) | 0.16 -1.56 |
| **hyperlipidaemia** | 0.496 | (0.291) | 0.16 -1.56 |
| **Constant** | 0.141*** | (0.075) | 0.16 -1.57 |

*** p<0.01, ** p<0.05, * p<0.1

#### 6.4.3.3 Classification based on decision tree

Based on CART analysis, the significant drivers and splitting attributes of higher postoperative LOS were age, type of surgery, and surgery priority. Figure 6-6 shows the regression trees for the testing and the validation datasets. Postoperative LOS was treated as a *continuous* variable.




(a) training sample results (b) validation sample results

**Figure 6-6 Regression tree for postoperative LOS**

The CART algorithm produced five terminal nodes. Resource utilisation groups can be extracted from this decision tree which are summarised in Table 6-10. As can be seen from Figure 6-6, the mean LOS considerably varies among splitting nodes. For example, the average LOS in node 6 was 10.5 days for CABG patients and 13.3 days (node 5) for non-CABG surgical patients. For patients younger than 52 years (first branch), the split was based on whether patients underwent valve surgery or other type of surgeries. A considerable difference in postoperative LOS was noted. For non-valve surgeries, urgency level was a significant driver of LOS (11.3 days for non-elective: node 9) and (7.2 for elective patients: node 7).

**Table 6-10 CART groups based on postoperative LOS>10 days (RH hospital)**

| Node | Description of patient groups |
|---|---|
| **1** | All patients who are older than 52 years and had CABG surgery |
| **2** | All patients who are older than 52 years and had other than CABG cardiac surgery. |
| **3** | All patients who are younger than 52 years and had isolated valve surgery. |
| **4** | All patients who are younger than 52 and had non-valve and elective surgery. |
| **5** | All patients who are younger than 52 and had non-valve and non-elective surgery. |

I attempted to build CART models for CICU LOS at different cut-off values. However, no variable emerges as a predictor. Even when 0 standard error was used to avoid over-pruning (error-based pruning),[277] the same outcome was observed and only a single node was produced refuting the hypothesis of over-pruning.

The second type of decision tree algorithm (C5.0) produced 13 rules (Table 6-11). The self-explanatory rules can be interpreted as *if* and *then*. The presence of arrhythmia, renal failure and unstable angina was associated with patients being categorised into high LOS. Similarly, the use of CPB and being non-elective surgery were associated with higher postoperative LOS.

**Table 6-11 The extracted rules from the RH dataset using C5.0 algorithm**

| | Antecedent | Consequence (postoperative LOS category)† |
|---|---|---|
| 1 | If CPB =1, and outpatient visits = 1 or 2, and operation type= non valve or CABG surgery | **1** |
| 2 | If age≤ 55, and sex= female, and recent CAG or PTCA= 0, and operation type= non valve or CABG surgery | **1** |
| 3 | If age ≤ 54, and outpatient visits= 0 or 1 or 2, and operation type= non valve or CABG surgery | **1** |
| 4 | If age ≤ 31, and sex= female, and operation type= valve | **2** |
| 5 | If sex=female, and priority= elective, and recent CAG=1, and renal failure= 0, and heart failure= 0, and operation type: valve | **2** |
| 6 | If sex=female, and arrhythmia=1, and renal failure= 0, and hypertension=0, and operation type= valve | **2** |
| 7 | If CPB=1, and arrhythmia=1, and operation type= valve | **3** |
| 8 | If sex=1, and outpatient visits ≤ 1, and hyperlipidaemia= 0, and operation type= valve | **3** |
| 9 | If age > 69, and priority = non-elective, and operation type= isolated CABG | **3** |
| 10 | If CPB=1, and previous number of CAG= 1 or 2, and hyperlipidaemia=1, and unstable angina=1, and operation type= CABG | **3** |
| 11 | If Renal failure=1, and operation type= valve | **3** |
| 12 | if age >67, and priority=non-elective, and outpatient visits=0, and unstable angina= 1 | **3** |
| 13 | If age= between 68 and 81, and CPB=1, and operation type= combined surgery | **3** |

**† Postoperative LOS categories: 1=Low (1 to 4 days), 2= medium (4 to 9 days) and 3= high (≥10 days)**

## 6.5 DISCUSSION

In this chapter I have I investigated how resource utilisation can be predicted based on data available from patient medical records. Regression modelling was used to identify factors affecting LOS. Additionally, two data mining techniques were used to overcome some issues inherited in regression models such as variable selection and assumption about data distributions. The aim of this chapter was achieved by identifying unique factors contributing to LOS in Oman following cardiac surgery. Hospital managers have several options in utilising these evidence-based models for resource allocation. For example, patients can be selected based on an objective measure that predict resource utilisation at different stages of hospital stay. The models that I proposed can be seen as tools for case mix measure that reflect the local characteristics of the population. In the absence of patients' classification systems such as the

DRG in Oman, building models using available data from patient records is an alternative option.

Much of the emphasis in this chapter was given to patients with prolonged LOS. Understanding this subpopulation has been the focus of several policies, resource allocation studies, and quality improvement initiatives.[209] Patients with prolonged LOS can exhaust resources and reduce operational performance. Several quantifiable variables as well as laboratory parameters were used to construct the models. The advantage of using available data is that they require less effort and thus cost to collect. HIS are widely used in all public hospitals in Oman. Many data are collected throughout the patient encounters with the hospital (e.g. outpatient visits). They provide a rich untapped source for resource planning.

### 6.5.1 Optimising CICU patients flow using a prediction model

Even though the number of cardiac procedures performed annually by the SQUH and the RH hospitals might be low compared to other centres in more populous countries, CICU units were limiting factor of patients flow. The two CICU units were essentially the bottlenecks in the cardiothoracic system and thus can be seen as the most critical resource for hospital inpatient production.[22] These two units are often admitting non-surgical patients transferred from other regional hospitals who are usually in critical conditions. This situation puts pressure on resource planners to ensure seamless patient flow and continuous operation. In Oman, there has been a chronic shortage in CICU beds as there were only 10 beds available during the study period. The two CICU units are expensive to maintain as the ratio of nurses to patients is 1 to 1. The bed managers at both hospitals were not using any method to estimate the number of required beds. However, they revealed their desire to adopt a methodology for this purpose.

The CICU prediction model developed in this chapter was intended to classify patients based on LOS. In general, the ideal scoring system would have the following feature:[278] 1) it should be based on routinely recordable variables 2) well calibrated 3) a high level of discrimination and 4) applicable to all patient population. The model that I developed for CICU met these criteria. The score system was derived from preoperative variables that are routinely collected by the two hospitals in Oman. The variables constitute "risk factors" for prolonged CICU LOS. The model was also externally validated. This simple approach provides an objective method for improved patient assignment.

The CICU scoring systems can be used as stand-alone tools in applications concerning resource management. Patients can be assigned scores before surgery either during the preoperative visit or early in their admission. The scoring system allows the staff to balance the ICU-OR capacity. For instance, if 4 of 5 patients scheduled for surgery have scores of at least 2, the hospital can anticipate that the 5 ICU beds will unlikely be available within the 48 hours. The probability of prolonged LOS (≥5 days) associated with scores of at least 2 is 26% or greater. Thus, a proactive strategy can be implemented (e.g. selecting patients for surgery with lower risk of prolonged LOS). This is highly feasible since most patients are elective and a short delay will not present a risk to patients. Conversely, if most patients have scores between 0-1, it is more likely that some beds will be available and surgery cancellations due to unavailability of beds become unlikely.

The CICU patient scoring system can be used in various ways for resource planning. First, patients with high scores can be scheduled for surgery at the end of the week to take advantage of weekends when no surgeries are scheduled. Second, patients at the lower score category can be assigned to a fast-track anaesthesia designed to minimise CICU LOS or bypass it altogether. Third, patients with high risk of prolonged CICU LOS can be admitted early to mitigate the negative effect of their comorbidities (in the model: only two comorbidities were significant: CHF and renal failure) as LOS was found to be higher for patients with comorbidities.[279] Fourth, human resources can be assigned in a way that can balance the workload expected for each patient category. Finally, aside from using this scoring system at the operational level, it can be utilised to compare patients' resource needs between hospitals at the macro level and thus facilitate efficiency analysis. By using an appropriate scoring system hospitals should minimise stay in CICU after surgery and as a side effect they may reduce adverse events such infections as more than 20% of all nosocomial infections are acquired in ICUs.[280]

When compared with previously published CICU prediction models, all of the predictors in this study have been reported before. However, these models differ considerably in their type of predictors. For example, Messaoudi et al [21] reported in a systematic review that the number of predictors among the reviewed studies ranged from 1 to 16 (with an average of 6 predictors). With such variation surrounding the selection of predictors among several studies, it would be inaccurate and misguiding to assume a model that was developed in one population would be valid for another. Therefore, the type of predictors (and the model) in this study should be relevant to the Omani hospitals and might also be applicable to other Gulf States. Moreover, unlike other studies which introduced models with many predictors, my findings suggest that predicting CICU LOS can be possible with fairly small number of predictors.

The development and implementation of a resource utilisation scoring system may not guarantee a successful facilitation of patient flow due to the dynamic flow of patients. To the best of my knowledge, there has been no study that examined the utility of resource prediction models in improving patient flow. This concept will be tested in the next chapter.

### 6.5.2 Preoperative factors predicting LOS

In the literature, several factors have been found to be predictors of prolonged postoperative LOS. These were notably age, BMI, priority, atrial fibrillation, myocardial infraction, renal failure, diabetes, and the type of surgery.[185, 281] These studies differ from my study in respect to the type of patients that are included, as previous studies were mostly based on single type of patient such as isolated CABG. Resource allocation prediction models based on a single type of patient are inappropriate for use in managing shared and interrelated hospital services.

Despite the high prevalence of diabetes in Oman,[282, 283] thought to be determined by genetic predisposition amongst the population,[284] it was not significant in the CICU and postoperative LOS models. The same thing can be said for obesity which was much higher in the study population than in the general population. The prevalence of obesity in Oman is 16.7% in men and 23.8% in women.[285] However, the observed obesity in the study population was 46%. Similarly, age was only significant in the univariate model and failed to be significant in the other models, contrary to the notion that older patients are expected to recover slower than younger patients. A possible explanation is that cardiac surgery is mostly performed in the elderly and thus age is less influential factor.

While several authors argued for the use of preoperative factors for predicting LOS, it might be difficult to predict LOS using patient characteristic at admission only.[286] The invasive nature of the surgery, for example, is associated with high risk and complications. This signifies the complexity of the interaction between patients characteristic, surgical and complications. However, results from this chapter revealed that patients can be successfully aggregated with high degree of confidence into groups based on their resource utilisation. Patient and treatment factors explained a high proportion of the variation in LOS. With such prior knowledge of patient likelihood of resource consumption, clinicians and managers can anticipate the workload and resources required for a particular group of patients.

### 6.5.3 Predicting admission following outpatient catheterisation

Admission after cath laboratory is inevitable for a small number of patients. This type of admission constitutes uncertainty that should be anticipated. Unexpected admissions from cath lab as well as the high number of emergency cases brought to the hospital had been a major issue in the hospital bed management. Identifying characteristics of patients in need of admission allows the hospital to provide appropriate capacity and accommodate these patients. The model developed to predict admissions after cath laboratory returned two significant variables: history of heart failure and history of previous PTCA. Other demographic and patients variables were not significant. In comparison to my study, Clark and Dolce found that patients with severe cardiac disease, patients suffering complications, and patients older than 65 were more likely to be admitted.[287] Toerper et al identified older age, male gender, invasive procedures, coronary artery bypass grafts, and a history of congestive heart failure as qualities indicating a patient was at increased risk for admission.[257] My model was limited by the amount of available data. To increase the predictive capability of the model, future models should be built with more variables. It is worth noting that the model had not been externally validated due to lack of data from the other hospital.

### 6.5.4 The utility of existing cardiac risk scoring systems in predicting resource use

The areas under ROC for the three risk stratification systems indicated a moderate correlation between increasing score value and prolonged LOS. If we considered an area under the curve that is greater than 70% to be associated with a good predictive value,[288] then, accordingly, none of the three prediction models is qualified as a relevant model for predicting LOS. However, an AUC of 60% or above has been considered adequate for classifying LOS.[243] From my results, EuroSCORE had superior predictive validity for both CICU LOS and postoperative LOS in general (AUC=70% for both). The STS model came second as the best predictive model.

The range of c-statistics obtained from my study (65% to 70%) is similar to what has been found by other researchers. For example, Messaoudi et al[289] found that prolonged CICU LOS correlate positively with EuroSCORE and the overall predictive performance, as measured by

AUC, was acceptable (c-statistics = 68% for >2 days and 75% for >5days). Similar results were achieved in other studies.[260, 290] Syed et al[291] applied Parsonnet as well as EuroSCORE from 194 patients to predict LOS in adult cardiac patients in Saudi Arabia. The obtained area under the curve was 63% and 67% for EuroSCORE and Parsonnet respectively. Lawrence et al[155] concluded that the Parsonnet score is a good predictor (c-statistic=70%) of short durations of ICU stay (< 24 hours) following cardiac surgery.

Even though the three scoring systems discussed here have most of the variables that I identified as risk factors for prolonged LOS, these scoring systems might not be in use in many hospitals (including the other hospital authorised to perform cardiac surgery in Oman). Moreover, the amount of data (and their availability) needed for calculating the scores can be preclude their use. Thus, when such scoring systems are not in use, a prediction model based on a smaller number of variables, like the one I proposed, can be of value to clinicians and bed managers who don't have sufficient data to build full risk models.

Surprisingly, the ASA grading system, which is a subjective measure, was a powerful predictor of prolonged LOS. Studies assessing ASA for cardiac patients are rare. However, ASA status was found to correlate with LOS in other surgical patients.[292 293] According to my results, LOS between different ASA classes was significant and that it exponentially increased as ASA scores increased. Therefore, it should be considered as an objective and impartial method for predicting prolonged LOS.

### 6.5.5 Decision tree as means to classify patients based on resource use

There are several statistical tests that are designed to address classification of data into meaningful groups.[218] These include discriminative analysis, finite mixture modelling, regressions, and decision trees. Literature around hospital resource use have utilised these methods to distinguish between groups. CART was identified among the top 10 algorithms in the data mining field.[219] Harper and Shahani[5] and Shahani et al[97] incorporated a CART algorithm in a simulation model for the planning and management of hospital resources.

Tree-based models have some advantages over regression-based methods. Unlike the two models in this chapter (namely logistic regression and Cox proportional hazard) the decision tree can uses a continuous variable as the dependent factor without the need to assume a cut-off period (i.e. event occurring). Second, CART are geared toward considering factors affecting subgroups of the population rather than determining the *average* effect of an independent variable on a dependent variable.[271] In comparison to results produced by CART, logistic regression equations are very difficult to use in clinical practice.[273] On the other hand, some authors such as Dwyer and Holte,[294] and Li[295] reported that decision trees are unstable methods. They can produce drastically different results from training sets that differ just slightly.

The goal of the predictive classification was to derive rules that use patient information to support decisions regarding patients grouping based on resource use. An important feature of C5.0 is the generation of classifiers called *rulesets*. These rulesets can be directly incorporated into simulation to facilitate the selection of resource allocation strategy. For example, from the C5.0 results, if a patient had renal failure and scheduled for valve surgery then the patient can be anticipated to experience prolonged LOS (High LOS ≥10 days).

Simulation languages are geared toward handling logic statements.[296] The rules-based approach should be valuable to modellers who seek to understand and enhance patient specific resource allocation. The C5.0 algorithm was found to be among the most accurate in the field of data mining.[219] The rules are also easy to understand and explain. In spite of this, a literature search revealed it is rarely in use in simulation modelling. The rules generated by the two decision tree models seem to be plausible and closely resemble results from other studies.

The accuracy of the model was 71% which means that 29% of the cases were wrongly classified. This likely occurred because the dataset has limited number of preoperative factors. Other variables were not available from the RH HIS system. These include important variables such as ejection fraction and creatinine level. The stability and the accuracy of the results can be improved by selecting a larger size as well as including other variables in the analysis.

## 6.6 CONCLUSION

It is critical to understand what factors impact resource utilisation and incorporate them in resource planning. Resource planning can be more effective if factors contributing to high resource use are appropriately managed. Clinicians can initiate preventive measures through aggressive treatment to reduce risk factors prior to surgery. A small reduction in LOS will result in a large cost saving. Risk stratification can be used to evaluate the appropriate patient management strategies (e.g. aggressive treatment of comorbidities), to communicate the likelihood of CICU LOS to the patient, to aid in scheduling surgery, or to be used when comparing CICU patients between hospitals.

I should mention here that there are several reasons for patients spending more time in hospitals which could be related to the current admission practices and the level of operational efficiency as I discuss in the previous chapter. Nevertheless, it should be a priority for these two hospitals to identify these factors in the face of limited number of beds and surgical facilities in the country.

The practical application of this research was delivered through: 1) the use of risk scoring systems as relatively accessible information to group patients based on their LOS and cost of investigations. 2) A new numerical predictive scoring system is proposed that accounts for several patient factors and their LOS. To classify patients by assigning scores based on known predictors. The resulting scores can be used for future prediction where predictors are known, but the value of the class (e.g. prolonged LOS) is unknown. By identifying and selecting patient attributes that are most directly associated with resource use, we are solving the “patient homogeneity” problem and that allocation of resource can be tailored to the population needs.

# Chapter 7

# ALLOCATING HOSPITAL RESOURCES BASED ON PATIENT INFLUENTIAL FACTORS TO RESOURCE USE

## 7.1 CHAPTER OVERVIEW

In the previous chapter, I examined the determinants of LOS. In this chapter, I investigate the concept of allocating resources based on factors that are influential to resource use. I provide an empirical evidence on how patient variability can be incorporated into DES to improve patient flow. The specific objectives of this chapter were: 1) to provide evidence for the utility of LOS prediction model in cardiac surgery for improving operational performance, and 2) to investigate the applicability and usefulness of patient-specific resource allocation strategies for cardiac care patients using DES modelling.

## 7.2 INTRODUCTION

Planning activities such as scheduling patients for surgery and determining the required capacity to meet demand is a significant hospital function.[297] As stated previously, existing techniques of hospital resource management do not incorporate patient variation.

### 7.2.1 Putting prediction tool into practice

Several resource utilisation prediction models (usually based on stratification systems) were proposed in the literature to help resource allocation in hospitals.[185, 298-302] However, some questions still remain unanswered regarding their applications, implementation, and integration with resource planning practices. First, there is a lack of evidence in the literature, as I have found from the two reviews in this thesis, on how a prediction tool can be used to manage resources. Second, even when such models get implemented, it is difficult to evaluate their overall impact beyond a single resource. This stems from the fact that hospital resources are interconnected. For example, higher ICU discharge rates that might have resulted from better management of ICU resources can increase the utilisation of conventional wards or step-down units lowering the ability to admit new patients (i.e. full occupancy of the downstream beds can eventually limit the discharge rate of ICU units).

### 7.2.2 The use of patient profile variables in resource management

In previous chapters, I discussed how patient profile variables can be used to predict resource utilisation. Now, I discuss how these prediction models can be used to optimise resource use. Adan and Vissers[17] used integer linear programming to solve a planning problem that involves generating a patient admission profile for a speciality, given targets for patient throughput and utilisation of resources while meeting given constraints. However, patients were categorised based on their LOS and clinical factors were not considered. Similarly, Vissers, Adan, and Bekkers[303] developed a mathematical model (a mixed integer linear program) to optimise the number of operating room hours and the number of patients from specific categories. While linear programming is a common technique for optimisation problems with given constraints, they fail to model complex patient flow dynamics.[13] In contrast, DES has a remarkable capability for capturing great detail from a complex system. For example, the DES model in this chapter considered operating theatre capacity, intensive care beds, ward beds, and different types of patients (emergency, elective, non-surgical patients). Interaction between patients and resources was modelled in a way to reflect the complexity of the real-world system.

### 7.2.3 The value of patient-specific resource allocation

It is often assumed that uncontrolled variation is the enemy of quality.[304] This is a highly relevant in hospital care. The use of basic information is no longer sufficient to manage and plan inpatient activities[4] which are influenced by patient variation. Therefore, the effect of variation might persist when resource allocation is based on deterministic models. As advocated in this thesis, factors contributing to variability in patient care should be integrated into resource planning and in simulation modelling to better tackle this issue. In chapter 2, I found that many of the reviewed studies appeared to have assumed that patient heterogeneity would not influence resource use. In essence, these studies have failed to adequately represent patient variability, an essential element in capacity planning.

Several factors such as patient severity and urgency are influencing the way how resources are allocated in hospitals. For example, emergency patients take precedence over elective patients for surgery. As I have demonstrated in chapter 5, cardiac patients are heterogeneous in their needs of resources. That is, the corresponding level of care varies from patient to patient. From clinical and operational perspectives, dividing patients into smaller homogenous sub-groups brings the benefit of increased certainty in predicting resource utilisation.[272] As it was previously asserted, patients with long LOS will naturally have different resource consumption patterns than those with normal LOS.[305] Likewise, patients with a similar diagnosis can be expected to consume similar resources, a concept in which the DRG was based upon.[61] However, diagnosis alone can’t inform resource allocation as patients with a similar disease can have significantly different resource requirement.[306]

## 7.3 METHODOLOGY

### 7.3.1 Resource allocation strategies using DES

There were three main objectives of the simulation study: First, the DES model was used to evaluate the value of incorporating certain patient factors into resource allocation (theoretical part). Second, by adding detail related to patients resource use to the DES model, several planning strategies can be implemented (practical part), therefore, augmenting the decision capability. Third, the model was used to assess the utility of implementing a resource utilisation prediction model in a hospital. The models and the parameters were based on extensive analysis of both hospitals datasets. Figure 7-1 depicts the four steps that I proposed in this chapter.

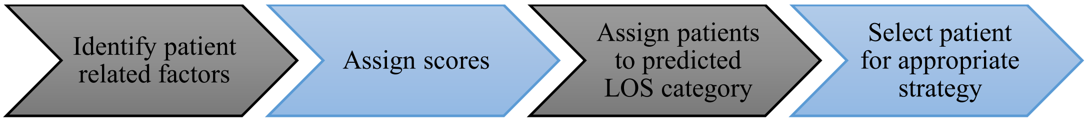



**Figure 7-1 Proposed steps in using patients profile variables for resource planning**

### 7.3.2 The model development

Figure 7-2 illustrates an overview of the cardiac care system. A specific conceptual model was created (graphically illustrated in Figure 7-3) to aid in the model development. Accordingly, I created the DES model (Figure 7-4) which contain the most relevant components. In the model, patients enter the system after their referral for admission. Surgical patients are allocated to the surgery waiting list. Immediately after their entry, patients will be assigned a profile. Scores based on the formulas obtained from the logistic and Cox models (discussed in chapter 6) are generated for each surgical patient. These scores are used to objectively evaluate the model resource allocation strategies. Non-surgical patients are discharged from the ward without being advanced to other components in the model. Urgent cases are given priority for admission and surgery.

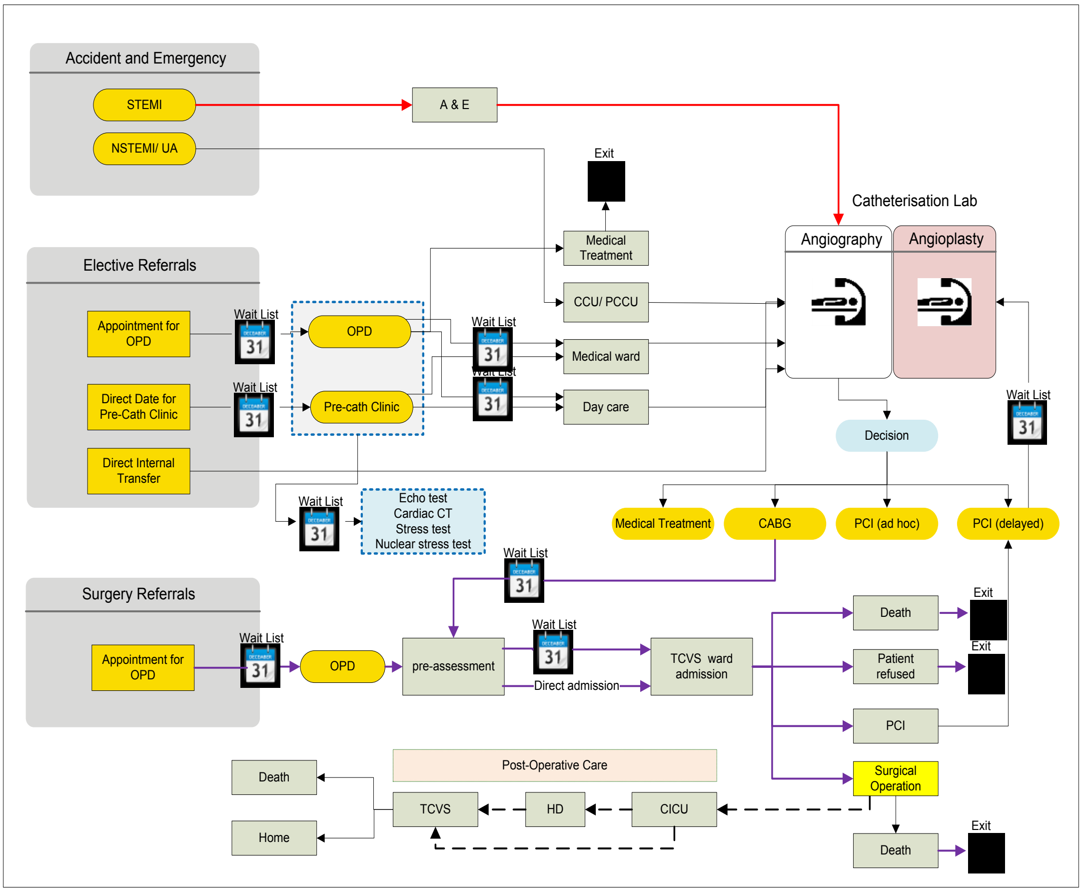



**Figure 7-2 An overview of the patient flow in the cardiac system**

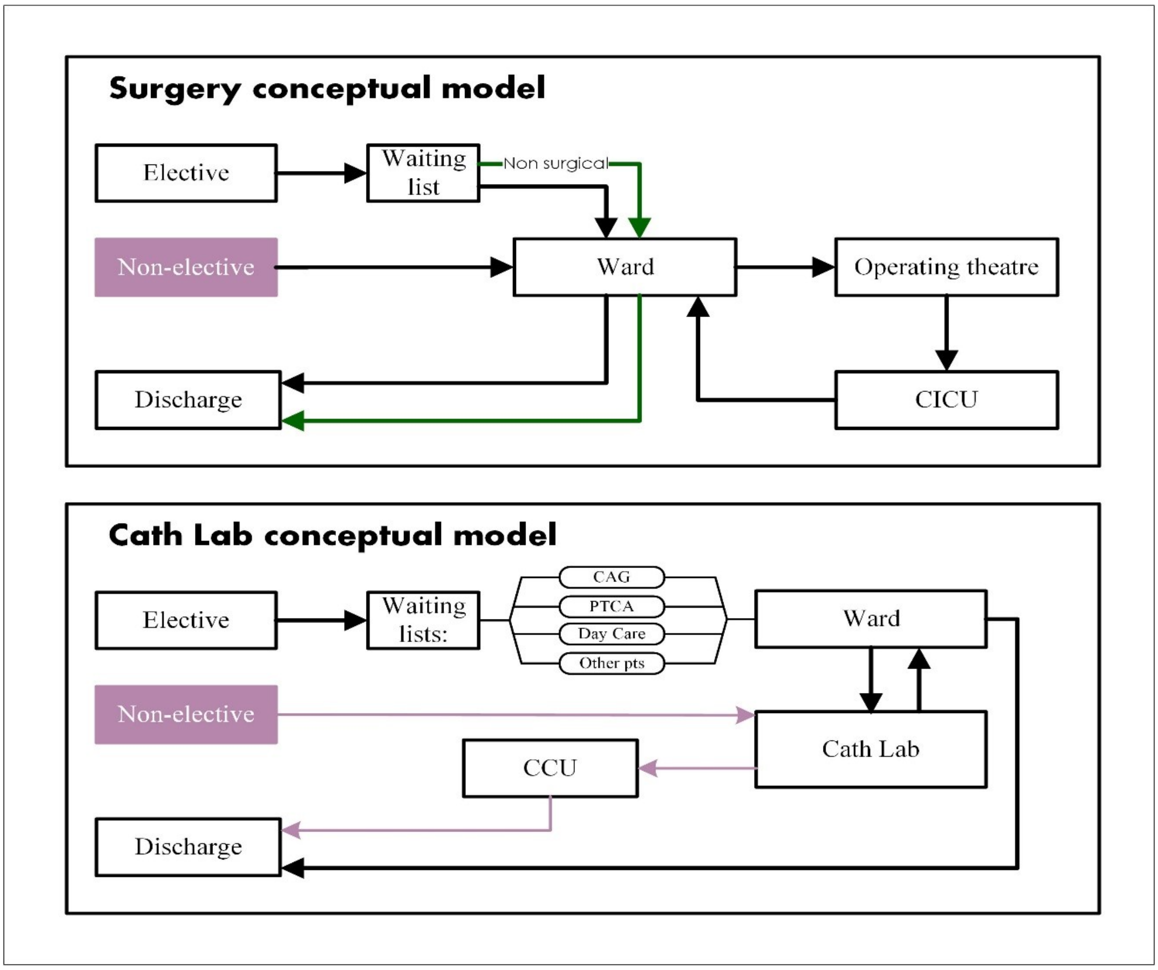



**Figure 7-3 The conceptual model of patient flow in the cardiac system**

The data have been analysed using Stat::Fit software in order to estimate the inter-arrival and service time distribution. The inter-arrival times of referrals were estimated to follow Poisson distribution, with a mean rate of one patient every 18 hours. Surgery duration was modelled using triangular distribution, with values (4, 4, and 6 hours) which includes the setup and patient preparation time. Table 7-1 provides the model's inputs. To prevent elective patients from admitted or discharged during any time of the day, the model only permits admissions from 7:30am to 4:00pm, and discharges from 9:00am to 6:00pm. The model also considers the working hours of the operating room which extend from 8:00am to 2:30pm.

**Table 7-1 Input parameters for the surgery model**

| Parameter | Value in baseline scenario | Distribution | Data source |
|---|---|---|---|
| Emergency patient inter-arrival (hours) | **48** | **Poisson** | **Existing data** |
| Elective patient inter-arrival (hours) | **18** | **Poisson** | **Existing data** |
| Preoperative LOS (hours) | **120, 144, 0, 1** | **Beta** | **Existing data** |
| Surgery duration (hours) | **4,4,6** | **Triangular** | **Expert opinion** |
| CCU LOS (days) | **1.04,1.6,48,11** | **Beta** | **Existing data** |
| %patients operated on CPB machine | **76%** | **-** | **Existing data** |
| Non-surgical patient inter-arrival (hours) | **79** | **Poisson** | **Existing data** |
| Postoperative LOS (hours) | | | **Existing data** |
| Isolated CABG | **0.87, 1.65, 121,577** | **Beta** | |
| Isolated valve | **1,2.21,121,685** | **Beta** | |
| CABG & Valve surgery | **121, 1.48, 199** | **Weibull** | |
| Other cardiac surgery | **121, 1.56, 90** | **Gamma** | |

#### 7.3.2.1 Model assumptions

The model makes the following assumptions about patient flow and delivery of services.

1) The model doesn’t take patient preference for surgery date.
2) Beds are considered available all times when patients are not occupying them. In reality, hospitals might not admit patients simply because beds are available. Other reasons such as unavailability of staff can prevent patients from being admitted.
3) Resource planning strategies were tested in the model irrespective of the operating room schedule for surgery types. The intention of the model was to test the concept of matching patients with an appropriate strategy rather than improving flow for particular types of patients.
4) LOS estimates were sampled from empirical distributions and they can’t be modified after the patient is admitted. In reality, the state of individual patient LOS changes according to factors related to treatment and adverse events.

5) In the CICU early discharge scenario, only patients who underwent surgery are permitted to be discharged early. There are non-surgical patients who are admitted to the CICU, yet these patients can’t be selected for expedited discharge as the scoring system is only applicable to the surgical patients. Ideally, an equivalent scoring system should also be applied to non-surgical patients who may spend substantial time in CICU.

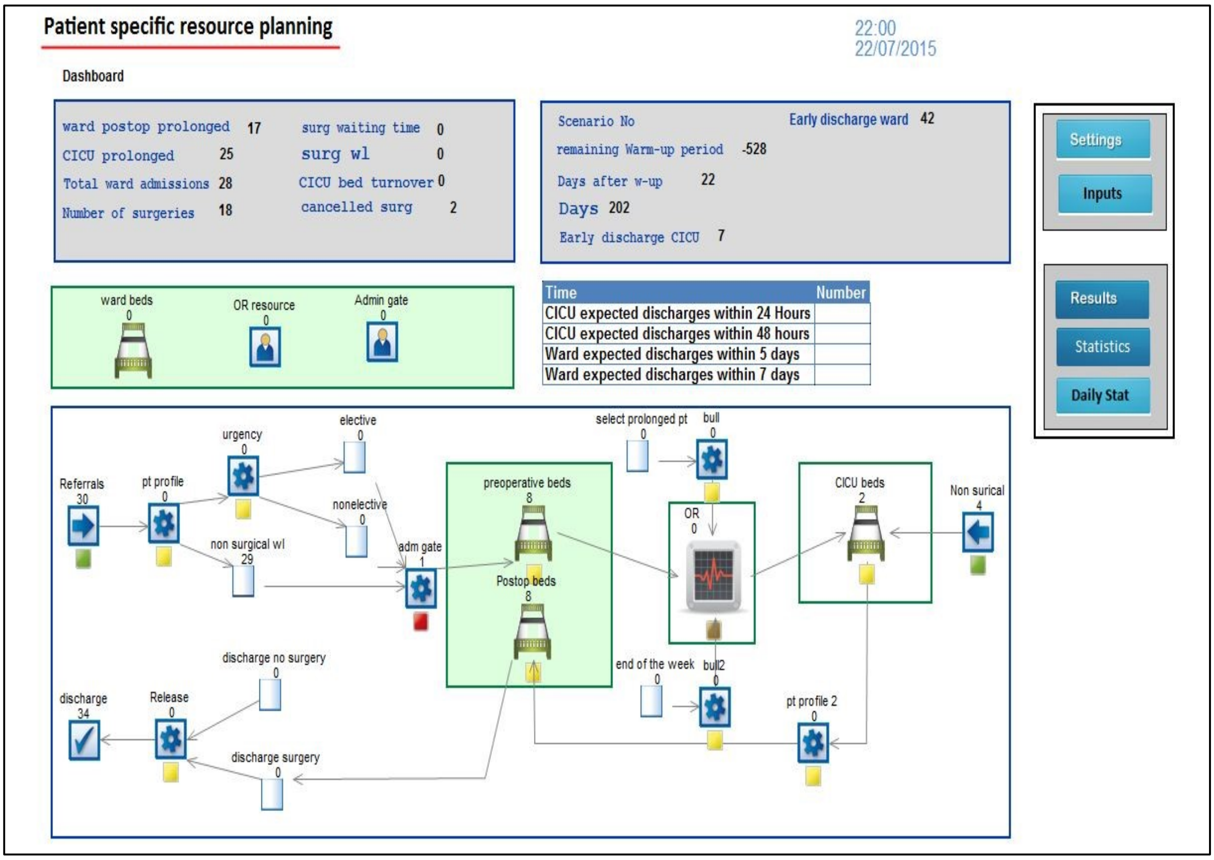



**Figure 7-4 Screenshot of the model (surgery model)**

#### 7.3.2.2 The outcome measures

The impact of resource allocation strategies, discussed next, are evaluated based on several measures. The following are collected from the simulation model:

- The proportion of non-clinical cancellations attributable to a lack of bed availability in the CICU or the wards.

- The number of surgical throughputs.
- The waiting list size and waiting times for surgery.
- Bed occupancy and turnaround.

At the end of each day (i.e. 24:00 hours) the model records statistics related to the number of bed occupied, percentage of LOS types (i.e. short, medium and long), time and date of surgeries, waiting times, number of patients with prolonged LOS, total ward admissions, and surgery cancellations of that day. The "bottleneck effect" related to bed occupancy was evaluated based on the number of times beds were fully occupied.

#### 7.3.2.3 Resource allocation strategies based on patients characteristics

Building upon previous statistical analysis, I will evaluate several strategies that can optimise patients flow based on factors that I found to be influential to resource use. These strategies were selected to demonstrate the value of incorporating information related to clinical factors on resource planning.

**1) The current "baseline" state**

The baseline or the status quo model reflects the existing state of the system. Patients are simulated in the model with several attributes that were randomly generated to reflect the proportion of important factors to resource utilisation. The baseline model was used to verify and validate the model.

**2) Selecting patients to optimise patient flow**

Patients are selected for admission based on expected LOS. Based on their total scores, the patients will be assigned to either low, medium, or high LOS categories drawn from three distributions. At the end of each day, the model calculates the expected number of beds that would be available in the next 24 hours. The model selects patients for admission based on the current case mix of admitted patients and their expected LOS. The following six selection scenarios were evaluated. See Appendix D for some example of Visual Logic codes.

**A) Selecting the right mix of patients to improve CICU flow:** The objective function of this model was to minimize CICU LOS for all patients in the unit. This is accomplished by selecting patients using Simul8's Visual Logic programming language. When only certain number of beds are available (this was set to two or less because it is considered as a critical level by the hospital), the model loops through all admitted pre-surgical patients and then select patients that meet certain criteria. The sorting mechanism involves calculating the expected LOS, the remaining LOS, and patients scores. For example, when there are only two beds available in the CICU, the model selects patients for surgery with minimum expected CICU LOS.

**B) Modifying the surgery schedule:** Another strategy involved the selection of patients for "end of the week surgery". In this scenario, patients who are expected to experience prolonged CICU LOS are scheduled for surgery at the end of the week to take advantage of weekends when no surgeries are performed. A basic premise here is that a fully occupied CICU in the weekend will not risk surgery cancellations. In the model, operations performed on Thursday (the weekend in Oman runs from Friday to Saturday) are only allocated to patients with expected high CICU LOS. A similar logic was applied as above. However, the selection of patients with expected long stay was only activated on Thursday at 1:00 am. If there are no patients that meet the selection criteria, the model selects a patient who is at the top of the surgery waiting list.

**3) Discharge prioritisation: early discharge from CICU and the hospital**

This scenario assesses whether an early discharge from CICU can result in some favourable outcomes. Patients selected for early CICU discharge if they have risk scores for prolonged LOS less than 2 and have completed not less than 48 hours in the CICU (the minimum time required by the hospitals). Respectively, patients in the model are only allowed to be discharged from the ward if they had a minimum of 5 days and risk scores indicating normal LOS. Early discharge from the CICU entails transferring patients to the ward.

**4) Don't refer to surgery**

The decision to refer a patient to cardiac surgery should not be confined only to the risk of death, but it should also considered the risk of long and costly hospital stays.[307] Patients with high expected LOS might be at risk of psychological and physical distress. Other less invasive treatments such as PTCA and medical treatment might be an alternative option for many patients. As in previous strategies, patients were selected based on their risk of prolonged LOS using the devised scores. The average score (combining CICU and ward scores) is calculated in the model. The number of patients with high scores was reduced by 10%, 20% and 30%.

**5) Altering the current policy regarding preoperative LOS: reducing the preoperative LOS**

For the surgical patients, it is possible to control the LOS by limiting the number of days that patients spend in the hospital before their operations. As I previously found, preoperative LOS was high and much of the patients stay in the two hospitals was unnecessary. Thus, I treated preoperative LOS as a modifiable risk factor. In the model, the average preoperative LOS was reduced to 3 days from the existing average of 6 days, a reduction of 50%.

**6) Modifying the rate of factors influential to LOS**

This scenario explores what if the proportion of factors influential to LOS were reduced. In practice, some patients are medically managed prior to surgery to reduce potential risks. Specifically, this scenario examines the effect of reducing the proportion of LOS risk factors prior to admission. Based on discussion with the surgeons the only feasible alternative was to reduce the number of patients who are operated with the CPB machine. The surgeons estimated that 15% of the patients can be operated without the use of CPB support. Reducing other influential factors: current heart failure, renal failure, pulmonary hypertension, surgery type, and non-elective status is not always possible. Only the severity of these factors can be mitigated which then may positively impact upon LOS. This relationship, however, is beyond the scope of this thesis.

#### 7.3.2.4 Model's warm-up period and number of replications

I determined the warm-up period using Welch's method.[71] This is a graphical method which involves calculating and plotting of moving averages collected from multiple runs of the model. The variable of interest to indicate the length of the warm-up period was waiting time for surgery. In Figure 7-5 the data appear to settle (smooth) at day 45. However, I increased the warm-up period to 90 days (three months) to accommodate any other variabilities. I utilised the Simul8's built in calculator for the number of replications using the same waiting time measure and a precision level of 95% CI. The number of runs was determined to be 154 runs.

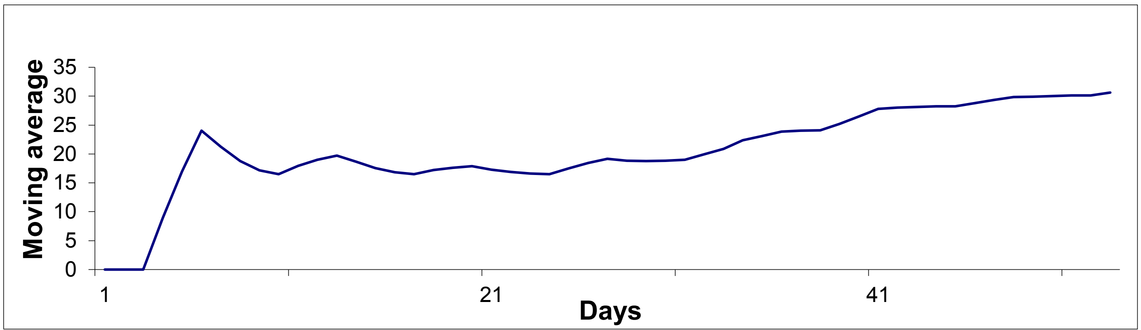



**Figure 7-5 Calculation of the warm-up period based on Welch's method**

### 7.3.3 An optimisation approach for minimising waiting time for Cath Lab procedure

I created a second DES model that examines how waiting times can be minimised by varying the Cath Lab capacity and the number of beds. The two particular factors that I found to be influential to patients admission following outpatient angiography, namely history of heart failure and previous PTCA, were included in the model. In the DES model, risk factors were

**Table 7-2 Input parameters for the Cath Lab model**

| Parameter | Value in baseline scenario | Distribution | Data source |
|---|---|---|---|
| Emergency patient inter-arrival (hours) | 16 | Poisson | Existing data |
| Elective patient inter-arrival (hours) | 2.5 | Poisson | Existing data |
| Preoperative LOS (hours) | m=24, SD=48 | Normal | Existing data |
| Cath Lab procedure duration (in minutes) | 20, 30, 60 | Triangular | Expert opinions |
| **% Patient types:** | | Percentage | Existing data |
| Angiography | 40 | | |
| Admitted angiography | 75 | | |
| Angiography day care (i.e. outpatient) | 25 | | |
| PTCA | 18 | | |
| Other patients admitted to the ward | 42 | | |
| CCU LOS (hours) | 48 | Average | Existing data |
| Day care LOS (hours) | 4, 5, 6 | Triangular | Experts opinion |

set based on a probability distribution. Patient with no risk factors constituted 83% of the patients, while 9% had previous PTCA, and 6% were previously diagnosed with heart failure. Another probability distribution was set for risk of admission following outpatient angiography based on the presence of the two risk factors. The probability that a patient will be admitted is 54% and 59% for having CHF and a previous PTCA respectively. Further parameters are provided in Table 7-2.

Another important aspect of patient mix included in the model was the urgency level. In essence, the model assumes patient urgency as well as the two factors are driving variation in resource use and therefore they can affect waiting time which has been a persisting problem. The Royal Hospital operates two cardiac Cath Labs. The number of beds available in the cardiology department is 30 ward beds in addition to 2 beds dedicated to outpatient Cath Lab procedures. If an outpatient case is deemed to require an admission, the patient will be admitted to the ward to keep the two beds vacant for the next patients. The optimisation involves the following steps: 1) specifying the objective function: minimising waiting time for angiography and PTCA patients from referral to admission, 2) identification of the resource variables that may require change (Cath Lab operating time and number of beds), and 3) identification of the constraints such as shift time which are implicitly defined within the model). I utilised the optimisation algorithm (OptQuest) that is integrated within Simul8 software to assess the best configuration of the number of beds and Cath Labs that would minimise the waiting time. Based on the previous method in section 7.3.2.4, the warm-up period of 3 months was set. The model was run for 50 one-year replications using common random numbers. The Simul8 model is illustrated in Figure 7-6.

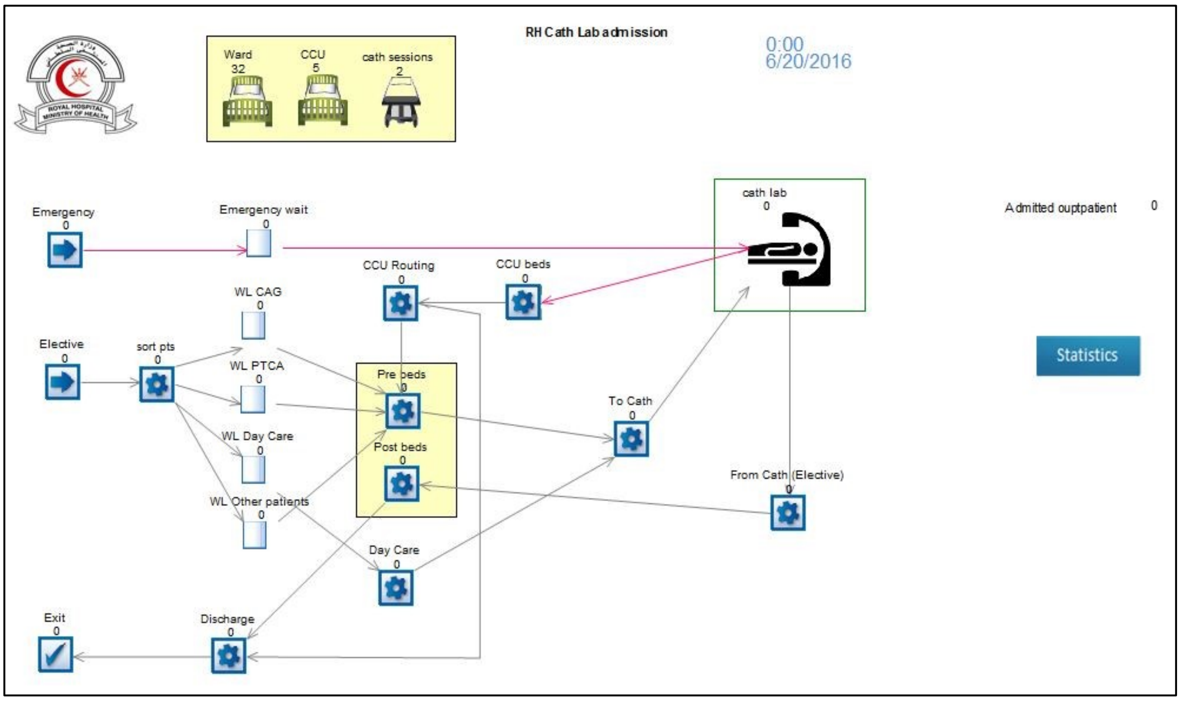



**Figure 7-6 Cath Lab outpatient admission screenshot**

## 7.4 RESULTS

### 7.4.1 Validation of the cardiothoracic surgery DES model

To develop and assess the underlying logic of the conceptual model, meetings were conducted with surgeons, nurses and bed managers at the hospitals. Patient flows were discussed in detail to identify all possible patient pathways. The final conceptual model was approved by three cardiac surgeons from both hospitals. For validating the output of the model, boxplots were used to compare the outputs with the historical results (Figure 7-7).

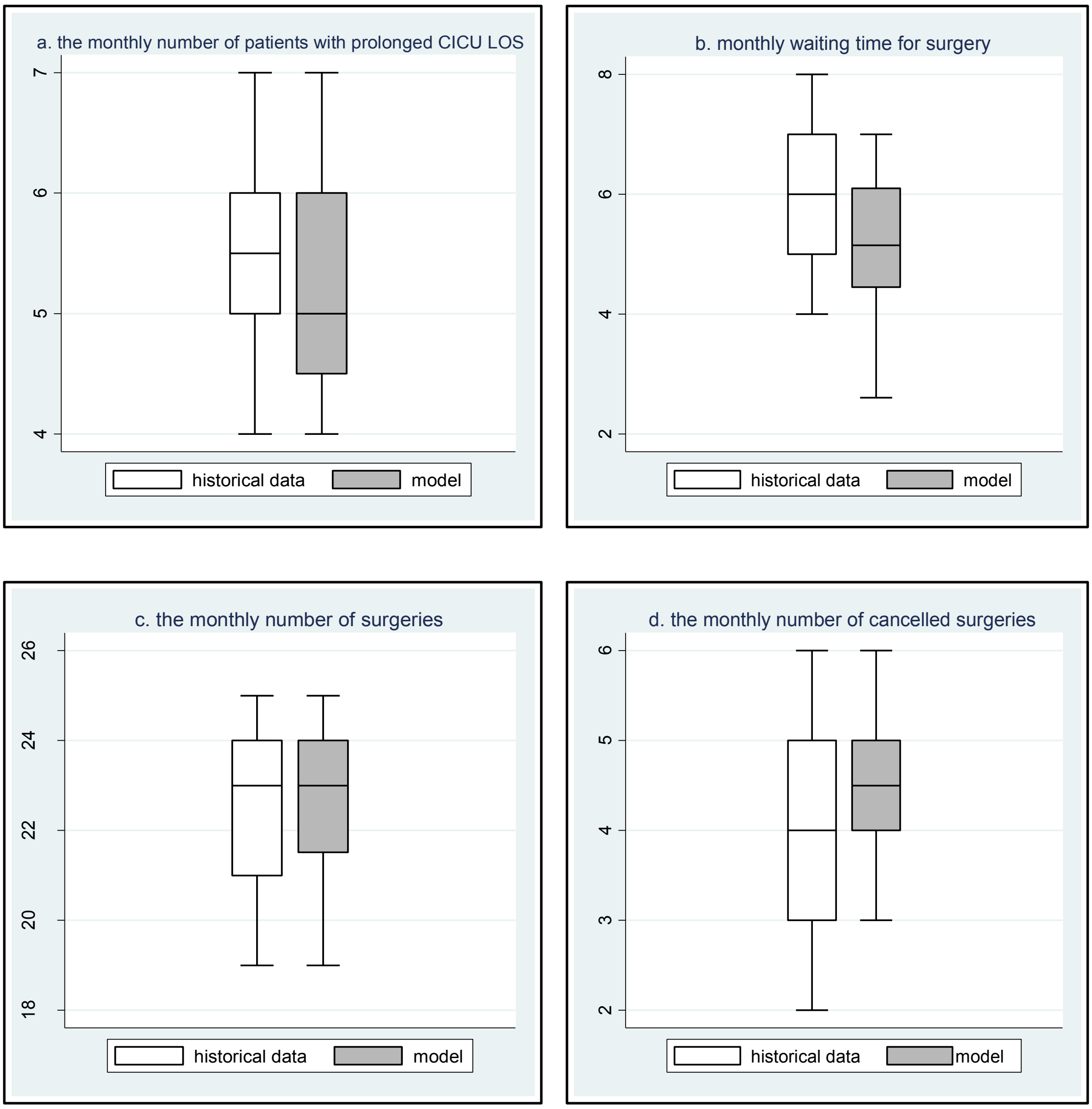



**Figure 7-7 Graphical comparison between simulated and actual data**

A graphical comparison between simulated and actual data is a subjective measure.[223] For this reason, I further performed independent t-tests to compare model results against the historical data as I discussed in Section 4.9 in the methodology chapter. Results are represented in Table 7-3.

**Table 7-3 Results from t-test for comparing the model results against the historical data**

| Variable (average per month) | Model | | Actual data | | t-value | $H_0$ |
|---|---|---|---|---|---|---|
| | Value | SE | Value | SE | | |
| **Performed surgeries** | 23 | 0.56 | 22.5 | 0.54 | 0.01 | Accepted |
| **Cancelled surgeries** | 4.50 | 0.23 | 4.00 | 0.34 | -1.19 | Accepted |
| **Surgery waiting times** | 5.14 | 0.39 | 6.00 | 0.36 | 1.60 | Accepted |
| **CICU LOS** | 3.58 | 0.14 | 4.08 | 0.22 | 1.83 | Accepted |
| **Score** | 2 | 0.14 | 2.25 | 0.13 | 1.68 | Accepted |
| **LOS for normal group <= 5 days** | 3.08 | 0.08 | 3 | 0.11 | 0.59 | Accepted |
| **LOS for prolonged group > 5 days** | 5.33 | 0.30 | 5.50 | 0.28 | 0.39 | Accepted |

### 7.4.2 Patient selection based on expected LOS scorings

**(1) CICU surgery schedule based on expected CICU LOS:** In the DES model, LOS was allowed to vary according to the patients characteristics. Results demonstrated the value of assigning the right patient mix when resources are limited. In the first strategy, patients were selected based on their expected LOS (which was calculated according to the presence of certain clinical factors). Selecting patients with minimum expected CICU LOS has reduced the average preoperative LOS from 8.7 days to 6.6 days (a decrease by 24%). Surgery cancellations were also reduced from 54 cancellations during the year to 41 cancellations (a decrease by 24%). The effect on patient waiting time was modest as it was reduced on average by only 1 day (from 6 days to 5 days). This is because this selection strategy was only applied when CICU was in critical capacity limit (as it might not be practical and useful to apply the strategy when the number of CICU beds is sufficient). Therefore, the selection strategy was applied only 75 times during the year in the model (27% of the surgical patients were selected based on this strategy). The second reason is that there was low demand for cardiac procedures in this particular hospital.

**(2) Scheduling patients with expected prolonged LOS for surgery at the end of the week:** Another application of the scoring system was demonstrated through the selection of patients with the highest expected CICU LOS after surgery. Based on the criteria specified in the model, the strategy was applied 50 times in the model during the one-year simulated period. This meant that 50 patients with prolonged LOS were selected for surgery on Thursday. Surgeries cancellations were reduced from 54 in the baseline model to 44 (a reduction of 18%). However, there was slight increase in the surgery waiting times from 6 days to 7 days. The increase is related to the improvement in the overall admission rates. As in previous strategy, freed capacity gained from the reduction of the overall LOS did not translate into a shorter LOS. Non-surgical patients (e.g. readmitted surgical patients and patients transferred from other wards) were allowed in the model to be admitted when bed occupancy was low. However, since priority in the model was given to surgical patients, their waiting times were much lower (8 days for surgical patients vs. 4 months for non-surgical patients). In the model, non-surgical patients are discharged from the ward without being advanced to other components in the model.

**(3) Early discharge strategy:** The total number of patients who were selected for early discharge were 36 CICU patients (13% of patients who underwent a surgery) and 127 (46%) ward patients. Applying the early discharge strategy for both CICU and the ward simultaneously has resulted in a decrease of cancelled operations from 54 to 46 (a decrease by 15%). The waiting time for operations was reduced from 5 days to 3.5 days (a decrease by 30%) and the number of operations increased by 5. However, when only CICU early discharge was applied, the cancelled operations were reduced to 34 (37%). In contrast, when the ward early discharge was applied (as the only strategy), cancellations have decreased by 3 from the baseline. The number of surgeries have increased just by 1 surgery and surgery waiting time has also increased from 5 days in the baseline model to 5.47 days. In the model, an early discharge from the ward means there is more opportunity for admitting patients from the waiting lists especially non-surgical patients. The non-surgical patients admitted to the ward have increased, and thus reduced the admission rate of surgical patients over the year. The use of "early discharge from hospital" strategy should be evaluated based on the trade-off between the priority of selecting surgical patients and delaying non-surgical patients. However, expedited discharge from the CICU seems to be an effective strategy.

**(4) Don't refer for surgery strategy:** The median combined risk score for prolonged LOS generated by the model was 1.5. Only 10% of the patients had a score that is higher than 5.5. The 75 centile was 3.5. Thus, patients with an average score of higher than 3.5 are considered to be at high risk of experiencing prolonged LOS postoperatively. The number of patients who met the criteria was 13, 20, and 29 for 10%, 20%, and 30% reduction in surgical patients respectively (Table 7-4).

**Table 7-4 Model results for don't refer to surgery scenario**

| Performance indicator | Baseline | 10% reduction | 20% reduction | 30% reduction |
|---|---|---|---|---|
| **Number of patient not referred to surgery** | 0 | 13 | 20 | 29 |
| **Cancelled surgeries** | 54 | 38 | 46 | 44 |
| **Number of surgeries** | 276 | 267 | 263 | 263 |
| **Waiting time (days)** | 5 | 3 | 2.7 | 2.8 |

High percentage of surgery reductions led to less improvement in performance. This is because it was possible to admit more non-surgical patients, allowing more patients to occupy the ICU unit and thus leading to higher bed utilisation and surgery cancellations. As indicated in Table 7-4, the most favourable option would be reducing the number of patients with high expected LOS by 10%.

**(5) Reducing preoperative LOS:** By reducing the average preoperative LOS by 50% for all patients, the cancelled surgeries have decreased by 24% (from 54 to 41). Similarly, waiting times decreased by 1 day from 5 to 4 days. The number of surgeries remains the same despite the decrease in the surgery cancellations. This is due to the low referral to surgery.

**(6) Modifying the rate of significant factors to LOS:** The only significant factor that can be controlled was the use of the CPB machine. 76% of patients were operated with the use of CPB machine. In the model, I reduced the percentage of these patients to 61%. Accordingly, the number of cancelled surgeries fell to 50 (from 54 in the baseline model). The number of surgeries have increased by 4 surgeries per annum, and surgeries waiting time was reduced by 1 day.

### 7.4.3 Results from the Cath Lab model

#### 7.4.3.1 Validation of the Cath Lab model

A face validation with the clinicians at the cardiology department has been firstly performed. The conceptual model (i.e. the logic and the structure of the model) was a true representation of the system. Secondly, I compared the model outputs to the historical data through a classic parametric statistical test (the *t* test). Specifically, I compared the monthly number of patients (year 2014) from each type of Cath Lab procedure to historical data. Simulated data were sufficiently close to the historical means (Table 7-5).

**Table 7-5 Validation of Cath Lab model based on the number of monthly procedures**

| | Angiography | Angioplasty | Total |
|---|---|---|---|
| **Real measure** | 171 | 107 | 3115 |
| **Simulation output** | 162 | 102 | 3092 |
| **Change** | -9 | -5 | -23 |
| **P value** | 0.124 | 0.325 | 0.285 |

#### 7.4.3.2 Minimising waiting time for Cath Lab procedures

According to the model, admissions due to the presence of the two influential factors increased the average waiting time slightly by 5% from 66 days (with admissions) to 63 days (without admission). The number of Cath Lab procedures (i.e. throughputs) was slightly reduced due to the admission of outpatient Cath Lab patients (reduced by 14 procedures per year).

According to the optimisation algorithm, the best configuration to minimise waiting time corresponded to reducing existing beds from 30 beds to 25 beds, reducing coronary care unit beds from 5 beds to 4 beds and adding one extra Cath Lab. This will virtually result in no waiting time for Cath Lab patients at existing demand. The results indicate that the Cath Labs were the bottleneck of the system rather than bed availability.

## 7.5 DISCUSSION

### 7.5.1 The utility of implementing a resource utilisation prediction model in hospital

As discussed in chapter 3, studies have not evaluated the utility of resource utilisation prediction models in hospitals. So, there is still ambiguity on the circumstances in which these scoring systems can be used as well as their utility in improving patient flow. In this chapter, I attempted to clarify these two important aspects.

Since the operating theatre and the CICU beds are interdependent, these resources have to be well balanced to avoid cancellations.[73] The surgery postponement rate was reduced when the scoring system was introduced in the DES model. Patient selection based on their expected LOS has facilitated better planning of CICU resources which was operating near full capacity. The bed turnover has improved considerably with the use of the scoring system in general. This is important in critical care where constrained resources can affect provision and quality of care.[308]

The introduction of patient assignment strategies utilising a scoring system has resulted in improved overall performance. The improved patient flow in the CICU unit has not affected the dynamic of patient flow in the cardiac care system. This is because sufficient capacity was available in the downstream ward and that there were relatively low numbers of emergency patients admitted to the department. For example, in the first scenario, on average the CICU was fully occupied 6 times per month. On the other hand, the ward was fully occupied on average 4 times. A sufficient capacity in the ward is critical for this strategy to be successfully implemented.

Hospital resource planners can have the leverage to improve patient flow and resource allocation by using validated scoring system to prioritise patients' selection. However, a LOS prediction model should not be developed in isolation of its intended use (e.g. reduce surgery cancellations). Simulation studies should assist in assessment and validation of LOS prediction models along with any resource management application. I encourage further use of DES to evaluate other models intended for optimising hospital resources in constrained environments. Stratification systems proven to be reliable can be integrated into hospital information system to aid in a critical decision process. The concern, however, extends beyond having a reliable scoring system. What is more important is the appropriate selection and implementation of strategies that would maximise the use of resources. I believe that it is this reason that makes the use of any resource allocation tool a challenging task. For instance, different parties managing the care of patients might not be willing to accept a new scheduling scheme. Stakeholders' engagement is a critical component in implementing any of the strategies discussed in this thesis.

The effectiveness of implementing patient stratification systems will depend mainly on their validity in reflecting factors related to patients as well as the care delivery context. While my study has accounted for the unique characteristics of patients, several contextual factors such as physician judgements regarding LOS (i.e. local policy) have not been reflected in the models. Moreover, implementing a stratification system would be more effective in settings where there is high demand on resources. In such settings, even a small gain in efficiency is more likely to make greater impact on patient flow.

### 7.5.2 Patient-specific resource allocation

The resource planning approach discussed in this chapter incorporated key prognostic variables that include type of surgery, urgency level, use of CPB, presence of any of the following: renal failure, congested heart failure, and pulmonary hypertension. I found that these factors to substantially determine patient resource consumption. Active patient assignment was implemented through the use of a validated prediction model. This work adds to the literature on hospital capacity planning by extending and evaluating the use of prediction models for scheduling patients. Thus, the effect of variation introduced by patients and treatment factors on patient flow is minimised.

It is difficult to anticipate the medical profile of each patient that are referred to the hospitals. However, hospitals still can influence the LOS by proactively selecting patients “controlled admission”. This can range from a complete refusal of accepting patients to postponing their admissions for interventions. The latter is done to ensure patients are fit for surgery. Patients, in this case, might continue to see their general practitioner or consultant in regional hospitals close to their homes. It is worth mentioning that the difficulty in gaining access to the two hospitals for some cardiac services has been a source of discontent in the country and was debated in several occasions in parliament. The cardiac care system in Oman is characterised by limited resources and bed availability is a major issue. Hospital beds are fundamental inputs in the provision of care and bed management is performed to ensure availability of beds using tactical and operational day-to-day decisions to allocate beds.[309] The strategies discussed previously ensure that beds are available when needed. The benefits expected from implementing patient-specific resource allocation can add value to patient care and improve hospital’s overall responsiveness to patient needs. Moreover, efficiency can help hospitals to use as few beds as possible which can result in less spending on costly services and personnel.[310]

CICU beds in Oman are in short supply while the pressure on other cardiothoracic beds are growing as requests for referral to the two hospitals have increased. Intensive care is a critical element in the hospital since resource shortage can result in dire consequences for the patients as well as it can act as a bottleneck.[311] I tested several strategies informed by patient expected LOS and I found that the predictability of prolonged CICU LOS lends benefits to the scheduling practice. For example, scheduling more complex cases with higher score to the end of the week when there are no scheduled surgeries has increased bed availability for other patients. Respectively, patients were allowed to be expedited from the CICU based on their expected LOS. While this is a valuable strategy, there is some evidence in the literature to suggest that when patients discharge from ICU is expedited, some patients will bounce back to the ICU[312] creating a scheduling challenge for planners. Discharge decisions should also be carefully evaluated on the basis of ethical practices.[313]

Overall, early discharge strategy was the most effective in reducing waiting times and the number of cancelled surgeries. It has also resulted in increased surgery throughputs. Patients can be discharged to step-down units which are introduced to improve critical care cost-effectiveness and patient flow without compromising quality.[314] While the hospital under study doesn't operate a step-down unit, an addition of this intermediate care unit can be considered as an option to reduce the number of patients residing in the CICU and safely discharge eligible patients.

Improvement in patient flow as a result of introducing a prediction system can, however, be overshadowed by increased utilisation in other areas especially when demand is high. For example, admitting patients early for treatment to lower their risks of being in the CICU for an extended period may increase bed occupancy of other beds in the hospital. If the downstream stage becomes fully occupied, access might be blocked for other patients upstream.[315] This happens because of the failure to consider patient flow as a continuum construct that span across multiple services.[316] It is often that decisions to increase capacity at any hospital location is taken independently of other locations. As a consequence, this will manifest in the form of longer waiting times and reduced accessibility.

Instead of attempting to schedule patients for optimum operational outcome, I designed the Cath Lab model so that an optimal resource configuration can be obtained. Unexpected admissions following outpatient procedure can distract operations. The model provides the optimum configuration accommodating patient characteristics. At the current situation, the ward beds may seem to be underutilised according to the model. Therefore, reducing beds and increasing Cath Lab capacity will minimise waiting time. Despite that investment in another Cath Lab will require substantial funding, it can save lives allowing the hospital to response to urgent cases. The saving from downsizing the number of beds in the cardiac department should provide the management with the incentive to pursue this option.

### 7.5.3 Integration with HIS decision support system

The chapter demonstrates that the use of simulation can be an effective mean of evaluating operational performance across patient journey. The concept of using routinely collected data in predicting resource use can be expanded to include a wide range of services. Given the numerous challenges facing healthcare, the two hospitals can take advantage of the available digital infrastructure to integrate predictive models with simulation modelling. As such, existing repositories of big data can help improve the predictability of these models as well as assist in designing patient-centred care.[317] Programming languages such as Java, a commonly used computer language, can be used to design DES simulation models[318] that can be integrated into existing HIS. The system should be able to provide a “complete picture”, at the operational level, of existing resource states. Resource managers can then objectively select among best alternatives to optimise resources.

### 7.5.4 Conclusion and limitations

The findings from this thesis confirmed my earlier hypothesis that patient factors influence resource use and their effect extend to influencing operational performance. The need to manage patients according to their anticipated resource utilisation is an area that should assist in reducing cost and improving efficiency. The availability of patient data in modern hospitals can enable a wide implementation of algorithms that can identify and allocate patients to optimise existing resources. Even though other factors unrelated to patient conditions can be major determinants of hospital resource use, factors related to patients -a source of natural variation- are less apparent and have not received greater attention in literature dealing with hospital capacity management. Finally, DES can be used to evaluate the utility of patient classifications systems for planning resources.

**Limitations**

There are two limitations that merit discussion. First, the original stratification system was developed using a cohort of cardiac surgical patients and thus only surgical patients were considered for prediction. Other non-surgical patients who utilise CICU services can impact the use of resources. However, there was no strategy that was applied to streamline the flow of these patients. Ideally, a prediction model should be applied to all type of patients using shared resources. Second, patients' assignment and selection for treatment is a complex process which involves a multidisciplinary team.[319] Resource allocation based on a single scoring system can be seen as an oversimplification of this process. However, my intention was to demonstrate the value of the scoring system, regardless of its granularity, on operational performance.

# Chapter 8

# QUANTIFYING VARIATION IN RESOURCE UTILISATION DUE TO COMPLICATIONS AND ITS IMPACT ON OPERATIONAL PERFORMANCE

## 8.1 CHAPTER OVERVIEW

In chapter 5, I demonstrated that complications were a determinant of resource use. In this chapter, I will further examine the relationship between postoperative complications following cardiac procedure and operational performance. This area has not received much attention in the literature. Our understanding of how complications can impact patient flow could yield several benefits such as focusing efforts on reducing complications and building a business case for investing in quality and safety measures. The first part of the chapter is dedicated to quantifying the incremental LOS and cost associated with postoperative complications. The second part evaluates how this incremental LOS affect operational performance.

### 8.1.1 Aims and objectives

This study is guided by the following two questions: Do complications exert an influence on a hospital's operational performance? If so, how can this knowledge be utilised to optimise resources in order to improve productivity?

**Aim:** To highlight the value of incorporating the impact of complications on patient flow metrics and to test scenarios that offer the most favourable outcomes to mitigate the effect of complications. The objectives were:

1. To quantify the incremental effect of adverse events on LOS (i.e. the attributable increase in LOS as results of adverse events).
2. To propose a measure of operational performance outcomes associated with adverse events.
3. To determine the relationship between capacity and complications (e.g. the amount of capacity that can be recovered by reducing or eliminating complications, and the optimum capacity required to mitigate the effect of complications).
4. To measure the cost associated with lost productivity due to complications.

### 8.1.2 Significant and originality

Previous studies have focused on capturing the cost and excess LOS associated with complications. Researchers also recognise that complications are a source of variation in inpatient care and hence they may exert an effect on operational flow. However, there is a scarcity of literature on how and to what extent complications might affect patient flow. This is due to the lack of a specific measure designed to evaluate how complications might affect hospital operations. Moreover, the use of simulation in understanding the effect of complications on care processes and resources has been relatively limited to date. This chapter contributes toward measuring the effect of complications on operational performance, thus providing decision makers with potential tools to assess their impact.

## 8.2 INTRODUCTION

In hospitals with sufficient resources, complications may play a lesser role in overall productivity. For example, a sufficient number of beds can offset the effect of excess LOS added by patients experiencing complications. However, when resources are constrained, complications can exert a series of sequential effects that might limit the availability of resources for other patients.

Optimum bed capacity is a key factor for smoothing patient flow. However, managing beds is difficult as patients stays tend to be influenced by uncertainty. This includes occurrence of complications which trigger the use of additional resources. A hospital's efforts to manage complications is challenged by the fact that complications are difficult to predict.[320] At a certain level of capacity, a high rate of complications can substantially constrain patient flow and could reduce hospital responsiveness to urgent cases.

In many resource planning approaches, there is a tendency to focus on average utilisation of a single resource such as the operating theatre without consideration to its relationship with downstream services such as intensive care unit beds.[108, 321] Since many hospital services are interconnected, the effect of complications should be evaluated across the patient hospital journey. Quantifying the effect of complications on patient flow permits managers to evaluate the effect of complications on measures such as waiting times and surgery cancellations. This understanding can yield several benefits such as focusing efforts on reducing certain complications and building a business case for investing in quality and safety programmes. Further, given the current economic climate, there is an imperative to operate hospitals in a more efficient way. Hospitals can incur significant costs in treating complications (e.g. nosocomial infections) and might not be compensated in return.[322]

DES has been applied to numerous health policy issues related to staffing, scheduling, and capacity management.[131, 132, 323] Much of the enthusiasm in using DES in healthcare stems from its capability to capture complexity and uncertainty. A substantial body of literature has focused on measuring patient flow improvements under alternative solutions, with the intent to provide quantitative evidence to support decisions. However, it is often that complications tend to be ignored in DES. This might be the case because modellers might not have access to sensitive patient data including details of adverse events. Because DES offers the flexibility to track interconnected and uncertain events across multiple parts of the system,[71] I believe that DES is an appropriate tool for evaluating the inherent uncertainty surrounding postoperative complications and their impact on resource utilisation.

Hospital managers need to be able to evaluate efforts to reduce adverse events based on the added benefits to the patients' health and the hospital in general. Complications that occur in the CICU might lead the care givers to allocate extra resources. As a result, other surgery may be cancelled due to lack of available beds. Failing to manage the ratio of bed to operating rooms results in one of the resources being underutilised.[73] Additionally, cardiac surgical patients with complications can undergo re-exploration if, for example, postoperative bleeding was identified,[324] potentially resulting in postponement of less urgent cases. Furthermore, patients already transferred from CICU may bounce back if they experience a critical complication.

### 8.2.1 Postoperative complications following cardiac surgery

Several factors related to patients and surgical procedures can increase the risk of complications. For example, patients with concomitant surgery (i.e. CABG and valve) are more likely to experience complications than patients with isolated surgery.[325] Patients undergoing an operation with a CPB machine are more likely to experience an inflammatory response.[326] Blood transfusion during surgery is also associated with increased morbidity.[327] The probability of complications exponentially increases as patients spend more time in the CICU.[328] On the other hand, high patient severity has been linked to occurrence of adverse events which in turn mediates on subsequent LOS.[329] For instance, Toumpoulis et al[151] found that as severity (measured by the EuroSCORE) increases, the risk of postoperative complications tends to increase.

Cardiac post-surgical complications include some life threatening complications such as myocardial infarction. Another potentially fatal complication is postoperative bleeding which will require reoperation. Studies suggest the reoperation rate for bleeding is in the range of 2-9%.[330, 331] The majority of patients will be re-operated within 24 hours of the surgery. When patients experience one or more postoperative complications, their conditions can rapidly deteriorate given that most patients are above 60 years old.

## 8.3 METHODS

### 8.3.1 Patients and data collection

To evaluate the effect of complications on resource use, I utilised data from 600 patients who underwent cardiac surgery at the SQUH hospital. These data were drawn from a prospectively collected database. The type of collected data included patient basic demographics, comorbidities, LOS detail, surgery detail, and postoperative complications. Several types of complications were examined such as cardiac complications, pulmonary complications, infection complications and neurological complications. In addition to the clinical data, I collected several parameters related to system operation such as surgery waiting times, non-surgical admissions, and surgery duration.

### 8.3.2 Statistical analysis

To inform the simulation model building, I first examined the relationship between resource use and complications. I then performed Poisson regression in order to: 1) evaluate whether complications can independently explain variation in LOS, 2) inform my simulation model building by selecting the most influential complications, and 3) quantify the excess LOS and cost associated with each type of complication so they can be used in the model.

To evaluate the independent effect of complications on postoperative LOS, I adjusted the model for basic demographic characteristics, comorbidities, and type of surgery. Excess LOS was assessed through the marginal effect of each significant factor. Poisson regression has been previously found to be suitable for modelling ICU and postoperative LOS data that are heavily skewed.[242, 286, 332] A value of $P < 0.05$ was considered statistically significant. All tests were 2 sided. Respectively, the incremental cost associated with hospital charges was estimated using the same methodology. Hospital charges were calculated based on an existing fee schedule (2013-2014) for room, surgery, and investigations (radiological and laboratory).[203]

Marginal Effects at the Means measures the changes in the response variable in relation to change in a covariate. For binary variables, the effect of discrete changes (i.e. from 0 to 1) is computed holding all other variables at their means.[333] In effect, the margins are computed for all variables related to the patient mix, the surgical characteristics and complications. Thus, they reflect the marginal changes related to the specific cohort of patients which the model was derived from. All statistical analysis was carried out using Stata Statistical Software: Release 12. College Station, TX: StataCorp LP.

### 8.3.3 System description

Following a decision to operate, patients are placed in a waiting list. There is no pre-assessment clinic in the hospital which means patients have to be admitted a few days prior to their procedure where an anaesthetist can assess their fitness for operation. Late cancellations due to unsuitability for surgery can arise, resulting in underutilisation of operating theatre time. A common surgical patient's pathway through the system was: 1) arrive in the cardiothoracic ward, 2) transfer to the operating Room (OR), 3) transfer to the CICU, 4) transfer to ward, and 5) discharge home. These are depicted in Figure 8-1. Death can occur at any stage of patient care.

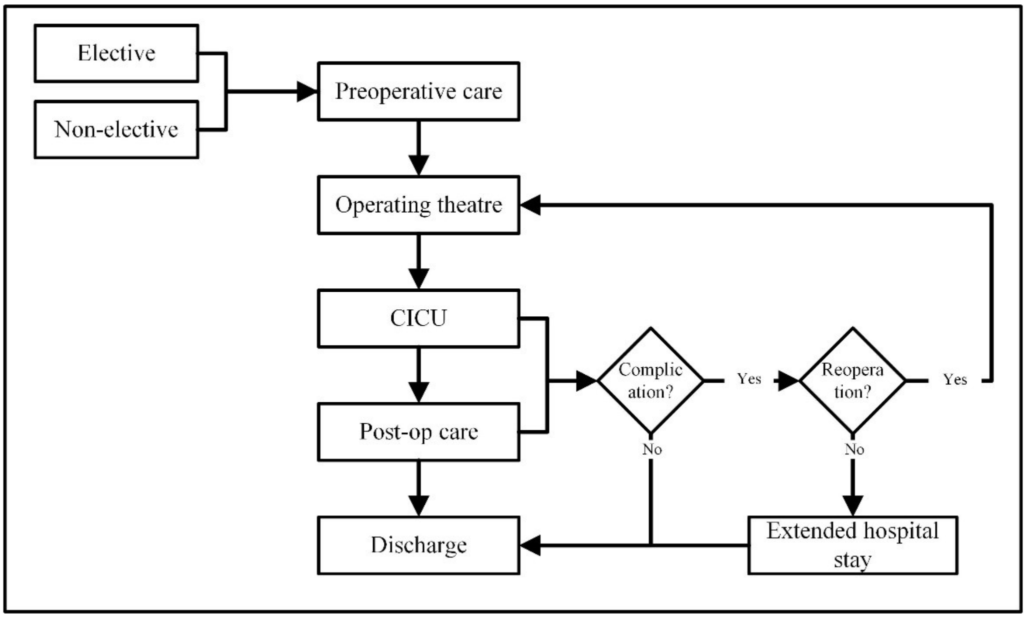



**Figure 8-1 An overview of patient flow in the cardiothoracic department**

There are three important components of the cardiothoracic surgical system:

1) **Operating theatre:** There is only a single operating theatre at the hospital that is solely dedicated to cardiovascular surgery. Procedures are performed four days a week (Sunday to Wednesday) from 8:00 am to 2:30 pm. An In-call staff can utilise the OR 24 hours, seven days a week to accommodate emergency cases which can disrupt the normal daily OR schedule. Only a single elective patient is operated on per day.
2) **Coronary Intensive Care Unit (CICU):** This unit provides an intensive care to patients immediately after surgery. Patients are kept in the CICU for at least 48 hours after the surgery where they will be extubated and continuously monitored. Level of pain, vital signs, ventilation, and surgical site are carefully monitored. CICU stay is an important milestone in the patient journey. Patients who are stable can be transferred to the cardiothoracic ward to continue their recovery. Patients can’t be checked into the OR unless a CICU bed is available. The limited number of CICU beds (only five beds) have restricted OR operations in the past. The patient to nurse ratio is 1:1 in this unit.

3) **The cardiothoracic ward**: This is the ward where patients are initially admitted preoperatively. Some admitted patients will not be scheduled for operations for reasons such as patient refusal or unfitness for surgery. Following a surgery, operated patients who required a lesser degree of care are transferred from CICU to this ward where they will continue their recovery. For most patients the ward is the last destination before discharge. There are 18 beds available.

### 8.3.4 Developing the DES model

The DES model I developed (a screenshot of the model is illustrated in Figure 8-2) collects various statistics concerning patient types, their urgency level, duration of operation, pre and post LOS, occupancy rate, surgery cancellation, and time beds were blocked.

Whenever a patient enters the model, a random sample of the same type is selected from a distribution based on historical data. Type of patients comprised patients with isolated CABG, isolated valve, combined CABG and valve, and other surgeries. The model then generates a profile for each type of complication based on results obtained from the Poisson regression. Once a patient is admitted, a preoperative bed will be assigned for both surgical and non-surgical patients. Preoperative LOS is determined based on historical data. Non-surgical patients will be discharged following the completion of their LOS. The model then checks for CICU bed availability before selecting patients for surgery. If all beds are occupied, the model calculates the time a bed was blocked. Once a bed becomes available, priority is given to non-elective patients.

Postoperative LOS was allowed to vary based on the type of surgery (e.g. CABG, combined surgery, isolated valve). Therefore, four types of distributions corresponding to postoperative LOS were set. From my previous analysis, there was an association between surgery type and postoperative LOS, sufficient to justify adding this level of detail to the model. Decisions for reoperation can be made any time post-surgery. Patients in the reoperation pathway are given priority over elective patients for surgery.

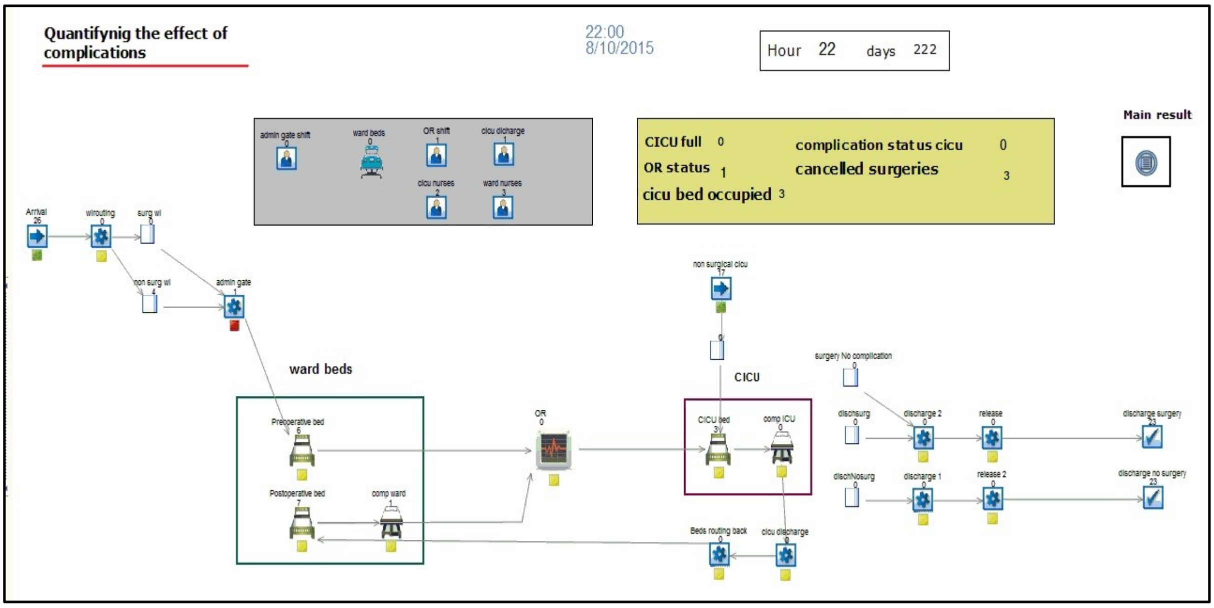



**Figure 8-2 Model screenshot of SQUH cardiothoracic simulation model**

The arrival rate of elective patients in the model is well approximated by the Poisson process. It is a common approach to model arrival to a system using this type of distribution.[334] I verified this selection using the Kolmogorov-Smirnov (K-S) test. The K-S was used for fitting other distributions. The distribution that best fit the data should produce the smallest K-S values that should be below the critical K-S statistics. Inputs parameters for the model are depicted in Table 8-1.

In practice, patients can experience complications during any time of their hospital stay, but rarely in their preoperative stay. In the model this is governed by the same probabilities obtained from the data. Once a patient experienced a complication, the model moves that patient to the complication state. In the model, the postoperative LOS distribution was estimated based on the LOS of patients who didn't experience complications. However, any patient who develops a complication will then be assigned an additional LOS corresponding to excess LOS that is equal to the marginal effect of the specific complication. For example, the additional LOS for a patient with pneumonia is 6.3 days, 23 days for stroke, and so on.

In order to obtain a steady state and improve output reliability, the model warm-up period and replications number were calculated. For the replications number (n), the half-width value of the confidence interval, h was used as shown in equation 8-2. In equation 8-1, n=required replication number, $n_0$= initial replication number, h= the desired half width of the confidence interval, and $h_0$= initial half width of the confidence interval. The deviation of the confidence interval on either side of the mean should be as low as possible (as determined by the user). The number of replications is selected at the point where the interval reaches and remains below the determined level of deviation.[71]

$$n = n_0 \times \frac{\mathrm{h}_0^2}{\mathrm{h}^2} \tag{8-1}$$

$$h = t_{n-1.1-\frac{\propto}{2}} \times \frac{s}{\sqrt{n}} \tag{8-2}$$

The number of replications was determined to be 30 replications. The value for a warm-up period was found to be approximately 6 months using the same graphical method described in section 7.3.2.4. The variable selected for measuring the warm-up period was the waiting time for surgery. Data were collected only after a steady state was achieved.

**Table 8-1 Input parameters used to calibrate the model**

| **Parameter** | **Value in baseline scenario** | **Distribution** | **Data source** |
|---|---|---|---|
| %of admitted patients who didn't require surgery | **10 %** | **-** | **Existing data** |
| Inter-arrival of non-surgical patients admitted to CICU (hours) | **55** | **Poisson** | **Existing data** |
| CICU LOS (days) | **1.04, 1.6, 48, 111** | **Beta** | **Existing data** |
| Referrals inter-arrival rate (hours) | **33** | **Poisson** | **Existing data** |
| Preoperative LOS (hours) | **1.61, 1.3, 75, 152** | **Beta** | **Existing data** |
| Postoperative LOS (hours) | | | **Existing data** |
| Isolated CABG | **0.87, 1.65, 121,577** | **Beta** | |
| Isolated valve | **1,2.21,121,685** | **Beta** | |
| CABG & Valve surgery | **121, 1.48, 199** | **Weibull** | |
| Other cardiac surgery | **121, 1.56, 90** | **Gamma** | |
| % Postoperative patients returning to theatre | **4 %** | **-** | **Existing data** |
| Surgery duration (hours) | **2.5,2.8,6** | **Triangula** | **Expert opinion** |

Decision on the model scope and level of detail are referred to as simplification and abstraction.[335] In my model, it was important to include the right level of detail and system components that were directly associated with examining the problem at hand.

#### 8.3.4.1 Collection of outcome measures

The effect of complications on the system operation was captured through collecting key performance indicators. In this section, I explain how these measures were derived:

**1) Number of surgery cancellations**

When a patient with a complication is identified in the model, a series of Visual Logic codes are triggered. For instance, the model inspects if a surgery was cancelled due to a complication or any other reasons as cancellations can also happen for reasons such as unavailability of theatre times or CICU beds. In the model, the following conditions must be satisfied for a cancellation to occur due to a complication.

1) All of the CICU beds are full.

2) At least one of the patients in the CICU is having a complication.

3) An admitted patient is ready and waiting a surgery.

4) The operating room is available during the regular working hour.

To distinguish between the types of surgery cancellations, the model records the number of cancellations due to unavailability of operating room sessions, unavailability of CICU bed as well as cancellations due to patients developing complications. At this stage, a patient is delayed from proceeding to the next event in the simulation. However, they will take precedence over other patients for surgery.

**2) Bed turnover ratio**

Bed turnover ratio is a measure of productivity of hospital beds and represents the number of patients treated per bed in a given period. It is computed according to the following equation 8-3.

$$\frac{\text{Total number of discharges (including deaths) for a given time period}}{\text{Average bed count for the same period}} \qquad \text{8-3}$$

I further calculated the "lost bed days due to complications" by observing the number of bed days that have been lost due to complication. The lost bed day rate is the forgone opportunity of admitting a new patient when a bed was not available.

**3) Waiting time and waiting list**

Waiting time can be a manifestation of insufficient capacity or inappropriate bed management.[336] Although complications might affect waiting time indirectly, it is important to trace their effect on waiting times to assess the hospital responsiveness. I only considered the waiting time related to patients scheduled for surgery. It should be noted that there are other elective patients who were admitted for non-surgical reasons. In the model, the order of the patient on the waiting list is updated each time a new patient enters the waiting list. At the end of the simulation, the model records both the means of the waiting time and the waiting list size.

**4) Surgical throughputs**

Throughputs is typically quantified by counting the number of patients who successfully received a needed services in a given time period.[337] This measure can be related to the surgical cancellation measure discussed previously. However, it is possible that one type of complication can lead to surgery cancellation, yet the overall surgery throughputs remain unchanged.

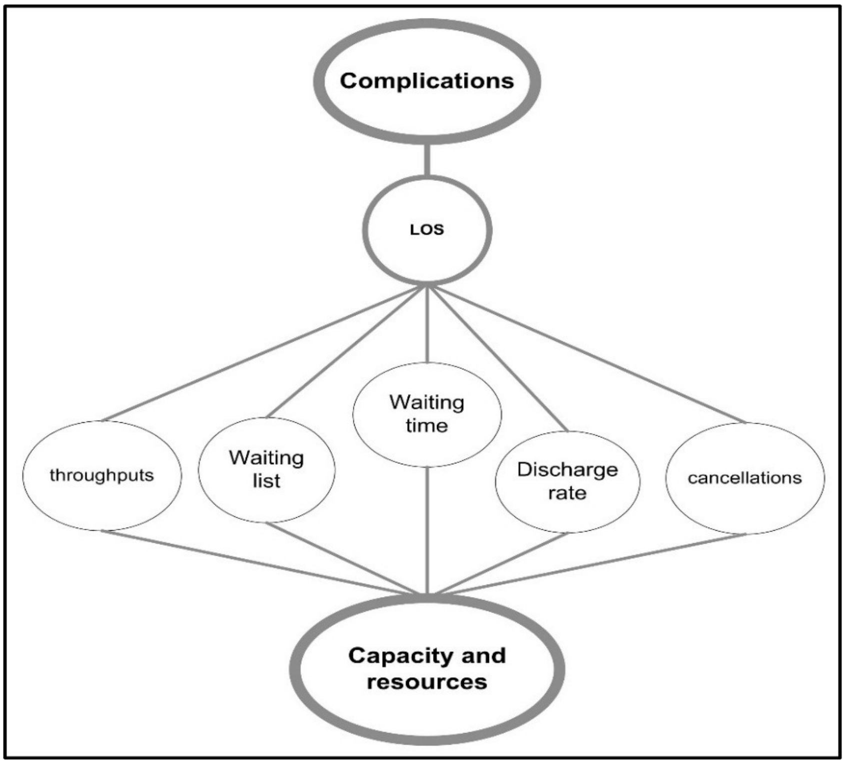



**Figure 8-3 Relationship between complications, capacity and performance metrics**

The previous outcome measures are also influenced by capacity and resources, as I illustrated in Figure 8-3, which will determine the degree to which complications can affect these measures.

### 8.3.5 Model assumptions

Owing to unavailability of some data, I made the following assumptions to simplify the model:

- I assumed that 40% of the postoperative complications occurred while patients were treated in the CICU unit and 60% occurred in the ward. This assumption was made since I didn't have relevant data regarding the location and time of where and when complications have occurred during the patient hospitalisation. However, since prolonged ventilation >24 hours was more likely to occur among CICU patients, this complication was limited to the CICU stay.
- All patients were categorised as elective or non-elective. In reality, another type of "urgent patient" is considered in the hospital priority system.
- Only one surgery can take place each day. Non-elective patients are given priority and are operated in the next day.

### 8.3.6 Scenarios evaluation

I evaluated several policies that I thought might offer some potential operational improvements. These were divided into the following two categories.

**a) Modifying the rate of complications:**

1) An extreme scenario was assumed to eliminate all types of complications.
2) Only complications deemed to be preventable were eliminated. In this case I focus on complications related to infections.
3) Elimination of the complications that are associated with the highest marginal hospital costs. Marginal cost that is equal to or greater than the 75 percentile was used as a cut-off to indicate a high charge. This was equal to 1057.48 USD. The type of complications

that met this cut-off were: permanent stroke, prolonged ventilation >24 hours, other pulmonary complications, and septicaemia.

**b) Indirect strategies that can mitigate the effect of complications:**

4) Scheduling more procedures by increasing the number of days in which surgeries are performed.
5) Adding more capacity to the CICU unit.
6) Lowering ward postoperative LOS: result have shown that only 5% of patients were discharged after the $5^{th}$ postoperative day which may reflect that the LOS was influenced by local practices rather than clinical reasons.

## 8.4 RESULTS

### 8.4.1 Results from statistical analysis

In the dataset, 48% of the patients experienced one or more complications. The most common types of complications were ventricular arrhythmia (16%) followed by new atrial arrhythmia (15.5%), prolonged ventilation longer than 24 hours (12.5%). The distribution of complications based on type is shown in Figure 8-4. Cardiac complications occurred in 26% of the patients, pulmonary complications occurred in 17%, neurological complications effected 9.5%, while 16% of the patients had infections. The difference in the postoperative LOS between patients with complications and patient without was statistically significant ($z = -9.320$, $P < 0.001$). On average, patients with complications spent 8 more postoperative days. The median postoperative hospital LOS was 8 days.

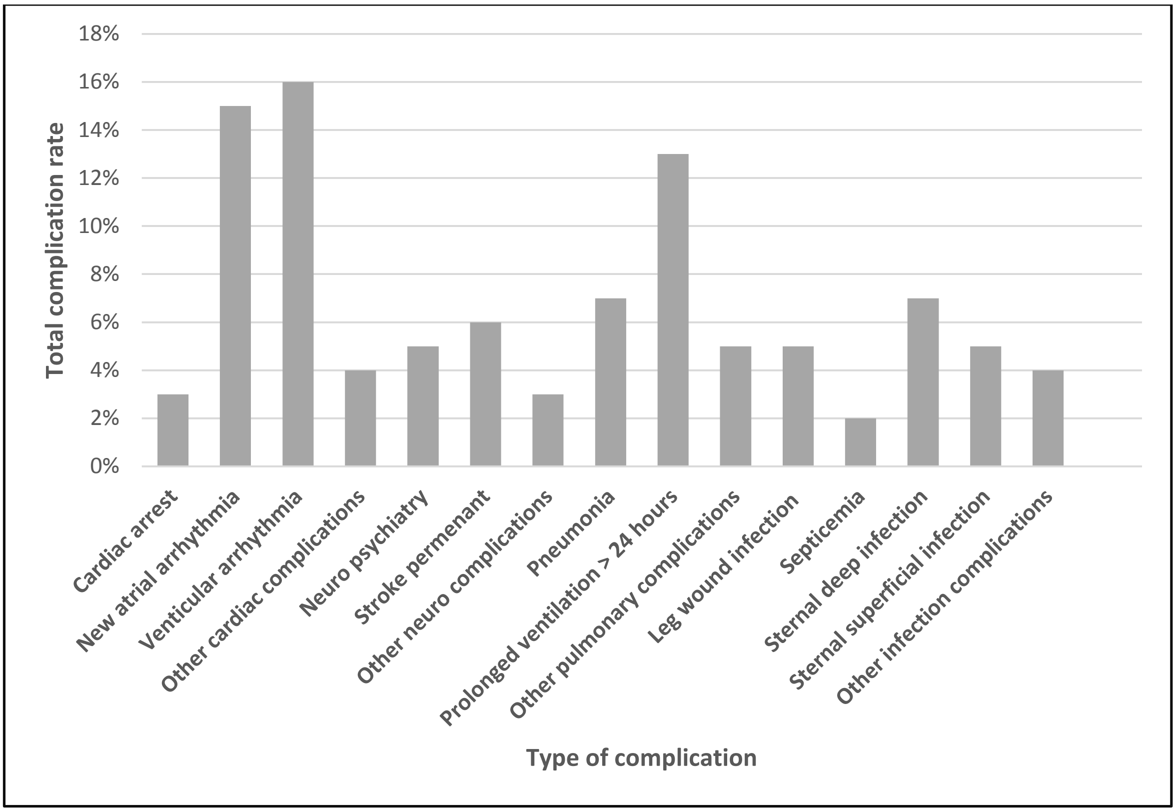



**Figure 8-4 Distribution of complications among the patients who experienced complications during their hospitalisation**

A Kruskal-Wallis H test revealed that postoperative LOS differs significantly according to the type of surgery: $\chi^2$ (3) = 41, $p < 0.001$. Therefore, I further examined postoperative LOS distributions for each type individually and reflected this in the DES model.

#### 8.4.1.1 The excess LOS due to complications

Table 8-2 lists the additional postoperative days associated with complications after adjusting for demographic variables and major comorbidities. The total number of additional days associated with infections was the highest, while cardiac complications have resulted in the lowest number of incremental days of hospital stay.

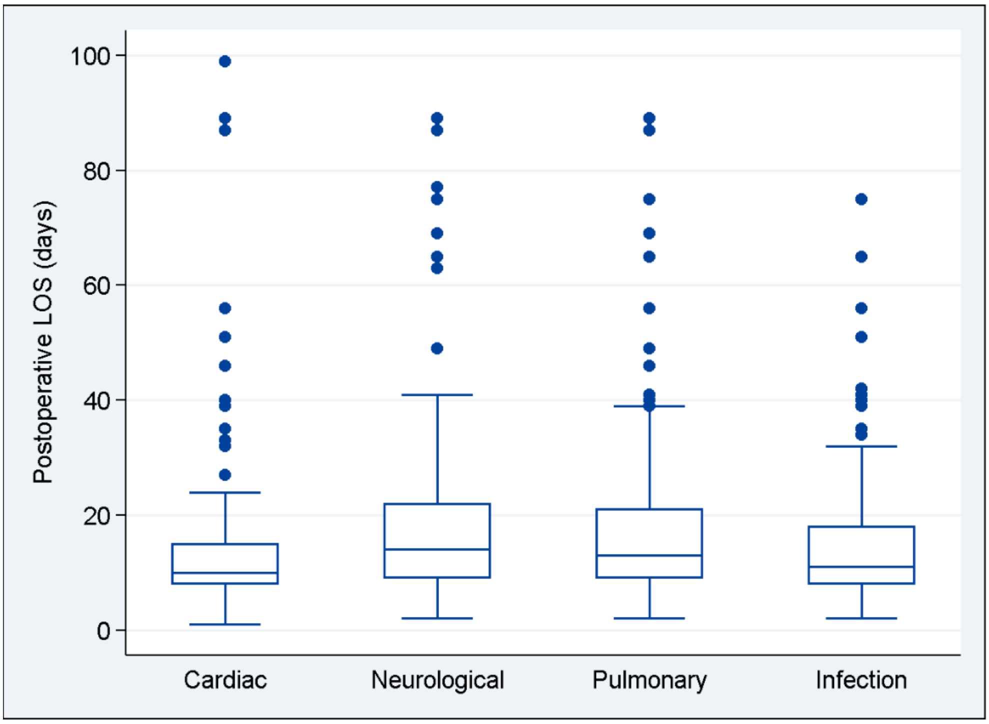



**Figure 8-5 Boxplot graph for postoperative LOS distributions among patients with different complications**

**Table 8-2 Marginal effect of complications on postoperative LOS**

| Variable | Coefficient | SE | Marginal effect (days) | *P* |
|---|---|---|---|---|
| **Cardiac complications** | | | | |
| Ventricular Arrhythmia | **0.08** | **0.04** | **0.94** | **.025** |
| Cardiac arrest | **-0.16** | **0.07** | **-1.59** | **.026** |
| New Atrial Arrhythmia | **0.02** | **0.04** | **0.27** | **.549** |
| Other cardiac complications | **0.19** | **0.06** | **2.28** | **.001** |
| **Neurological complications** | | | | |
| Stroke permanent | **1.17** | **0.04** | **22.96** | **< .001** |
| Neuro psychiatry | **-0.06** | **0.06** | **-0.59** | **.360** |
| Other neurological complications | **0.25** | **0.06** | **2.94** | **< .001** |
| **Pulmonary complications** | | | | |
| Prolonged ventilation > 24 hours | **0.39** | **0.04** | **4.70** | **< .001** |
| Pneumonia | **0.49** | **0.05** | **6.33** | **< .001** |
| Other pulmonary complications | **0.76** | **0.06** | **11.34** | **< .001** |
| **Infection complications** | | | | |
| Sternal deep | **0.35** | **0.05** | **4.30** | **< .001** |
| Septicaemia | **1.18** | **0.07** | **22.90** | **< .001** |
| Leg wound | **0.26** | **0.07** | **3.09** | **< .001** |
| Sternal superficial | **0.34** | **0.06** | **4.11** | **< .001** |
| Other infection | **0.41** | **0.06** | **5.19** | **< .001** |
| **Constant** | **1.78** | **0.09** | | **< .001** |

From Table 8-2, only two types of complications were not associated with LOS: neuropsychiatry complication (p=0.36) and new atrial arrhythmia (p=.55). Surprisingly, ventricular arrhythmia which was the highest type of complication (Figure 8-5) was associated with only 1 extra day of postoperative LOS. The extra postoperative LOS attributable to stroke and septicaemia (both at 23 days) was the highest. Likewise, the corresponding average change in LOS associated with pneumonia was 6 days.

Cardiac surgery was associated with a sizable number of expensive complications (Table 8-3). The highest marginal effect for hospital charges was related to stroke (3211 USD). The extra hospital charges associated with ventricular arrhythmia was only 170 USD, despite its high prevalence. Septicaemia and other pulmonary complications had significant associated costs (2452 and 2457 respectively). On average, patients with pulmonary complications had the highest additional cost 1415 USD vs. 1375 USD for neurological complications, 561 USD for cardiac complications, and 793 USD for infection. The results confirmed the need to use individual complications instead of aggregating them (e.g. cardiac) as some complications were proportionally higher than others in the same category.

**Table 8-3 Marginal costs associated with different types of complications**

| **Variable** | **Marginal effect (US dollar)** | ***95% CI*** |
|---|---|---|
| **Cardiac complications** | | |
| Ventricular Arrhythmia | **170.01** | **133.94 - 206.11** |
| Cardiac arrest | **950.91** | **867.32 - 1034.49** |
| New Atrial Arrhythmia | **70.07** | **32.06 - 108.06** |
| Other cardiac complications | **1054.62** | **983.74 - 1125.49** |
| **Neurological complications** | | |
| Stroke permanent | **3210.55** | **3139.09 - 3281.98** |
| Neuro psychiatry | **204.34** | **139.44 - 269.22** |
| Other neurological complications | **709.91** | **630.76 - 789.05** |
| **Pulmonary complications** | | |
| Prolonged ventilation > 24 hours | **1057.48** | **1012.16 - 1102.80** |
| Pneumonia | **733.85** | **677.09 - 790.63** |
| Other pulmonary complications | **2452.22** | **2373.12 - 2531.30** |
| **Infection complications** | | |
| Sternal deep | **516.02** | **461.28 - 570.78** |
| Septicaemia | **2456.99** | **2342.65 - 2571.30** |
| Leg wound infection | **598.71** | **531.52 - 665.91** |
| Sternal superficial | **169.24** | **106.82 - 231.67** |
| Other infection | **224.92** | **157.77 - 292.07** |

### 8.4.2 Results from the simulation model

For each scenario, the simulation model was run for one year with patients waiting times, surgery cancellations, surgery throughput, bed turnover, and cost as the output of interest. Comparison of averages over multiple simulation runs was necessary to accommodate the effect of random variation (e.g. LOS duration, arrival of new patients, etc.).

A close inspection of the results revealed that patients occupying a bed due to a complication have a significant effect on several outcome measures. It was intuitive to compare the effect on the outcome measures when all complications were eliminated (scenario 1). Table 8-4 provides a comparison between a hypothetical state of no complications and the existing state.

**Table 8-4 The effect of eliminating all complications on the system**

| Indicator | prevalence of complication | | | | change |
|---|---|---|---|---|---|
| | None | 95% CI | Existin g state | 95% CI | |
| Average surgery waiting list | **12.33** | **1 - 25.97** | **23** | **5.85-40.39** | **10.67** |
| Average surgery waiting time | **1.36 days** | **1.20 – 1.52** | **5 days** | **3.32-5.98** | **3.64** |
| Surgery throughputs | **197** | **173.12 – 220.48** | **174** | **146.22 - 202.98** | **- 23** |
| Surgery cancellations | **0** | **-** | **9** | **5.81 - 11.52** | **9** |
| CICU bed turnover | **68.21** | **60.02 – 76.41** | **60.76** | **50.84 - 70.68** | **- 7.45** |
| overall bed turnover | **18.23** | **16.06 – 20.40** | **15.66** | **13.13 – 18.20** | **- 2.57** |
| CICU nurses utilisation | **67.70** | **63.79 – 71.61** | **82.59 %** | **79.65 – 85.54** | **14.89** |
| Ward nurses utilisation | **73.79** | **72.85 – 74.73** | **73.47 %** | **72.62 – 74.42** | **- 0.32** |

The purpose of the scenario 1 (albeit unrealistic) was to estimate the burden of complications on outcome measures and provide a sense of scale of this burden. A change in all statistical indicators was observed when complications were eliminated (Table 8-4). For example, waiting time for surgery fell from 5 to 1.36 days, a decrease by almost 73%. In the model with zero complications, 23 more surgeries were performed. While CICU bed turnover was improved by a reasonable number (+7.45), overall bed turnover improved by lesser amount (+2.57). This is due to the limited number of beds in the CICU unit. The total bed days lost due to complications was 310 days. On average, each bed in the cardiothoracic department was occupied 15 days a year by patients with complications.

I further examined the effect of each type of complications on the system performance by adding each type to the model separately. Complications were aggregated based on four types (cardiac, pulmonary, infection, and neurological). The results are shown in Table 8-5.

**Table 8-5 The effect of each type of postoperative complications on operation metrics based on the location where patients experienced complications**

| Key performance Indicator | Type of complication † | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Cardiac | | Pulmonary | | Infection | | Neurological | |
| | CIC | Ward | CICU | Ward | CICU | Ward | CICU | Ward |
| **Average surgery WT** | 1.37 | 1.39 | 1.53 | 1.74 | 1.57 | 1.48 | 1.61 | 1.51 |
| **Bed turnover** | 18.13 | 17.81 | 14.77 | 17.23 | 19 | 17.51 | 18.90 | 16.64 |
| **Surgery throughputs** | 195 | 191.97 | 159.23 | 185.30 | 204.17 | 189.07 | 195.51 | 180.10 |
| **Surgery cancellations** | 1 | 0 | 6.31 | 4.83 | 3.17 | 0 | 5 | 0 |

† The effect of each category was measured when other complications types were set at zero. Additionally, in order to estimate the effect of complications occurring in the CICU and ward separately, complications were only allowed to occur in the respective location in the model.

As can be seen from Table 8-5, pulmonary complications were the most common type associated with surgery cancellations. This is the case because pulmonary complications were common in the CICU and consequently they reduced availability of beds leading to surgery cancellations. According to the model output, it was unlikely that a surgery would be cancelled if patients are treated for complications in the ward. A notable exception was when patients experienced pulmonary complications in the ward which have resulted in approximately 5 surgery cancellations. The category “other pulmonary complications” which constitutes 4.5% of the total type of complications were associated with substantial postoperative excess LOS (11.34 days). These complications were consequently responsible for delaying patients transfer from the CICU unit. Pulmonary complications had also reduced the surgery throughputs more than any other type of complications.

### 8.4.3 Scenario experimentations

In this section, I provide results from other scenarios experimentations. Six performance metrics are listed in column 1 of Table 8-6.

**Table 8-6 Comparison of various scenarios on performance. 95 CI are in brackets**

| Scenarios | Waiting for surgery | | Theatre performance | | Bed turnover | |
|---|---|---|---|---|---|---|
| | WT (days) | WL size | cancellations | throughputs | CICU | overall |
| **Baseline** | **5** **(3.32-5.98)** | **23** **(5.85-40.39)** | **9** **(5.81-11.52)** | **174** **(146.22-202.98)** | **60.76** **(50.84-70.68)** | **15.66** **(13.13-18.20)** |
| **1. no complications** | **1.36** **(1.20-152)** | **12.33** **(1-25.97)** | **0** **-** | **197** **(173.12-220.48)** | **68.21** **(60.02-76.41)** | **18.23** **(16.06-20.40)** |
| **2. eliminate infections** | **3.31** **(2.72-3.89)** | **14.25** **(1-28.46)** | **10** **(7.77-12.50)** | **188** **(165.60-211.80)** | **65.61** **( 57.55-73.67)** | **17.47** **(15.37-19.58)** |
| **3. eliminate high cost complications** | **1.711** **(1.49 -1.93)** | **14.06** **(1-28.15)** | **3** **(2.26-3.74)** | **188** **(164-212)** | **65.33** **(56.92-73.73)** | **17.50** **(15.28-19.73)** |
| **4. Increasing OR operating days** | **3.89** **(3.20-4.58)** | **15.17** **(1-18.92)** | **15.17** **(11.71 – 18.62)** | **204.17** **(186 -221)** | **70.58** **(64.50 – 76.66)** | **18.45** **(16.87-20.02)** |
| **5. Extra 1 ICU bed** | **3.52** **(2.92-4.12)** | **2.02** **(1.71 – 2.44)** | **3.87** **(2.87 -4.87)** | **218.47** **(215.80 -221.13)** | **75.60** **(75.06 -76.14)** | **19.84** **(19.65 -20.03)** |
| **6. Lowering postoperative LOS by 40%** | **1.36** **(1.19-1.54)** | **13.29** **(2-29.64)** | **18.67** **(15.58 – 21.76)** | **196.60** **(174.70 – 218.50)** | **68.47** **(60.86 – 76.08)** | **18.43** **(16.40 – 20.47)** |

A substantial system improvement can be gained by lowering the rate of infections. The only outcome measure that was not improved by eliminating infections was the surgery cancellation. It has increased by 1 cancellation from the baseline scenario. Since septicaemia was associated with a very high incremental LOS, I examined the effect of reducing this complication by 50%. The number of bed days that can be essentially saved by eliminating septicaemia are (23 days × the number of patients experiencing septicaemia). In the model, 50% reduction in septicaemia has resulted in reduced waiting times by 9% from the baseline.

Scenarios number 3 examined the elimination of high cost complications. As such, the results compared favourably across all outcomes. The rest of the scenarios were related to modifying the existing system. An increase in OR operating days has dramatically increased the number of throughputs (204 vs 174 in the baseline). However, this increase was offset by the increase in surgery cancellations (15 vs. 9 in the baseline). Additionally, waiting time improved modestly (4 days vs. 5 days). In contrast, the addition of 1 extra CICU bed decreased waiting list and cancellations. It has also resulted in increased surgery throughputs and bed turnover. The proportion of patients who waited for surgery has fallen considerably when an extra bed was added. Finally, the reduction of postoperative LOS by 40% has reduced waiting times. However, it has stimulated more cancellations than any other scenario.

### 8.4.4 Model validation

To validate the model I first met with the surgeons to ensure conceptual validity of the model (face validity). The aim was to verify that the simulation model was a credible representation of the system and that the theory behind its construction was acceptable. Second, as discussed in the methodology chapter, historical data from one year were compared against predicted data (average from 30 simulation runs).[23] To this end, the first step was to identify the key parameters with which to validate the model. These are presented in the first column of Table 8-7. The t-test distribution was used to test the null hypothesis (there is no statistical difference between the real and simulated sets). Then the null hypothesis of the two-tailed test is to be rejected if $H_0$: $|T| \leq t_{\alpha/2,\, n-1}$. Results of this test are presented in Table 8-7.

**Table 8-7 Validation of the model against historical indicators using hypothesis testing**

| Statistical indicator for one | Observed data | Average from simulation runs | p-value | Variance % | $H_0$ |
|---|---|---|---|---|---|
| Average preoperative LOS | 5.1 days | 4.9 days | .09 | -3.92 % | Accept |
| Average postoperative LOS | 8.8 days | 9.8 days | 0.07 | + 11.36 % | Accept |
| Average postoperative LOS in patients with | 17 days | 16 days | 0.22 | -5.88% | Accept |
| Average waiting time | 11 days | 9 days | 0.12 | -18.18 % | Accept |
| Completed surgeries | 164 | 193 | - | +17.68 % | - |

The observed and simulated datasets were similar with small discrepancies. Thus, it can be concluded that the baseline model adequately represented the behaviour of the real world system. I couldn't validate the number of cancellations that occurred due to complications as there were no records kept anywhere in the hospital. However, the obtained average number of cancellations from the simulation runs was verified by the surgeons and found to be reasonable and approximate reality.

## 8.5 DISCUSSION

My goal was to examine the effect of complications on some essential patient flow metrics. The findings from this study suggest that several postoperative complications were independently associated with increased hospital stay. Moreover, the marginal LOS attributable to these adverse events was a significant source for surgery cancellations, lower bed turnover rates, and extended waiting lists.

The dynamic complexity of hospital processes raises the difficulty in assessing the impact of complications on the hospital performance. The main challenge is to trace this impact across several processes and to isolate the effect of complications on resources from among other factors. For example, surgery cancellations can occur because of several medical and non-medical reasons.[338] The challenge is also exacerbated by uncertainties surrounding patient care such as arrival of emergency patients that can impact upon operational performance. For these reasons, I used DES as a tool to integrate all these factors along with data from existing complications to assess how different parts of the system would behave if a change in the existing system was introduced. DES is the methodology of choice for operational problems involving sequential events and where lack of resources might lead to delays.[339]

### 8.5.1 The utility of measuring the effect of complications on operational performance

The research was motivated by lack of existing mechanism to measure complications impact on operational performance. The feasibility of modelling adverse events and their effect on hospital resources and thus operations can provide compelling evidence for building a business case for quality improvement initiatives. Second, given the current economic climate in Oman, it is imperative to understand how adverse events such as infections would impact bed occupancy. Therefore, a measure that can quantify the potential gain from reducing adverse events should have a contemporary relevance.

As I have demonstrated, hospital operations can be improved by reducing complications, an intangible factor that often less considered in planning resources. Modelling the effect of adverse events on hospital operations permits decision makers to identify the specific services that would be impacted and to provide empirical evidence on the effect on performance.

### 8.5.2 The effect of complications on the operational performance

Adverse events are directly linked to increased cost,[340] and LOS.[341] The economic feasibility gained from reducing complications is well documented.[342] A study in the United States found that pneumonia following valve surgery was associated with $29,692 increase in hospital costs and 10.2-day increase in median LOS.[343] Post-CABG complications resulted in incremental increase of 5.3 days in LOS among Medicare beneficiaries.[340] Patients with excessive postoperative haemorrhage were at risk of experiencing higher stay in CICU for longer than 3 days, receiving ventilation for longer than 24 hours, and returning to operating room for reexploration.[344]

The current study expands the effort to measure the effect of complications on several operational performance metrics. I found that the incremental LOS associated with complications was a source of variation that affected operations. The variation was introduced as a result of series of events triggered by the occurrence of complications. I demonstrated that this effect can be measured across patient hospital stay. The results demonstrated that adverse events which occurred early in the CICU had higher impact than those that have occurred in the ward. This was due to the limited number of beds in the CICU unit. Much of the reduced operational performance was related to occurrence of pulmonary complications. This can be attributable to two reasons. First, pulmonary complications such as postoperative respiratory failure are common following cardiac surgery.[345-347] This was also reflected in the dataset. For example, pneumonia and the need for prolonged ventilation were among the most common reported complications. Second, these complications are often associated with prolonged LOS.[169, 209] Hospitals might target more resources to reduce some modifiable risk factors prior to surgery. Potentially modifiable risk factors of pulmonary complications include body mass index, smoking status, and chronic obstructive pulmonary disease.[348]

Stroke remains a devastating complication despite advances in perioperative care.[349, 350] 6% of the patients in the dataset developed stroke and their LOS were among the highest in all patients. Like other complications, the predictors of strokes are known and much of the improvements can be realised by effectively dealing with potentially modifiable risk factors.[351]

Atrial fibrillation is the most frequent complications that occurs after cardiovascular surgery.[237] Unlike previous studies that have found significant LOS attributable to atrial fibrillation,[161, 163] the excess LOS associated with atrial fibrillation in my study was less than 7 hours.

Improvement in the standard treatment of this complications might have contributed toward lowering patient LOS.

#### 8.5.2.1 The impact on patient flow

In the model I had two waiting lists (for surgical and non-surgical patients). Surgical patients were given priority to non-surgical patients. The average waiting time for surgical patients was considerably lower as waiting time for a cardiac surgery was not an issue in this particular hospital. However, waiting for cardiac surgery has been considered as one of the most important issue in many hospitals.[249] I incorporated waiting time in the model as many operational issues eventually manifest in the form of extended waiting times.

There are many factors that affect waiting time. Previous research has not linked them to the occurrence of adverse events. In fact, the focus was given on determining the effect of prolonged waiting time on morbidity and mortality.[352, 353] Under the six scenarios, waiting times were favourably compared to the existing state.

I observed that by adding an extra CICU bed, the waiting time has not improved considerably. This mainly occurred as a result of the increased number of patients. It is known that demand for resources in healthcare is dependent on supply.[354] Hence the expression “if you build it they will come” can be relevant in this situation. Extra capacity can induce demand for services and unless complication rates can be reduced, adding physical capacity might not be the optimal solution. In traditional resource management, increasing capacity is well regarded as an option for improving operational performance.[75]

The average waiting time increases at higher levels of utilisation.[355] The relationship can be expressed by the following simple equation (8-4): [355]

$$\text{utilisation}/\,(1-\text{utilisation}) \qquad \text{8-4}$$

For example, the utilisation of CICU beds in the example was .82. The ratio of .82/ (1-.82) equates to 5.55. When an extra bed was added, this ratio increased to .86/ (1-.86) = 5.85.

In the model, eliminating infections or high cost complications are viable option that can save life, improve patient satisfaction and contribute toward improving the hospital productivity. The choice between adding more resources such as 1 extra CICU bed and investing in quality programmes to reduce complications should be evaluated based on how much potential cost will be avoided (e.g. costs associated with the extra LOS).

While ICU capacity strain is linked to increased morbidity and lost hospital revenue, increasing the number of ICU beds increases the hospitals fixed costs at the same time.[356] Based on the results, some efficiency can be gained by reducing complications. This will allow the maximisation of the use of existing resources to produces the greatest output. The CICU services at the facility were in constant high demand from surgical and non-surgical patients. With limited number of CICU beds in the country, non-refusal policy for CICU access is critical for unimpeded flow of patient.

Theoretically, many infections are reasonably preventable.[357] In for profit hospitals, the extra cost that might be incurred to finance quality initiatives aimed at reducing infection for example could be defrayed in part by increased revenue from the increased number of admitted patients possible by improved bed turnaround (scenario 1, 2, and 3). However, it should be noted that high bed occupancy might leave units understaffed, and in return, increase the number of patients experiencing complications.[358]

While my intention was to model postoperative complications, postoperative LOS appeared to be an issue in this hospital. Less than 5% of the patients were discharged home after the fifth day post-surgery which could reflect the influence of local practice rather than the medical conditions of the patients. I chose to test a scenario where postoperative LOS was reduced by

40%. The decrease was coupled with increased cancellations rate. The freed capacity in the ward has stimulated an increase in the number of patients who were treated in the CICU, thus contributing to the high utilisation of its beds leading to higher cancellations. Respectively, preoperative LOS was considerably high averaging 5 days. This has been recognised as a problem in many healthcare systems. The move toward "same-day surgery" programs was a response to avoid unnecessary LOS that adds cost and might not add value to the patient's care.[359] In general, prolonged hospitalisation is associated with increased risk of complications[360] and may indicate shortcoming in patient safety.[361]

### 8.5.3 Simulation vs. analytical methods

Other analytical approaches such as queuing theory can be used to model relationship between complications and capacity. However, analytical methods contain less details than simulation, and are based on simplified models.[362] The interaction and interdependency between resources in the DES model cannot be effectively analysed using analytically derived formulas.

## 8.6 LIMITATIONS

### 8.6.1 Limitations of the statistical models

One potential limitation of this study is the extent to which of its results can be generalisable. The data pertain to a specific population and specific setting, therefore, results might not be generalisable to other populations or settings with different characteristics. However, the method and interpretation of the models are generalizable.

There are various factors affecting LOS and resource utilization beside complications such as physician judgments, hospital policy, and adequacy of resources. The current study was limited by data availability that was routinely collected. Therefore, the factors that were not accounted for when calculating the excess LOS attributable to each type of complications might have a significant effect. However, I think the existing data were sufficient to provide an overall measure for predicting excess LOS evident by high discriminative power.

### 8.6.2 Limitations of the simulation model

One of the limitations of the simulation model was the absence of data on the location where each complication has originated. This can have a significant impact on results concerning resource utilisation in the CICU and the ward. As such, complications leading to prolonged LOS in the CICU would have a greater impact on patient flow than complication occurring in the ward. Second, it was difficult to track whether cancellation was due to occurrence of complications in the downstream beds or for other reasons. Instead, I obtained a subjective expert opinion to compensate for this missing variable.

The reader should be aware that the number of cardiac procedures in the hospital under study was relatively low. The implication for this is that the pressure on resources was relatively less compared to other hospitals. Thus, the hospital might not have the incentive to expedite patient discharge. Moreover, hospitals in Oman are not required to meet specific waiting time targets for cardiac surgery. In healthcare systems where waiting times are closely monitored, LOS are expected to be shorter to accommodate more patients from the waiting list.

## 8.7 CONCLUSION

The study provides evidence supporting the need to incorporate adverse events in resource planning to improve hospital performance. I attempted to quantify the effect of complications using DES. I found a significant impact of complications on LOS, surgery cancellations, and waiting list size. The effect on operational performance was profound when complications occurred in the CICU where a limited capacity was observed. Excess LOS spent in the hospital constitutes a lost opportunity for admitting more patients. A marked decrease in adverse events would be required to effectively deal with the negative consequences on system performance.

The growth of cardiac care services in Oman has been slow relative to the population density. Maximising existing resources would be an option as adding more resources might not guarantee higher level of services. One way to accomplish this is by reducing avoidable complications. In the model this has not only reduced cost, but also significantly improved performance of other metrics.

As there is scarce research quantifying the effect of complications on patient flow and overall operational performance, I recommend further research in this area. An explicit measure of complication should be an integral part of hospital resource planning to improve resource utilisation and perioperative patient experience. Hospitals may consider integrating the method discussed in this study into existing health information system.

# Chapter 9

# GENERAL DISCUSSION

## 9.1 CHAPTER OVERVIEW

In this chapter I will provide a general discussion of the results and how they fit to the overall objectives of my research. I will highlight the value of planning resources by incorporating variation among patients and the importance of segmenting patients based on their expected resource utilisation. In the last section, I will discuss the study limitations.

## 9.2 THESIS OVERVIEW

The purposes of this study were to explore the relationship of patient variability in predicting resource utilisation, in addition to optimising patient flow by considering this variation. There were four research questions. The first two were to explore factors affecting resource variability among cardiac care patients. The third question was to investigate how variability related to patient profiles can be incorporated into resource management. The fourth question was related to the effect of complications (which are regarded as a source of natural variability) on operational performance. A descriptive study of the two hospitals was used, and routinely collected data were obtained from local hospital information system. Descriptive statistics of some important indicators were presented in chapter 5. A multivariate analysis was then presented in chapter 6. In chapter 7, I presented an application of managing patient flow and admission utilising patient variability. Finally, I made the case in chapter 8 for the need to consider complications in hospital resource planning.

### 9.2.1 LOS as a proxy for resource utilisation

LOS was selected to approximate resource use in this research because patients' LOS occupies a central place in hospital resource planning. It perhaps the most single used indicator of resource consumption since data on LOS are relatively easy to retrieve and can be more reliable than other types of data such as cost (both hospitals lack detailed cost data). Only few resource utilisation measures, namely LOS and readmission, have been endorsed by the National Quality Forum in America.[363] It is also a common practice in many research to use LOS as an indicator for hospital performance.[364]

#### 9.2.1.1 LOS skewed distribution

It is tempting to use ordinary least squares regression for modelling LOS. However, this method requires that the dependent variable to satisfy normality, homoscedasticity, and independence assumptions (more formally, the residual error must satisfy these assumptions).[23] Health utilisation and costs data are not normally distributed, as they tend to be highly skewed to the right (i.e. asymmetric).[23, 365] For this reason, models based on the normality assumption would produce results that do not represent the observed LOS distribution. It is surprising to see that much LOS research utilise models assuming unskewed data such as ordinary least regression (see some examples in the systematic review by Mingshan Lu et al[366]). Such practice has led some researchers to claim that most studies on LOS have not been subjected to well-designed modelling.[253]

### 9.2.2 Justification for using discrete event simulation as a research tool

I used DES mainly as a tool to answer the research questions. Law and Kelton[334] describe DES as the modelling of a system as it evolves over time by representing the instantaneous change in the state variables at separate points in time where events will occur. Based on my research questions, the methodology of choice had to: 1) be able to reflect interconnected activities that are linked to waiting lists which are subject to random variation, 2) quantify the effect of introducing several scenarios, 3) be able to handle process timing for individual patient (e.g. LOS), and 4) reflect the individual characteristics of patients.

DES was the best choice over other simulation modelling techniques such as agent based and system dynamics simulations that have been previously used to solve issues related to healthcare. In agent based simulation, agents have attributes or characteristics and interact dynamically with other elements in the model based on certain rules.[367] Even though agent based simulation shares common features with DES such as entities interacting with each other, agent based simulation is inappropriate for incorporating "system rules"[368] such as working hours, routing disciplines, and priority system. System dynamics, on the other hand, addresses issues by considering aggregates (stocks and flows) not individual entities.[369] A central tenet of system dynamics is that the complex behaviours of organizational and social systems are the result of ongoing accumulations of people, material or financial assets, information, or even biological or psychological states.[370] Unlike in DES, the state of the system gets updated continuously in system dynamics simulation.[371] System dynamics approach is deterministic whereas DES is stochastic.[371] This approach was not appropriate for my research because the emphasis is on policy rather than decisions as system dynamics are not used for optimisation or point prediction.[368] Differences between the three common types of simulations in terms of abstraction level and use are depicted in Figure 9-1.

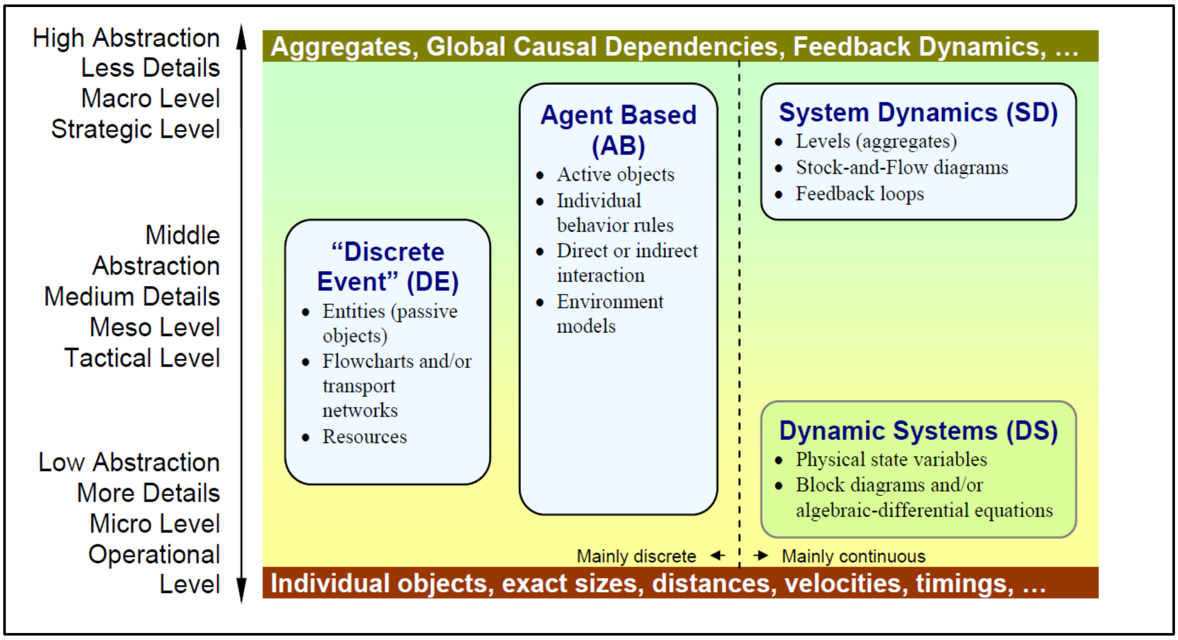



**Figure 9-1 Comparison between common simulation modelling types**
Source: Borshcheve and Filippov[367]

Several non-simulation techniques are also commonly adopted to understand issues related to resource allocation in healthcare facilities. These include queuing theory (based on Erlang equation),[372] Markov chain analysis, and linear programming.[216] Other modelling approaches such as statistical and mathematical modelling, are commonly used in healthcare operational research.[64] However, analytical models have several limitations including failure to accommodate complexity of dynamic systems.[334] For example, queuing theory assumes the arrival rate, service rate, and service capacity are all stationary. This mean that while variation may be present, the mean of a process does not change with time.[373] In real systems, this assumption doesn't apply. Conversely systems parameters are not required to be stationary in DES and can be drawn from appropriate distributions. Many of the concepts in my research such as tackling bottlenecks, waiting times, and cancellations have been previously addressed with the application of queuing theory.[374-376] However, models in these studies do not reflect the complexity and interdependencies of the subsystems which cannot be effectively analysed using analytically derived formulas.

DES provide lot more modelling flexibility and are capable of modelling real-world system with complex patient flow and care process. Eldabi et al[377] suggest that DES has several advantages over common quantitative methods (Table 9-1). DES permits modelling the details of complex patient flows with more realistic representation, hence greater confidence in the results.[378] DES also, as seen in chapter 2, has been widely used to inform decisions regarding optimal allocation of resources.[339]

**Table 9-1 The use of DES to cope with weakness in quantitative methods**

| Quantitative Methods | Discrete Event Simulation |
|---|---|
| Orderliness and linearity | Deals with non-linear relationships and incorporates feedback loops |
| Lack of concern over the influence of resource constraints | Ability to incorporate resources and constraints |
| Exercise in "post-decision rationalisation" | Can be used for problem structuring and discovery |
| Use of closed survey instrument reduces deeper understanding of what is actually occurring | Possible to include soft variables from open surveys and expert opinions |
| Relatively weak when used with the objective of discovery; relatively poor discoverability during data collection | Rich in discovering problems during development and processing as well |
| Methodology of verification rather than discovery | Used for enhancing understanding and testing hypotheses |
| Inability of researchers to observe something without changing it | Provides rich pictures of interactions and helps in objective analysis |
| Positivism demands an absolute level of generalisation | Offers capabilities to model different possible scenarios |
| Relies on measurable evidence and therefore influences a high degree of control over the phenomenon | Able to generate measurable evidence as well as intangible evidences |
| Do not recognise the variability that is inherent in human behaviour | Cope with high levels of variability within/between the modelled variables |

Source: Eldabi *et al*[377]

The rapid advancement in simulation software technology has created numerous new application opportunities.[77] Intangible information (e.g. patient preferences, complications effects, satisfaction, patient severity, etc.) can be retrieved and incorporated into DES.

Therefore, simulation can facilitate knowledge discovery that otherwise difficult to obtain using traditional scientific enquiry methods.[377] DES has been used as research methodology to test hypotheses about the system behaviour towards changes.[334] Simulation modelling, thus, can be considered as a quantitative method that can incorporate measurable aspects.

The outcomes of interests in this thesis have been around capturing patient waiting times, resource availability, surgery cancellations, and bed turnover rates. These system performance measures are directly linked to resources and processes variation within hospital. In DES, entities (i.e. patients) can take several attributes which can govern specific interactions with resources. Furthermore, entities states (e.g. complications) can also be changed as simulation model progresses through time. In the context of this research, patients can experience complications (events) during hospital stay and hence trigger more resources. Therefore, the spell-over effect of adverse events is passed to other processes. The interconnection between patients' attributes, resources, uncertainty level, and system constraints makes DES to be the most appropriate method for achieving the objectives of this research.

Currently, there are several simulation packages available in the market. It was difficult to determine beforehand which simulation software or which functionality of the software are most relevant for this project. My selection of Simul8 was based on its popularity among healthcare modellers, ease of use, and flexibility. Most importantly, unlike some other software, Simul8 uses internal programming language known as Visual Logic which allows more complex representation of processes and interactions.

## 9.3 PATIENT VARIATION AND ITS EFFECT ON OPERATIONAL PERFORMANCE

In section 5.5.2, I found that some of the variation in LOS can be explained by hospital type. This suggests that the artificial variation related to the local practices is contributing to the observed differences in resource utilisations between the two hospitals. These differences between the hospitals could be anticipated for two reasons. First, the two hospitals belong to different governmental organisations. Second, they differ in the core function of their mission. SQUH is an academic hospital linked to a medical school and teaching students is among the priorities of the hospital.

In regards to patient planning, there is consensus amongst researchers that artificial variation should be minimised.[18, 20, 379, 380] Fortunately, it is easier to control artificial variation rather than to manage natural variability.[20] For example, hospitals have greater control over admission and discharge practices, staff scheduling, human resource management, and even the level of staff competence. However, based on my experience, changing any of these aspects is still a difficult task. Hospitals are bureaucratic organisations with many departments operating in silos.[381] So promoting changes within different stakeholders requires commitment from top-level decision makers, possibly at the national level. Another difficulty stems from measuring intangible factors such as physicians behaviours and preferences.

Analysis of patient characteristics of this study population revealed the sample to be different from other published cardiac care studies. It involved a younger population. Patients also had higher rates of diabetes, hypertension, hyperlipidaemia, and obesity in comparison to other studies.[382-384] The average LOS was also higher than what has been reported in most studies. The patient related factors explained some of the variability in LOS. Age which has been found in several studies[175, 185, 269, 301, 384] to be a determinant factor of CICU LOS after a cardiac surgery, was not associated with postoperative LOS in my study. Comorbidities such as renal failure or dysfunction, congestive heart failure, and pulmonary hypertension had an influence on resource utilisation.

In the current study I found that variation among patients undergoing cardiac interventions was significant which should warrant some attention. Inappropriate management of this variation can lead to unnecessary utilisation of resources. Both hospitals do not monitor how patient mix affects resource utilisation. Such measure can provide an indication of the level of imbalance between capacity and demand. I demonstrated how DES models can bridge this gap.

Only two remedies are usually considered in response to limited resources in hospitals: rationing or continued addition of staff and beds in wasteful cycles of expansion.[380] Both alternatives are difficult to implement in the two Omani hospitals. The Omani government has recently cut funding to the healthcare sector in response to the sharp decline in oil prices. Further austerity measures are expected to be approved. Meanwhile, the government is obliged to provide healthcare services free of charge to all citizens and rationing existing services will be met with greater public discontent. Therefore, efficient practices that include limiting artificial variation as well as managing natural variability is a viable solution. Managing the natural variability represents a promising area. As publicly funded hospitals in Oman continue to be challenged by resource constraints and aging population, it is my view that strategies dealing with patient variability will become important tools in managing patients. The price of ignoring this variability can be dire to hospitals. Inefficiency in patient flow can diminish operational performance. In the absence of variation measures, hospitals might increase resources in areas that are not bottlenecks which yields no benefits to operational performance.[385]

The present study revealed that natural variation can be measured and its effect on resources and operational performance can be estimated. Poorly understood dependencies between patient variations and resource use may have contributed to the lack of resource management models designed for managing variation.

### 9.3.1 Planning for variability

Variation exists in processes, people, systems, and in the outputs produced by systems.[386] Several studies examined factors that impact LOS without attempting to suggest strategies to cope with variation introduced by these factors. I found out that there is a gap in literature about incorporating these factors into hospital resource planning. My results revealed that natural variability directly influences resource utilisation. By using simulation models, I was able to identify how this variation has also affected operational performance. More importantly the analysis confirmed that variability in resource utilisation is predictable. Several factors emerged to be significant to resource utilisation among cardiac patients from which LOS prediction can be made. Given the uncertainty about the factors that actually determine patients flow in the cardiac care, this thesis contributes toward understanding and managing variations in resource use related to patients and treatment factors.

Most of the healthcare simulation studies that I reviewed in chapter 2 attempted to achieve this aim. That is, they had put more emphasis on fixing variation caused by the structure or the design of the delivery system rather than ways to accommodate natural variation. Artificial variation has been called "unnecessary variation" that is often linked to cost and process inefficiency.[387] Healthcare managers are primarily concerned with the performance of care process over time. Their goal is to create processes that are stable and effective.[388] Techniques such as six sigma, statistical process control, and lean thinking were adopted from other sectors to address system variability in healthcare.[389] On the other hand, natural variability is more difficult to measure and eliminate. Providers expect delay, cancellations to be caused by individual differences between patients including complications. However, managing this type of variation in order to optimise resources has not received as much attention due to the perception that it is less significant than system variation.[19, 390]

I do not, however, underestimate the consequences of inefficient system structure (e.g. uncoordinated activities and processes). In fact, I found that preoperative care was excessively long in both hospitals, possibly due to lack of effective surgical pre-assessment care or due to practices not related to patient condition (e.g. cultural considerations). The need to eliminate inefficiencies in the Omani healthcare system has been previously highlighted by Al Farsi et al.[391]

In chapter 6, I identified clinical factors that explained differences in LOS. The premise here is that knowing in advance these factors - both clinical and non-clinical- would allow better planning of patient care and thus smooth patient flow. There was substantial variability in LOS among surgical care patients. Thus, a significant variability in patient flow can be attributed to factors associated with LOS. This type of variability can introduce stress to the system which can contribute to operational dysfunction and adverse patient outcomes.[20] In chapter 7 I offered some practical ideas on how clinicians and hospital managers can gain greater control over patient scheduling and monitor the impact of patient assignment.

In chapter 7, waiting times and surgery cancellations were reduced when scheduling was based on patients' factors. The strategies involved 1) minimising LOS in the CICU unit by scheduling patients based on their expected LOS, 2) scheduling patients toward the end of the week, 3) early discharge of patients based on expected LOS, and 4) reducing the number of surgical patients who would otherwise be expected to stay longer in hospital. These examples demonstrate the value of using determinant factors for LOS in planning patients scheduling and admissions.

When admission and scheduling are based on patient mix, hospitals become proactive in optimising patient flow.[392] Waiting lists provide some degrees of freedom for a hospital to select on priority. However, the policy on selecting patients differs greatly between hospitals.[392]

Table 9-2 provides some examples that distinguish reactive vs. proactive strategies in balancing capacity with demand.

**Table 9-2 Basic strategies to match supply with demand (some example)**

| | Reactive | Proactive |
|---|---|---|
| **Level strategy** | Delaying admissions following a high bed occupancy | Admitting patients based on real-time information on bed utilization |
| **Chase strategy** | Opening and closing beds following the bed occupancy rate | Allocating beds to the emergency department using forecasts on the expected number of emergencies |

Source: Gemmel & Van Dierdonck[392]

While several researchers have consider patient mix in resource planning, they have done so from a general perspective. For example, Adan et al[17] distinguished cardiothoracic groups based on whether the patient was simple or complex case, short/long procedure, and duration of intensive care use. It is unclear how these groups were derived. A definition of patient mix may also include whether a patient is elective or non-elective.[41] Patient mix can also be defined according to the types of speciality[5] or diagnosis (i.e. DRG groups).[393] Patient grouping, apart from a medical grouping, is essential for planning resources.[17] Gemmel & Van Dierdonck argued that classifying patients into resource-homogenous groups is crucial in order to predict the resource requirement of a scheduled patient.[392] Grouping patients according to their workload for resources will make this planning problem more manageable. Whether a particular patient mix definition is sufficient for resource planning will depend on the level of homogeneity within individual groups which can be evaluated statistically. Using patient characteristics rather than diagnosis to create patient groups according to resource utilisation in this research was a way to enable further investigation of these factors. In addition, grouping patients in this way, is a common approach for prediction models which many clinicians are familiar with.

In Oman, cardiovascular risk factors have increased in the past decade. For example, the prevalence of hypertension has been estimated at 27% in 1999 and 40% in 2008.[10, 394] So sicker patients with several comorbidities are expected to be admitted in higher numbers. The impact of comorbidities on patient flow and thus hospital operational performance should not be underestimated. The effect of variability in resource use introduced by patient conditions can be managed through scheduling and admission policies that effectively account for patient differences. For example, aggressive treatment of comorbid diseases prior to surgery can speed up patient recovery.[56] Patients can also be selected for fast-track pathways based on their prognosis to reduce LOS.[395]

Oman has also experienced population increase due to an influx of foreign workers (the population increased from 3.5 million in 2010 to 4.4 million in 2015).[396] This is more likely to put pressure on existing cardiac care services. Coupled with already decreased funding, the two hospitals are more likely to experience higher waiting times. Wait times have been described as a systemic problem.[397] The extent to which factors related to patients and treatment affect waiting time is not clear. In the present study I was able to link waiting time, an important measure in western countries for healthcare performance,[398] to patient variability (including occurrence of complications). The approach is different from previous literature which associate waiting times more often with a shortage of capacity and process.[399, 400] Silvester et al[385] claim that lack of capacity is not the primary cause of queuing in the National Health Services. Rather, it is the demand and capacity variation that create long waiting time. Similarly, I found that patients' variability is a source of fluctuation in resource utilisation and that with appropriate scheduling of patients, variation can be mitigated which eventually result in shorter waiting times.

A closely related operation performance indicator is surgery cancellations. procedures can be cancelled due to reasons related to patients and availability of resources.[401] It is certainly a common problem in Oman. In the cardiac care system, the most obvious manifestation of systemic inefficiency in the CICU is surgery cancellations when all beds are filled. The CICU patient classification model proposed in chapter 6 can be used for early identification of patients at risk for a prolonged LOS. Selecting the right mix of patient for CICU admission can lead to reduction in CICU stay and reduce bed blockage. Consequently, surgery cancellations might be expected to decrease.

#### 9.3.1.1 The relationship between natural variability and access to CICU

CICU units in Oman frequently presented bottlenecks to patient flow. To explore the nature and impact of variability I used regression modelling in combination with DES. The results suggest that patient characteristics and complications can explain some of the bottleneck effect. Through the use of simulation, the effect of factors influential to resource use can be tracked which allows evaluation of accessibility and responsiveness to urgent cases. The CICU units were operating at high capacity and this has resulted in surgery cancellations and some patients being denied admissions. Under this resource constraint situation, it is crucial to adopt new approaches to optimally match supply and demand for CICU services. Whenever resources are limited, management of variability becomes critical to the efficiency and effectiveness of the CICU unit. This will smooth patient flow and prevent demand fluctuation which is perceived to be a significant barrier to efficient distribution of ICU services.[380]

Systems that operate near capacity may benefit greatly from strategies discussed in chapters 7 and 8. Controlling natural variability will still be applicable to other hospital services. Any system that addresses both artificial as well as natural variabilities will function optimally under resource constraints. I provided an objective approach to deal with natural variation by accounting for factors influential to LOS. An optimum patient flow could be achieved by reducing complications or scheduling patients to prevent bed blockage in the CICU.

## 9.4 COPING WITH NATURAL VARIATION THROUGH A MANAGEABLE PATIENT GROUPING

The characteristics of patients with potential prolonged LOS was the focus of resource optimisation in this thesis. Dividing patients based on their potential resource use is important for hospital resource planning. In any hospital, a relatively small number of patients will consume disproportionately large fraction of resources (and thus costs). In England, for example, roughly half of all hospital bed-days are attributable to just 5% of the population.[402] Predicting whether a patient is going to experience a prolonged LOS is a challenging. There are several variables related to patients and treatment that need to be collected.

### 9.4.1 Grouping based on existing cardiac risk stratification models

Another way of classifying patients is based on their severity (i.e. risk). Disease severity, as measured by cardiac risk stratifications, was associated with resource utilisation. Cardiac risk stratification models such as EuroSCORE, Parsonnet, and STS were valid predictors of LOS classes among the Omani population. I found risk stratifications systems to be impartial and objective measures of hospital resource utilisation evident by good predictive accuracy. Higher scores, suggesting higher severity, were associated with prolonged LOS. Since these risk scores are routinely prepared before patient admission in some hospitals, they should be accessible by hospital resource planners. The type of variables included in these models are informed by research.[34] However, the variables in risk stratification models are more likely to remain the same for many years. For example, EuroSCORE was slightly modified in 2011 from its original 1999 version. Thus, the contemporary relevance of these models to resource utilisation prediction can be low if new treatments of risk factors emerged. For the same reason, risk stratifications are found to overestimate death.[33, 403] Nevertheless, the time and expense involved in collecting the large amount of data required to estimate resource utilisation is one reason why existing risk stratification models are an appealing alternative.

### 9.4.2 Patient classification using data mining

The two data mining techniques used in chapter 6 are an attempt to establish patient groupings in response to: 1) the lack of satisfactory patient groupings in the two hospitals, 2) data availability, and 3) assumptions requirement for regression modelling. Classification based on decision tree is one of the most widely used methods of data mining in healthcare organisations.[404] I identified several classes that can be used in simulation models for further analysis. Most statistical software today are capable of performing data mining techniques. Essentially, hundreds of variables from large repositories can be included to reveal associations between these variables and resource utilisation. Data mining techniques are also suitable for the Omani HIS systems where many data reside in unstructured fields such as medical notes. Data mining was proven to be effective for extracting and analysing such data.[405] However, sceptics sometimes argue that data mining is a fishing expedition, rather than a scientific method.[406] Data mining techniques usually assumes no prior hypothesis, thus results should be evaluated by experts for clinical merit and validation.

## 9.5 THE IMPORTANCE OF REFLECTING PATIENTS VARIABILITY IN SIMULATION MODELS

I have found that DES modelling can provide objective estimates of the interaction between several elements in the system. DES allows for any amount of interaction between hospital parts while accommodating uncertainty in the system. Several models on hospital capacity [73, 89, 407, 408 12, 21-23] make the assumption that systems are passive in their admission decisions. That is, patients are admitted whenever there is available capacity.[409] However, strategies demonstrated in this chapter involve an active patient scheduling where patients are managed taking into account expected resource usage and important factors influencing resources.

Rather than modelling patients as a homogenous group, their individual detail can be incorporated into simulation models. For example, individual patients can be assigned a numerical value based on their clinical and procedural characteristics. A LOS distribution for each patient type can be drawn from the several validated empirical distributions. In this way, the patient flow dynamics are reflected in a way that enables monitoring individual patient outcomes and obtains results that are otherwise difficult to capture. Incorporating these detail into patient flow simulation model can mitigate the "homogeneity problem" discussed previously. A meaningful segmentation of patients into groups would allow several decisions to be explored that include selecting the right mix of patients for admission. Currently, the integration between patient groups and resource use is seldom referenced in the healthcare simulation literature.

The use of DES to link different elements (e.g. process duration, patient factors, etc.) allowed the interrelationship between these elements to be quantified. Even experienced managers may struggle to predict the consequences of changes across complex service system when a resource strategy gets implemented. An example of this is presented by Goldacre, Lee, and Don who found that as surgical admissions from the waiting list increased, paradoxically so did the size of the waiting list,[410] an example of induced demand. DES is the ideal environment to evaluate the potential consequences of selecting a strategy. All this is done in a risk-free environment.

## 9.6 THE EFFECT OF COMPLICATIONS ON OPERATIONAL PERFORMANCE

Postoperative complications in the hospital under study were relatively high and 48% of the patients developed some sort of complication. It would be naïve to assume complications at this level will not affect operational performance. As discussed in chapter 8, elimination of complications may result in a substantial reduction in waiting time. It is also resulted in improvement in CICU bed turnover rates and cancellations. The effect on operational performance was determined by the type of complication and the location where they originate. The impact of complications was more significant at the CICU unit which has limited capacity. The relationship between the level of capacity and the complication rate, to my knowledge has not been studied before. Many commentators have discussed the gap between the demand for and supply of intensive care.[411-413] However, complications are less discussed as risk factor constraining capacity.

Complications were the strongest predictors of all factors explored in the current study. Unlike comorbidities which are known preoperatively, complications are difficult to predict prior to admission. Management of complications is essential for efficient patient flow. The exerted effect of complications on SQUH patient flow was substantial. In the absence of intermediate care at the hospital, CICU will still be at risk of operating at full or near full capacity. Capacity strain in CICU can impact quality which, as per the Institute of Medicine, is defined as care that is safe, effective, patient-centred, timely, efficient, and equitable.[414] Strained ICUs put pressures on medical teams to discharge patients more rapidly to create room for new admission.[415] The implication of such situation is more re-admissions and higher adverse events.[416] The collective impact of complications on the ability of hospitals and healthcare systems to response to population needs has not been assessed. This should provide an avenue for future research. Quantifying the effect of complications on resource use assists in estimating how much more patients and surgeries can be accommodated if these complications were reduced or eliminated.

Some of the complications associated with cardiac surgery are theoretically preventable. For example, surgical site infections, myocardial infarction, urinary tract infections, and ventilator-associated pneumonia are some of the common complications that can be prevented.[417] SQUH should put more effort in reducing some of the complications discussed in chapters 8. This will lead to better patient flows.

## 9.7 ETHICAL CONSIDERATIONS

As previously discussed, an implementation of any resource management strategy should be evaluated based on its added utility to the system and compliance with the ethical medical practices.

Bed availability is a persisting issue in many hospitals around the world. Dolkart et al found that patient satisfaction was low among patients who stayed in post-anaesthesia care units longer than 12 hours due to unavailability of ward beds.[418] In situations where critical care beds are limited, several factors, including age, illness severity, and medical diagnosis, are used to triage patients. Sinuff et al concluded in a systematic review study that rationing critical care beds through the refusal of patients who are perceived not to benefit from critical care is often associated with increased risk of hospital death.[411] The ethical aspect of the scenarios suggested in chapter 7 adhere, in principle, to the prevailing norms of the medical practice. An American Thoracic Society Statement on fair intensive care unit resource allocation[313] indicated that when demand exceeds supply, medically appropriate patients should be admitted on first come, first served basis rather than on the "ground of relative benefit". However, they further suggest that "*prior to health care institutions limiting access to ICU care on the basis of limited benefit, relative to cost, prerequisites for efficient use of health care resources, fair redistribution of savings, and public disclosure must be fulfilled".* The "early discharge scenario" suggested in this chapter is an objective tool that intended to assist hospital planners to make room for a new CICU admission. However, it should only be applied when other clinical thresholds are met.

## 9.8 INTEGRATING THE RESEARCH CONCEPTS INTO HIS

The application of DES to the Omani healthcare context is both novel and promising. However, hospitals are not incorporating the capability of computer simulation in decision making. In this thesis, I demonstrated an application of DES for evaluating the effect of complications on patient flow which was largely neglected area. The same thing can be said to the management of patients' admission and discharged based on factors influential to resource utilisation. These concepts and others can be integrated into existing HIS.

It might be argued that many healthcare organizations are not transforming their data to a form that might serve as a basis for useful decision support regarding future planning needs.[419] The wide use of HIS has assumed unprecedented importance. Currently hospitals have the ability to extend the possibility of using data also for healthcare planning.[420] However, it was evident from the discussion with key IT staff at the two hospitals that the use of patient data for resource planning was very limited. In Oman, existing HIS lack the capability to support resource allocation decisions. Historically, the Ministry of Health has introduced HIS as a means to automate the existing manual system[421] with no consideration to support patient flow decisions.

Algorithms such as decision trees can be directly integrated into HIS system using common programming languages. Isken and Rajagopalan[137] demonstrated an application of a data-mining technique that can support simulation data requirement from large databases. Similarly Robertson and Perera[422] argue that data collection for simulation projects can be automated by integrating simulation tools with organisation data repositories. Some simulation software such as Simul8 can directly interface with databases using Structured Query Language to read and write data to and from a data source. The connection allows huge volumes of real data stored in separate databases to be collated and process in single location.[423]

Successful integration of simulation system that is based on patient data into HIS can create a unique decision support system for hospitals. Such system can accurately model individual patient journeys through the system and assign patients to appropriate resources. However, there is a lack of expertise in Oman in building such support systems. Simulation is still unused in solving healthcare issues in Oman. A substantial investment is required to train staff and facilitate model building capability that can be spread to different hospitals in the country.

## 9.9 THE UTILITY OF ROUTINELY COLLECTED DATA

Little attention has been given to explore the value of routinely collected patient data for simulation studies. Such data, when appropriately utilised, can augment model decision capability and allow more realistic representation of patient health and their associated use of resources. The use of routinely collected data should expand beyond conventional process timing and patient routing probabilities to include other variables related to patient medical conditions and their determinant effects on resource utilisation.

## 9.10 RELEVANCY OF RESEARCH FINDING TO HOSPITAL RESOURCE PLANNING IN GENERAL

The relevancy of the findings from my research to hospital resource planning can be summarised in the following:

1) The patients mix is an important determinant of resource use and patient individual factors should be considered in resource planning. Existing deterministic approaches used in managing resources may underestimate resource requirement due to substantial inherent variation.
2) Factors influential to resource use are important aspect in resource planning. They should be continuously surveyed. It would require multidisciplinary team to decide on the strategies that are most appropriate to deal with these factors. For example, patients

may be managed prior to surgery to mitigate factors that are influential to resource utilisation.

3) The rate of complications in any hospital should not be considered in isolation of resource management. The level at which complications can impact operational performance will depend on the type of complication, and the available capacity among other factors. As I found, complications can limit the ability of a hospital to admit new patients. However, the relationship between complications and accessibility is rarely discussed. We need to bear in mind that certain type of surgeries (e.g. vascular surgery) will have higher rate of complications than others.[424]
4) Resource planning in hospitals might be more effective if the focus has been placed on patients expected to stay longer in hospitals. The difference between normal and prolonged LOS in resource use is substantial and there is no reason to assume that high stay would not impact patients flow.

## 9.11 RECOMMENDATIONS

- The discussion so far has been on optimising resources at the individual hospital level. However, the provision of cardiac care services should be a national priority irrespective of hospital type. As I found, there are considerable differences between the two hospitals in terms of LOS. Several contributing factors to these differences should relate to the local practices. It is in the interest of the government (since both hospitals are publicly funded) to examine inefficient practices. Public reporting of waiting times, level of complications, and LOS should increase public scrutiny and incite competition to improve services. The oil revenue in Oman has decreased sharply, worsening the financial condition. This has increased sensitivity to operational costs. Unjustified variation in LOS is a source of great operational expense.

- Outpatient and inpatient data are digitally stored, resulting in much easier and faster data acquisition. However, HIS systems in Oman are still not amenable for resource planning programmes and operational research. For example, the systems don't have the capability to track patients across the hospital journey, precluding modelling patient pathways and obtaining information about process timings. Much work is required from the part of specialised IT personnel. Effort should be made toward integrating patients and process data already recoded in the system into a single system. Beyond the use by hospital management, these source of data can provide researchers with valuable information.
- Related to the previous point, there are crucial data related to complications, waiting times, and surgery cancellations that are not easily accessible or appropriately presented. The importance of this for researchers lies in the ability to distinguish between system related factors (e.g. cancellations due to unviability) and patient related factors. Such data should also be publically available.
- Hospital managers should move from using traditional approaches of estimating capacity needs or planning other resources to approaches that are sensitive to patient variations. My research provides an evidence into the capability of DES in facilitating this objective.
- Simulation modelling is not used in Oman by the healthcare sector. I recommend introducing this methodology to healthcare planning departments across the country. Several potential strategies can be evaluated such as allocation of existing resources. In the current economic situation, simulation models can be used to evaluate the effects of reducing capacity on the overall system. Shifting the use of DES from the domain of operational research practitioners to healthcare decision makers not only can improve quality of models but also can encourage implementations.
- Wider application of understanding patient variation can extend beyond hospital resource planning. For example, comparison between hospitals can be made based on patient mix

and the proportion of patients groups that are influential to resource utilisation in each hospital.

## 9.12 STUDY LIMITATIONS

My research has some limitations that merit discussion.

- **Generalisability:** The models discussed in this thesis are organisational-specific. Results obtained from these models might not be generalisable to other settings. For example, in hospitals that practice a protocol of fast tracking, the normal duration of stay post cardiac surgery will be less than for hospital that don't implement this system. It also will depend on whether patients can be transferred to a step-down unit which is less resource-intensive than conventional ICUs. Cots et al suggest that the size of the hospital can affect LOS. As such, large urban teaching hospitals had higher patients with very high LOS compared to medium and small community hospitals.[425]
- **Modelling only one part of the hospital system:** Modelling care at a single microsystem rather than attempting to interface operations with other services undermine the power of simulation modelling as a system improvement tool. Hospital units are rarely self-contained entities. The DES models that I built were only designed around common pathways in the cardiac care system. Other interdependencies between patients in the cardiac care and other services should be added when there is a direct link between units.
- **Data availability and their quality:** There is difficulty involved in estimating the precise effect of individual factors on resource utilisation. Disentangling the main effect from potential confounding factors require careful analysis which should start from ensuring wide range of demographic and clinical variables are available. The data collected from the RH hospital involved extracting variables using ICD-10 codes. This method is surrounding by some issues including the quality of the coding, and lack of coded diagnosis among

many patients. These issues have restricted the number of variables that were collected. While lack of comprehensive and reliable data for statistical model is a problem, it is less an issue for building simulation models.[339] Sensitivity analyses can reveal the circumstances under which the model's conclusions remain robust.

- **Validation of the simulation models:** The availability of data for validating the simulation models is among the main limitations. First, data on the locations of where complications have originated were not available from the collected data. Second, surgery cancellations due to unavailability of beds were not recorded by the hospitals. However, Byer[339] contends that decision-making does not necessarily need an exact prediction, rather a reliable assessment indicating which of several options is most promising will suffice.
- **Actual implementation:** None of the models discussed in this thesis have been implemented. Actual use of these models (statistical or DES) can offer an avenue for users feedback and further enhancement. In such highly bureaucratic organisations as hospitals, approving such tools to be used is a formidable task. It is perhaps this is one of the reasons for low implementations of simulation models in healthcare.[64, 131]

# Chapter 10

# CONCLUSION AND FUTURE WORK

## 10.1 CHAPTER OVERVIEW

The chapter provides a summary of the findings from this research. I will also briefly discuss the future work that can be carried out to further strengthen the methodology outlined in the thesis.

## 10.2 SUMMARY OF MAIN FINDINGS

In this thesis, I carried out two literature reviews. The aim of the first review was to understand how variation around patients and treatment factors was represented in simulation models. I discovered that factors related to patients such as age, diagnoses, or complications are rarely incorporated into simulation models. It was common practice in most of the reviewed simulation studies to ignore this level of detail. One exception was patient urgency level which was used in several studies to inform potential patient pathways. Furthermore, the review asserted the appropriateness of DES as a methodology for healthcare capacity problems. The second review highlighted several factors that are influencing resource use in cardiac care.

Results from this review have assisted me in selecting the type of variables to be included in this research.

Predicting patient expected LOS classes was the first step toward understanding resource utilisation in relationship to individual patient characteristics. I assessed the association between several factors and LOS among patients who underwent cardiac interventions in two hospitals in Oman. Several variables that were associated with LOS in the univariate analysis failed to be significant in the multivariate analysis. These include age, sex, BMI, and number of comorbidities. Several factors such as renal failure, pulmonary hypertension, non-elective surgery, combined surgery, and the use of CPB machine were significant in explaining variance in ward LOS. The ward postoperative model was validated using non-parametric bootstrapping. Furthermore, I created and validated a prediction model for prolonged LOS in the CICU unit. Factors found to be predictive of extended stay were non-elective surgery, current CHF, renal failure, combined surgery, and other type of surgeries that are not CABG or valve. I externally validated the CICU model by using a separate dataset from the RH hospital. The model had AUC=72% when applied to this new dataset. The CICU was regarded as the main bottleneck in the system. As far as resource planning concerned, the model can be used as a stand-alone tool to balance existing capacity by predicting the likelihood of long stay. It can also be incorporated into a simulation model to examine an optimum resource planning strategies. This has contemporary relevance as CICU capacity has been an issue in both hospitals.

I found that existing cardiac risk stratifications (EuroSCORE, STS, and Parsonnet) had moderate discriminatory power for predicting LOS classes in the CICU and the overall postoperative LOS. All risk stratification models had an AUC that is equal or greater to 65%. Moreover, I observed a univariate association between ASA scores and the CICU and postoperative LOS. The results imply that such risk stratification systems can be used to reasonably predict LOS classes and might preclude the need for several variables to be collected. The present study was also the first study to validate three risk stratification systems as well as ASA scores for predicting LOS in Oman.

Results from decision trees indicate that roles of resource utilisation can be created to support resource allocation in cardiac care services and aid DES models building. Based on CART analysis, the significant drivers and splitting attributes of higher postoperative LOS were age, type of surgery, and surgery priority. However, when I used the CICU LOS data, CART failed to split data into any subgroups. Algorithm based on C5.0 produced 13 rules for predicting LOS classes which can be valuable in resource management.

The DES models discussed in this thesis have incorporated patients' factors as well uncertainty inherent in planning of resources in hospitals. While these models concerns cardiac services, the need to balance capacity based on patients factors will be familiar to many resource planners across diverse clinical domains. For many readers combining DES and resource prediction can be relevant. This is the case because traditional resource allocations are well known to disregard variation among patients. The flexibility of DES and the capability of modern simulation software to include complex interactions are some of the features that should increase its appeal to hospitals.

Finally, I have proved that complications can have significant effect on patient flow and operational performance. Patient with higher complications required more bed days. The accumulative effect of incremental LOS due to complication has reduced accessibility to the CICU unit, increased surgery cancellations, and waiting time.

## 10.3 FUTURE WORK

Future research may consider the following improvements:

- Since DES is capable of handling complex logics, resource rules such as the ones produced by C5.0 algorithm in chapter 6 can be discovered from HIS by integrating appropriate algorithm into the system. Such machine learning capability can greatly increase accuracy. Thousands of patients' records can be instantaneously analysed and rules related to patient resource use can be created. A decision support system for resource planning can make use of decision tree algorithms. Harper[62] advocated combining data mining techniques with simulation modelling for better understanding of variability. However, very limited research emerged since then.
- The research can be expanded onto a larger scale. Data from different hospitals can be consolidated, thus prediction of resource utilisation can be made at the national level considering a wider population. Simulation modelling can be carried out, at the national level, taking into consideration the respective hospital characteristics. Such models can provide powerful insights into the performance of individual hospitals according to the case mix and patient severity. A centrally operated system can suggest to individual hospitals the best strategy to implement in order to improve responsiveness.
- While analysis on complications (chapter 8) was based on cardiac surgical patients, the methodology can be applied to other specialties. For further development, researchers should aim at investigating the effect of complications related to other specialities such as general surgery which are associated with higher volume. Moreover, modellers should consider surgical complications that occur in OR. In hospitals with high demand for operating theatre, unexpected complications can lead to unusual surgical time exceeding the allocated slot. This eventually will result in other procedures being postponed. Secondly, in the same analysis, I didn't model the relationship between prolonged hospital stay and the increased likelihood of morbidity. Future research might consider this relationship. Finally, a hospital-wide modelling of complications is needed. Such a system

thinking approach will allow a better understanding of how complications impact resource and hospital performance.

- LOS was used as a proxy for resource utilisation in this research. Studies analysing data from hospitals with more advanced HIS can utilise other indicators such as human resources, consumables, medications, etc.
- Researchers should investigate other scheduling and resource allocation strategies that can be used in conjunction with patient specific resource planning.
- Simulation modelling is currently not used in planning resources or optimising patient flow in Omani hospitals. Future studies are needed to identify barriers and enablers to the efficient use of simulation methodology in Oman and elsewhere.

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# APPENDIXES

### Appendix A: Papers and research presentations related to the thesis

### Papers

Accepted:

1. **Ahmed Almashrafi**, Hilal Alsabti, Mirdavron Mukaddirov, Baskaran Balan, Paul Aylin. "Factors associated with prolonged length of stay following cardiac surgery in a major referral hospital in Oman: a retrospective observational study." BMJ open 6.6 (2016): e010764.

2. **Ahmed Almashrafi**, Mustafa Elmontsri, and Paul Aylin. "Systematic review of factors influencing length of stay in ICU after adult cardiac surgery." BMC Health Services Research 16 (2016). p.318.

3. **Ahmed Almashrafi,** and Laura Vanderbloemen. "Quantifying the effect of complications on patient flow, costs and surgical throughputs." BMC Medical Informatics and Decision Making 16.1 (2016): 136.

### Research poster presentations:

1. "*Optimising cardiac services using routinely collected data and DES"*. Primary Care and Public Health PhD symposium, 02 Sep 2015.

2. "*Quantifying the effect of complications on patient flow, costs and surgical throughputs: a discrete event simulation study*". The 8th IMA Conference on Quantitative Modelling in the Management of Health and Social Care, 21 – 23 March 2016.

BMJ Open

# Factors associated with prolonged length of stay following cardiac surgery in a major referral hospital in Oman: a retrospective observational study

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## ABSTRACT

**Objectives:** Two objectives were set for this study. The first was to identify factors influencing prolonged postoperative length of stay (LOS) following cardiac surgery. The second was to devise a predictive model for prolonged LOS in the cardiac intensive care unit (CICU) based on preoperative factors available at admission and to compare it against two existing cardiac stratification systems.

**Design:** Observational retrospective study.

**Settings:** A tertiary hospital in Oman.

**Participants:** All adult patients who underwent cardiac surgery at a major referral hospital in Oman between 2009 and 2013.

**Results:** 30.5% of the patients had prolonged LOS (≥11 days) after surgery, while 17% experienced prolonged ICU LOS (≥5 days). Factors that were identified to prolong CICU LOS were non-elective surgery, current congestive heart failure (CHF), renal failure, combined coronary artery bypass graft (CABG) and valve surgery, and other non-isolated valve or CABG surgery. Patients were divided into three groups based on their scores. The probabilities of prolonged CICU LOS were 11%, 26% and 28% for group 1, 2 and 3, respectively. The predictive model had an area under the curve of 0.75. Factors associated with prolonged overall postoperative LOS included the body mass index, the type of surgery, cardiopulmonary bypass machine use, packed red blood cells use, non-elective surgery and number of complications. The latter was the most important determinant of postoperative LOS.

**Conclusions:** Patient management can be tailored for individual patient based on their treatments and personal attributes to optimise resource allocation. Moreover, a simple predictive score system to enable identification of patients at risk of prolonged CICU stay can be developed using data that are routinely collected by most hospitals.

## Strengths and limitations of this study

- This is the first study to identify factors affecting length of stay (LOS) after a cardiac surgery in Oman, considering the unique characteristics of the local population.
- The study included a small sample size relative to other previously published models.
- Our selection of the 75th centile for defining prolonged LOS can be viewed as an arbitrary cut-off in the absence of predefined clinically acceptable value in the literature.
- The prediction model was not externally validated. Thus, the model lacks generalisability which limits its portability.
- The analysis of the association was only limited to the variables available in the hospital database and that were routinely collected.

## INTRODUCTION

Managers and clinicians seeking to maximise resources are often interested in patient variation and how it might influence resource utilisation. This is based on a basic premise that understanding the factors relating to patients, treatment and iatrogenic events on length of stay (LOS) will aid in the management of complex hospital systems. Physical limitations and government regulation can restrict expansion of hospital capacity.[1] Thus, management of some of the factors that impact resource consumption can be an alternative to adding costly resources.

Prolonged LOS after cardiac surgery can have serious cost implications. Patients with high risk of prolonged LOS are an important hospital subpopulation because they tend to consume a disproportionate amount of intensive care unit (ICU) resources.[2] As a result, patient variation can reduce operational performance which can manifest in the form of cancelled surgery or extended waiting lists.

In many parts of the world, critical care resources are still limited, calling for best practices in resource management. A valuable decision-making tool is to predict cardiac ICU

(CICU) LOS in advance for every cardiac surgical patient. Therefore, an appropriate management strategy can be applied such as mitigating risk factors before surgery, instituting fast-track anaesthesia, deciding on staffing level and scheduling patients for surgery based on expected LOS. Ultimately, influential predictors of LOS can be integrated into hospital resource planning process. This can be a solution to the traditional practice of using average bed numbers as a measure of resource planning, which may not adequately reflect patient mix and fails to predict future demand.[3]

Several studies have identified factors associated with prolonged CICU LOS[4–8] and postoperative LOS[9 10] for patients undergoing cardiac surgery. A common feature of these studies is that they are only applicable to the original study populations as they are mostly based on a single institution. No previous research was conducted to investigate factors predicting LOS after cardiac surgery in our local population. We have undertaken this study to investigate this area, considering patient and surgical unique characteristics.

## METHODS

### Patient population and data

We included all adult patients who underwent cardiac surgeries during the 4-year period from 2009 to 2013 at the Sultan Qaboos University Hospital (SQUH). A total of 600 consecutive patients were included. We excluded patients who died during admissions (n=25) from our analysis on the basis that they will be more likely to have prolonged LOS had they survived. Data were collected prospectively during the patient's admission and entered into a database for research purpose. Postoperative outcomes included several complications, all of which are defined according to the Society of Thoracic Surgeons database definitions.[11–13]

The type of cardiothoracic surgery performed included isolated coronary artery bypass graft (CABG), isolated valve surgery and combined procedures. The latter category includes several complex procedures such as aortic aneurysm and aortic dissection surgery or congenital defect repair. We included them because patients who had these procedures shared the same typical resources (operating theatre, wards, etc) and from the perspective of hospital operation management, these patients compete with other patients for resources.

### Statistical analysis

Continuous variables were presented as means with SD, while categorical variables were presented as frequencies. LOS at CICU and postoperative LOS were dichotomised to designate two groups (normal LOS and prolonged LOS). We defined prolonged LOS as ≥75th centile. In the absence of a prescribed LOS in the literature and to confirm the appropriateness of our selection, we consulted the surgeons for their judgement who agreed on this cut-off value. In general, there is a variability in medical research for defining the period at which a stay is considered as prolonged.[14] Moreover, the use of the LOS at the 75th centile is consistent with other studies. Postoperative LOS was defined as the time between the day of surgery and discharge from the hospital, while CICU LOS was defined as the time in days between the admission and discharge from CICU. For identifying difference between groups, we used t-tests for continuous variables, Mann-Whitney for non-normally distributed variables and $\chi^2$ for categorical variables.

For identifying predictors of postoperative LOS, a univariate logistic regression was first performed to select variables that are significantly related to the postoperative LOS. Factors with $p<0.10$ were then included in the multivariate analysis. These included sex, age, body mass index (BMI), history of diabetes, history of renal failure, history of cerebrovascular disease, history of respiratory disease, pulmonary hypertension, congestive heart failure (CHF) at current admission, preoperative arrhythmia, preoperative inotropic support, left ventricular ejection fraction (≥40% vs <40%), preoperative haematocrit (Hct) level, non-elective surgery, type of surgery, use of cardiopulmonary bypass (CPB) machine, inotropic support after operation, use of packed red blood cells (PRBC) and number of complications. A backward stepwise logistic regression was used to identify factors that had an independent effect on the postoperative LOS. A p value of 0.1 to enter a factor and 0.2 to remove it were used.

### The cardiac ICU prediction model

For deriving the CICU LOS prediction scores, only preoperative factors known prior to surgery were considered. These included sex, age, BMI, body surface area (BSA), current smoking history, diabetes, renal failure, hypertension, cerebrovascular disease, peripheral vascular disease, history of respiratory disease, pulmonary hypertension, history of angina, CHF on admission, cardiogenic shock, arrhythmia, inotropic support, left main coronary artery (LMCA) disease, myocardial infarction (MI) <24 hours, use of thrombolysis, previous percutaneous coronary intervention (PCI), preoperative Hct level, left ventricular ejection fraction (≥40% vs <40%), non-elective surgery and type of surgery. The same process was repeated as for the first model for selecting candidate variables. The statistically significant variables ($p<0.10$) were then included in the backward stepwise logistic regression using the same entry and exit criteria as in the postoperative LOS model. A simplified score system was devised by rounding the OR of each predictor to the nearest 0.5.

We assessed the validation and discriminatory power of the predictive model through internal validation. The models were assessed using the Hosmer-Lemeshow goodness-of-fit statistics and the receiver operating characteristic (ROC) curve. A bootstrapping on the β coefficient and SEs was performed with 200 replications. Additionally, we compare our prediction model with two different cardiac risk stratification systems: the European System for Cardiac Operative Risk Evaluation (EuroSCORE) and Parsonnet score.

Assumptions were assessed using different techniques. Multicollinearity was assessed using the Pearson correlation statistics and the variance inflation factor (VIF). Highly correlated variables, for example, renal failure and dialysis, patients with diabetes and patients with insulin dependency were not combined into a single model. Moreover, influential cases are computed using Cook's distance. A case is said to be influential in logistic regression if its Cook's distance is >1.0.[15] As a rule of thumb in logistic regression, there should be at least 10 events per predictor to obtain reliable estimates of regression coefficients as suggested by Hosmer and Lemeshow.[15] Inspection of candidate predictors revealed that some complications had rare events (<10); consequently, they were either dropped or combined with other complications in a separate category as appropriate. All statistical analyses were performed using Stata V.12 (StataCorp LP, College Station, Texas, USA).

## RESULTS

### Baseline and clinical characteristics

Table 1 presents patient, surgery and LOS characteristics. The majority of patients were men (69.7%), 13% of the patients being older than 70 years, and there were 12 octogenarians in the dataset. The mean age of cardiac surgical patients was 58.6 years. The mean age of patients who underwent isolated CABG was 59.3, valve surgery 53, combined surgery procedures 64.2 and other types 55.3. Patients aged 40 years or younger constituted 5.6% for CABG, 5% for valve surgery, 6.7% for combined CABG plus valve surgery and 5.3% for other types of surgeries.

The 75th centiles of the CICU LOS and postoperative LOS were 5 days and 11 days, respectively. The study group used a total of 2816 cardiac ICU patients days. Patients with prolonged postoperative LOS (183 patients) had 60% of the total patients days. Only 5% of the patients who underwent cardiac surgery were discharged by the 5th postoperative day. The majority of the patients (61%) were discharged between 6 and 10 postoperative days.

In total, 45% of the patients undergoing heart surgery had diabetes mellitus. Hypertension was prevalent in 67% of the patients. There were 229 patients who had CHF. Nearly 27% of the patients had unstable angina and 6.3% were diagnosed with atrial fibrillation. Approximately 12% of the patients had renal failure preoperatively; among these patients, only 1.3% were on dialysis. Based on BMI as used by the WHO,[16] patients were either underweight (<18.50)=3%, normal weight (18.50–24.99)=35%, overweight (25.00–29.99)=38% or obese (≥30)=24%. Male and female patients had statistically different distributions of BMI, p=0.01 (t=2.46). About 4% of the patients died after surgeries during their hospitalisation, and they were excluded from the analysis. The numbers of patients who died based on surgery type were as follows: CABG: 12, valve: 7, combined surgery: 5 and other surgeries: 1.

The average EuroSCORE was 6.6 for all patients. The distribution of EuroSCORE was significantly different between patients with normal and prolonged LOS.

Table 2 presents the predictive factors that were significant. All variables were significant below the α level of 0.05. Patients with higher BMI were more likely to experience prolonged LOS. Likewise, patients who received PRBC had 2.3 times greater likelihood of postoperative LOS≥11 days (OR=2.5, 95% CI 1.5 to 4.1, p<0.01). The association between urgency of the surgery and the postoperative LOS remained statistically significant after adjusting for other patients' factors in the multivariate model. Non-elective surgery was associated with higher LOS (OR=2.1, 95% CI 1.27 to 3.2, p<0.05). Patients who were operated with the use of CPB (76%) had odd ratio=2.1 (95% CI 1.8 to 3.9, p=0.012), which suggests that these patients had twice greater probability of extended stay after surgery than patients who were operated off pump. In addition to the above, patients who underwent an isolated valve or combined surgery (valve and CABG) were more likely to have postoperative LOS≥11 days than patients who underwent isolated CABG.

Finally, complications were the strongest predictors of postoperative LOS. There was a stepwise risk-adjusted increase in probability of prolonged stay for 1 (OR=2.8, 95% CI 1.68 to 4.78, p<0.01), versus 2 complications (OR=5.7, 95% CI 3.15 to 10.54, p<0.01), versus 3 or more complications (OR=27, 95% CI 11.56 to 62.51, p<0.01). At least half of the patients experienced one or more complications. The type of complications mainly included cardiac, pulmonary, neurological and infection.

The Hosmer and Lemeshow test suggests that the model fits the data well: $c^2$ (8)=8.90; p=0.351; pseudo $R^2$ (McFadden's)=0.27. The model correctly classified 80.5% of the patients with prolonged LOS with 11 days or more, and finally the area under the ROC curve was 0.82.

### Prediction model for CICU LOS

The following variables emerged to be statistically significant (table 3): non-elective surgery, current chronic heart failure, renal failure, combined surgery, and other none CABG-Valve surgery. The combined surgery was the strongest predictor of prolonged LOS (OR=6, 95% CI 3.3 to 10.0, p<0.001).

To further assess the effect of including the patients who died during their hospitalisation on our results, we conducted sensitivity analysis whereby data of patients who died were included in the model. The independent risk factors identified originally remained unchanged.

The scores for the prediction model (table 4) were obtained based on the coefficients from the multivariate regression model. The scores were then assigned to each

**Table 1** Demographic and perioperative characteristics

| Variable | All patients (n=600) | ICU LOS (days) <5 | ≥5 | p Value | Postoperative LOS (days) <11 | ≥11 | p Value |
|---|---|---|---|---|---|---|---|
| Continuous variables: mean±SD | | | | | | | |
| Age* | 59±12 | 59±12 | 58±13 | 0.47 | 58±12 | 60±12 | 0.05 |
| BMI* | 27±5.4 | 27±5 | 26.8±6.4 | 0.73 | 26.7±5.3 | 27.7±5.6 | 0.04 |
| BSA(in $m^2$)* | 1.71±.21 | 1.71±.20 | 1.70±.21 | 0.58 | 1.71±.20 | 1.72±.21 | 0.44 |
| Length of stay† | | | | | | | |
| Total LOS | 18±17 | 16±15 | 27±29 | <0.001 | 12.8±5 | 31.1±29 | <0.001 |
| Postoperative LOS | 13±17 | 11±12 | 21±29 | <0.001 | 7.4±2 | 24.6±27 | <0.001 |
| Cumulative bypass time (in min)† | 118±47 | 115±46 | 130±50 | 0.004 | 110.6±43 | 132.8±51 | <0.001 |
| Preoperative troponin level† | 1.39±8.7 | 81±5.3 | 4.10±17 | <0.001 | 0.94±6.7 | 2.40±12 | 0.02 |
| EuroSCORE† | 6.6±12.3 | 5.8±11 | 10.2±17 | <0.001 | 5.5±11 | 9.3±15 | <0.001 |
| Categorical variables: ‡ n (%) | | | | | | | |
| Female | 182 (30.3) | 142 (78) | 40 (22) | 0.06 | 118 (64.8) | 64 (35.2) | 0.069 |
| Male | 418 (69.7) | 353 (84.4) | 65 (15.6) | | 302 (72.2) | 116 (27.8) | |
| CPB use | 461 (76.8) | 369 (80) | 92 (20) | 0.04 | 302 (65.5) | 159 (34.5) | <0.001 |
| Isolated CABG | 478 (79.7) | 425 (88.9) | 53 (11.1) | <0.001 | 345 (72.2) | 133 (27.8) | 0.021 |
| Combined CABG+valve surgery | 63 (10.5) | 51 (81) | 12 (19) | 0.073 | 28 (44.4) | 35 (55.6) | <0.001 |
| Isolated valve surgery | 165 (27.5) | 109 (66.1) | 56 (33.9) | <0.001 | 90 (54.5) | 75 (45.5) | <0.001 |
| Non-elective surgery | 92 (15.3) | 68 (73.9) | 24 (26.1) | 0.018 | 53 (57.6) | 39 (42.4) | 0.005 |
| LVEF<40% | 246 (41) | 199 (80.9) | 47 (19.1) | 0.388 | 163 (66.3) | 83 (33.7) | 0.096 |
| PRBC use | 374 (62.3) | 297 (79.4) | 77 (20.6) | 0.010 | 231 (61.8) | 143 (38.2) | <0.001 |
| Inotropic support (after surgery) | 411 (74.6) | 329 (80) | 82 (20) | 0.007 | 277 (67.4) | 134 (32.6) | 0.013 |
| NYHA Class | | | | 0.004 | | | 0.003 |
| 1 | 9 (3.7) | 5 (55.6) | 4 (44.4) | | 7 (77.8) | 2 (22.2) | |
| 2 | 36 (14.8) | 31 (86.1) | 5 (13.9) | | 28 (77.8) | 8 (22.2) | |
| 3 | 137 (56.1) | 111 (81) | 26 (19) | | 96 (70.1) | 41 (29.9) | |
| 4 | 62 (25.4) | 38 (61.3) | 24 (38.7) | | 29 (46.8) | 33 (53.2) | |
| Current smoker | 62 (10.3) | 50 (80.6) | 12 (19.4) | 0.685 | 42 (67.7) | 20 (32.3) | 0.682 |
| Diabetes | 270 (45) | 234 (86.7) | 36 (13.3) | 0.015 | 179 (66.3) | 91 (33.7) | 0.073 |
| Hypercholesterolemia | 375 (62.5) | 319 (85.1) | 56 (14.9) | 0.033 | 272 (72.5) | 103 (27.5) | 0.080 |
| Renal failure | 73 (12.2) | 48 (65.8) | 25 (34.2) | <0.001 | 39 (53.4) | 34 (46.6) | 0.001 |
| Hypertension | 403 (67.2) | 339 (84.1) | 64 (15.9) | 0.135 | 282 (70) | 121 (30) | 0.985 |
| Cerebrovascular disease | 44 (7.3) | 32 (72.7) | 12 (27.3) | 0.076 | 24 (54.5) | 20 (45.5) | 0.020 |
| Peripheral vascular disease | 29 (4.8) | 23 (79.3) | 6 (20.7) | 0.643 | 17 (58.6) | 12 (41.4) | 0.170 |
| Pulmonary hypertension | 74 (12.3) | 50 (67.6) | 24 (32.4) | <0.001 | 37 (50) | 37 (50) | <0.001 |
| MI<24 hours | 21 (3.5) | 14 (66.7) | 7 (33.3) | 0.052 | 14 (66.7) | 7 (33.3) | 0.734 |
| Unstable angina | 160 (26.7) | 136 (85) | 24 (15) | 0.331 | 104 (65) | 56 (35) | 0.107 |
| CHF on admission | 153 (26.3) | 110 (71.9) | 43 (28.1) | <0.001 | 93 (60.8) | 60 (39.2) | 0.003 |
| Preoperative arrhythmia | 72 (12) | 52 (72.2) | 20 (27.8) | 0.014 | 39 (54.2) | 33 (45.8) | 0.002 |
| Previous CV intervention | 44 (7.4) | 34 (77.3) | 10 (22.7) | 0.349 | 32 (72.7) | 12 (27.3) | 0.671 |
| LMCA disease (>50% stenosis) | 65 (11.4) | 58 (89.2) | 7 (10.8) | 0.120 | 49 (75.4) | 16 (24.6) | 0.304 |

BMI, body mass index; BSA, body surface area; CABG, coronary artery bypass graft; CHF, congestive heart failure; CPB, cardiopulmonary bypass machine; CV, cardiovascular; EuroSCORE, European System for Cardiac Operative Risk Evaluation; ICU, intensive care unit; LMCA, left main coronary artery; LOS, length of stay; LVEF, left ventricular ejection fraction; MI, myocardial infarction; NYHA, New York Heart Association; PRBC, packed red blood cells.
Test of difference between groups is based on the following:
*t-Test.
†Wilcoxon rank-sum (Mann-Whitney) test.
‡$\chi^2$ test.

patient in the dataset where the highest total score was 14. Patients total scores were divided into three groups: 0–1, 2–4 and >5. A Kruskal-Wallis test revealed a statistically significant difference in CICU stay among the three score groups: $\chi^2(2)=14.19$; p<0.001. The average CICU LOS was 4, 5 and 6.5 days for the first, second and third score groups, respectively. The probabilities of prolonged CICU LOS were 11%, 26% and 28% for group 1, 2 and 3, respectively.

The predictive score model was tested by means of Hosmer-Lemeshow and ROC curve. The model demonstrated a good discrimination according to the Hosmer-Lemeshow test: $c^2(8)=3.18$; p=0.922. The area under the ROC curve was found to be 0.75 (SE=0.027).

Since the first 200 patients were scored using Parsonnet score, we restricted the comparison of the three scoring systems to these 200 patients. Our simple model compared favourably to the logistic EuroSCORE

**Table 2** Predictors of prolonged postoperative LOS

| Variables | OR | SE |
|---|---|---|
| Patient factors | | |
| BMI | 1.076*** | (0.022) |
| *Surgical factors* | | |
| Type of surgery* | | |
| Valve | 3.034*** | (0.904) |
| Combined valve and CABG | 2.062** | (0.733) |
| CPB use | 2.152** | (0.660) |
| PRBC | 2.521*** | (0.631) |
| Non-elective surgery | 2.123** | (0.630) |
| Number of complications† | | |
| One complication | 2.843*** | (0.756) |
| Two complications | 5.714*** | (1.786) |
| Three or more complications | 26.89*** | (11.57) |
| Constant | 0.003*** | (0.002) |

***p<0.01; **p<0.05; *p<0.1.
*Omitted reference category is 'CABG'.
†Omitted reference category is 'no complications'.
BMI, body mass index; CABG, coronary artery bypass graft; CPB, cardiopulmonary bypass; LOS, length of stay; PRBC, packed red blood cells.

and the additive Parsonnet. The areas under the curve were 0.75 for our model, 0.70 for the EuroSCORE and 0.65 for the Parsonnet score.

## DISCUSSION

We developed two models to identify factors predictive of prolonged LOS. The first model identified predictive factors for the overall postoperative LOS. We also derived a second model to predict prolonged LOS in the CICU, a major bottleneck in many hospitals. The good performance of these two models was evident by the good discriminative power (AUC=0.82 and 0.75, for the overall postoperative LOS and for the CICU LOS models, respectively).

An early recognition of patients at risk of prolonged LOS was the main objective of several studies.[17] Some applications of stratifying patients based on their expected LOS include identifying patients that can be selected for fast-track protocols to minimise ICU stay or bypass it altogether,[18] providing anaesthesiologists with enough time to correct risk factors[19] and facilitating the selection of resource planning strategy based on patient risk of prolonged LOS. With the current economic climate in Oman, hospitals are left with no option but to efficiently manage their resources. We believe much of this efficiency can be accomplished through proper management of care process for patients at risk of prolonged stay.

**Table 3** Preoperative variables predicting CICU LOS

| Variables | OR | SE |
|---|---|---|
| Non-elective surgery | 1.779* | (0.545) |
| Current CHF | 1.894** | (0.482) |
| Renal failure | 4.015*** | (1.268) |
| Combined valve and CABG surgery | 5.835*** | (1.610) |
| Other surgery type | 5.067*** | (2.760) |
| Constant | 0.079*** | (0.016) |

***p<0.01; **p<0.05; *p<0.1.
CABG, coronary artery bypass graft; CHF, congestive heart failure; CICU, cardiac intensive care unit; LOS, length of stay.

**Table 4** Predictive score for length of CICU stay

| Variables | Score |
|---|---|
| Surgery urgency level | |
| Elective | 0 |
| Non-elective surgery | 2 |
| Current CHF | 2 |
| Renal failure | 4 |
| Type of surgery | |
| Isolated CABG or isolated valve | 0 |
| Combined valve and CABG surgery | 6 |
| Other surgery types | 5 |

CABG, coronary artery bypass graft; CHF, congestive heart failure; CICU, cardiac intensive care unit.

Even in a relatively homogenous group such as cardiac surgical patients, we found wide variation in resource use. An implication of this to hospital planners is that resource allocation should be planned based on individual patient characteristics. Factors related to patients and treatments that are known to prolong postoperative LOS can be valuable information for planning hospital staff and beds.

Our findings are consistent with previous studies that have explored postoperative LOS after cardiac surgery. For example, combined cardiac surgery was predictive of prolonged LOS.[20] The use of CPB was also found to be associated with longer hospitalisation.[14 21–24] The conclusion that can be drawn from these studies is that on-pump patients were more likely to stay in hospital longer and develop complications compared with patients operated without the use of CPB machine. In general, complications are known to prolong LOS following cardiac surgery. For example, new onset of atrial fibrillation,[25–27] renal dysfunction[28] and deep sternal wound infection[29] were associated with increased ICU and postoperative LOS. We found that the hospital stay increased monotonically with the number of complications.

The incremental cost associated with complications such as septicaemia or stroke can be substantial.[30] In the hospital under study, a higher number of patients experienced postoperative complications (at least half of the patients). In reality, many of the complications encountered by the patients such as infections are preventable.[31] Quality and safety initiatives aimed at reducing the number of complications can substantially lower hospital cost by indirectly reducing LOS.

Despite the high prevalence of high lifestyle diseases among the Omani population[32] and among patients in our dataset, diabetes and hypertension were not predictors of prolonged LOS. In contrast to our findings, diabetes in particular was found to be a predictor of prolonged LOS among patients with CABG in previous studies.[33 34]

While the available capacity in a cardiothoracic ward can affect cardiac patient discharge rate from the CICU,[35] this was not the case in the hospital under study as sufficient number of beds were allocated in the ward. If the downstream capacity was limited, we would expect a higher proportion of patients to have prolonged LOS for this system-related reason which can impact on our results.

It is worth mentioning that patients in our sample had considerably higher overall postoperative LOS in comparison with what has been found in other studies.[10 36] Consequently, the benefits of risk-stratifying patients based on their expected LOS for optimising resources can be outweighed by the inefficiency in the use of hospital beds introduced by factors unrelated to patient condition such as hospital discharge policy and physician judgement. This should be considered in future studies investigating allocation of resources based on influential factors related to patients.

### The use of the CICU prediction model

We developed an objective scoring system, yet simple, that was able to reasonably predict prolonged CICU stay based on a few preoperative variables. Previous research has suggested the use of existing risk stratification systems such as the EuroSCORE and the Parsonnet for predicting ICU duration.[37 38] Originally, these scoring systems were designed as a prognostic tool to predict mortality. Even though the EuroSCORE has all the variables that we found to be predictive of CICU LOS, this scoring system might not be in use in many hospitals (including the other hospital authorised to perform cardiac surgery in Oman). Moreover, the amount of data (and their availability) needed for calculating the EuroSCORE can be a precluding factor of its use. Thus, a prediction model based on smaller number of variables, like the one we proposed, can be of value to clinicians and bed managers who do not have sufficient data to build full-risk models.

Non-elective surgery and the type of surgery were independently significant in both models. Contrary to some previous studies that have found age[39–41] and sex[5 41] to be risk factors for prolonged CICU stay, these two basic demographic variables were not statistically significant in our models. Renal failure and renal dysfunction were both previously linked to increased CICU stay after cardiac surgery.[34 41–43] CHF at admission was only significant in the CICU model. This is consistent with other studies.[18 40]

When compared with previously published CICU prediction models, all of the predictors in our study have been reported before. However, these models differ considerably in their type of predictors. For example, Messaoudi *et al*[17] reported in a systematic review that the number of predictors among the reviewed studies ranged from 1 to 16 (with an average of 6 predictors). With such variation surrounding the selection of predictors among several studies, it would be inaccurate and misguiding to assume a model that was developed in one population would be valid for another. Therefore, the type of predictors (and the model) in our study should be relevant to the Omani hospitals and might be also applicable to other Gulf States. Moreover, unlike other studies which introduced models with many predictors, our finding suggests that predicting CICU LOS can be possible with fairly small number of predictors.

### Implications for hospital resource planning

Resource planning can be more effective if factors contributing to high resource use are appropriately managed. Clinicians can initiate preventive measures through aggressive treatment to reduce risk factors prior to surgery. A small reduction in LOS will result in a large cost saving. Risk stratification can be used to evaluate the appropriate patient management strategies (eg, aggressive treatment of comorbidities), to communicate the likelihood of CICU LOS to the patient, to aid in scheduling surgery or to be used when comparing CICU patients between hospitals.

## STUDY LIMITATIONS

Our study has some limitations that merit a discussion. First, the prediction model was not externally validated. Thus, the model lacks generalisability which limits its portability to other settings. Nevertheless, it is worth mentioning that a universal LOS prediction model may also be difficult to develop because LOS distributions depend on institutional policies which greatly influence discharge practices.[40] Second, the study included a small sample size relative to other previously published models. Despite this limitation, our dataset had some rare events such as stroke, renal failure and pulmonary hypertension that may not be expected to be captured in small datasets. Third, we acknowledge that there are some other non-clinical factors that might have influenced LOS but not included in our models due to unavailability of data. Such factors include physicians' judgements, hospital policy and demand and capacity considerations. Finally, our selection of the 75th centile for defining prolonged LOS can be viewed as an arbitrary cut-off in the absence of predefined clinically acceptable value in the literature.

**Contributors** AA, PA and HA designed the study. AA performed the literature review, wrote the first draft of the manuscript and conducted the statistical analysis. HA directed the collection of the data. MM and BB performed the data collection and interpretation of the results. PA appraised the study quality and assisted in statistical analysis. All authors contributed to drafts of the manuscript and approved the final manuscript.

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# Systematic review of factors influencing length of stay in ICU after adult cardiac surgery

Ahmed Almashrafi*, Mustafa Elmontsri and Paul Aylin

## Abstract

**Background:** Intensive care unit (ICU) care is associated with costly and often scarce resources. In many parts of the world, ICUs are being perceived as major bottlenecks limiting downstream services such as operating theatres. There are many clinical, surgical and contextual factors that influence length of stay. Knowing these factors can facilitate resource planning. However, the extent at which this knowledge is put into practice remains unclear. The aim of this systematic review was to identify factors that impact the duration of ICU stay after cardiac surgery and to explore evidence on the link between understanding these factors and patient and resource management.

**Methods:** We conducted electronic searches of Embase, PubMed, ISI Web of Knowledge, Medline and Google Scholar, and reference lists for eligible studies.

**Results:** Twenty-nine papers fulfilled inclusion criteria. We recognised two types of objectives for identifying influential factors of ICU length of stay (LOS) among the reviewed studies. These were general descriptions of predictors and prediction of prolonged ICU stay through statistical models. Among studies with prediction models, only two studies have reported their implementation. Factors most commonly associated with increased ICU LOS included increased age, atrial fibrillation/ arrhythmia, chronic obstructive pulmonary disease (COPD), low ejection fraction, renal failure/ dysfunction and non-elective surgery status.

**Conclusion:** Cardiac ICUs are major bottlenecks in many hospitals around the world. Efforts to optimise resources should be linked to patient and surgical characteristics. More research is needed to integrate patient and surgical factors into ICU resource planning.

**Keywords:** Cardiac ICU resource utilisation, Length of stay, Cardiac surgery

## Background

Cardiac Intensive Care units (ICU) are specialised units that provide care to patients after cardiac surgery or those who are critically ill. Care provided in ICUs is costly and labour intensive. This is also coupled with limited number of ICU beds leading most ICUs to operate near full capacity [1]. Thus, unavailability of beds become an issue and may substantially impact upon other services such as operating theatres. Simply extending ICU capacity may not be feasible, due to physical limitations, resources or government regulation [2].

Patients receiving cardiac care are a heterogeneous group in their use of resources. The wide variation in length of stay (LOS), for example, is influenced by several clinical and non-clinical factors. This is also exacerbated by the complexity and the invasive nature of heart surgery. Most patients, depending on the hospital setting, are expected to be admitted to an ICU after their surgery. Standard care will be provided that include continuous ECG monitoring, hemodynamic management, pain control, renal monitoring, ventilation

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support and respiratory management [3, 4]. Thus, ICU stay is an important milestone in the cardiac patient hospital journey.

Several studies attempted to identify the effect of patients, treatment and institutional factors that can best explain variation around ICU LOS. However, there is still ambiguity and lack of concise recommendations on how resource planning can be improved by monitoring variation. Understanding variability could allow healthcare resource planners to allocate patients or resources in a way that maximises patient throughputs. However, integrating patient and treatment-related factors into the resource planning process is an area that still needs to be addressed. In general, there is a scarcity of literature about understanding how factors affecting ICU LOS can be translated into practice to optimise ICU resources.

While many studies [5–9] have identified factors associated with prolonged ICU LOS for patients undergoing cardiac surgery, the conclusions reached have not been reviewed as to how they can be of practical use to patients or resource management. Among several options available to clinicians and hospital managers are: targeting specific modifiable risk factors, expected LOS-based scheduling, capacity management, fast track anaesthesia, staffing levels and other resource planning strategies. This review aims to provide recommendations on how to approach this gap.

### Objectives

To systematically review the available literature in order to identify factors associated with LOS in ICU following cardiac surgery and to explore the evidence on the link between understanding these factors and patient and resource management. We provide recommendations on how these factors can be incorporated into decisions to improve resource utilisation.

### Questions

Our systematic review was driven by the following two questions: 1) what type of factors influence cardiac ICU length of stay? 2) Do the selected studies explore any application (i.e. medical or administrative) to improve cardiac ICU resource allocation based on an understanding of these factors?

## Methods

The systematic review was conducted and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta Analyses Statement (PRISMA).

### Search strategy

Electronic searches of Embase, PubMed, ISI Web of Knowledge, Medline and Google Scholar were conducted using the following free text terms: prolonged length of stay OR long stay OR excess, intensive care unit OR critical care, determinants OR predictors OR risk factors OR factors, cardiac OR heart. Terms are summarised in Table 1. References contained in the included studies were checked for additional papers that were not identified in the electronic search.

#### *Study criteria*

Abstracts were examined by two reviewers (AA and ME) and were selected or excluded based on the following criteria:

### Selection criteria

Studies were included if they met the following criteria: 1) reported association between variables of interest and postsurgical LOS for adult patients who underwent cardiac surgeries only, 2) were published between January 2005 and January 2015 in English language and in peer-reviewed journals. We restricted search to this time period to account for advances both in treatment and medical technology. It is more likely that factors affecting LOS have changed over time due to reduction of severity of several risk factors influential to LOS. Recent advancements in perioperative care may have also contributed to this change. Therefore, we believe a period of 10 years is a reasonable time to reflect these changes, and 3) we also included studies with main goal of evaluating ICU LOS predictive models since these models were derived from statistically significant factors influential to LOS.

### Exclusion criteria

Studies were excluded if they 1) had no reference to length of stay as a measure of outcome (e.g. studies reporting costs only), 2) studies that have investigated resource utilisation among medical patients (e.g. heart failure) and have not included patients who underwent a cardiac surgery, and 3) studies that have exclusively investigated factors affecting the general postoperative LOS without a reference to factors affecting LOS in the intensive care setting.

#### *Data extraction and quality assessment*

Using a standardised data collection form, we extracted data from the selected studies relating to design, patient sample size, identified significant factors, type of surgery, statistical method used and number of hospitals in the study. We also reviewed any

**Table 1** Search term used in electronic database

| | Search terms |
|---|---|
| LOS | LOS, Extended LOS, long LOS, prolonged LOS, excess LOS |
| Surgery | Cardiac surgery, heart surgery, AND post* |
| Intensive care unit | Critical care, cardiac ICU, ICU, and intensive care |
| Management strategies | Resource planning, bed management, patient flow, scheduling, throughputs, and efficiency |

*used to find other derivates associated with theterm

reported recommendations on resource or patient management interventions. We define management intervention in this context as any strategy geared toward improving patient scheduling, reducing LOS, improving patient flow or resource allocation in general, utilising knowledge on factors affecting LOS.

### Quality assessment

A quality assessment of papers was conducted using an adapted version of the Newcastle-Ottawa Scale (NOS) [10]. The NOS uses a star rating system to judge the quality of a study. We assessed each article for adhering to the following criteria:

### Selection

1) Representativeness of the sample: a) the sample is truly representative of patients who underwent cardiac surgery (all subjects or random sampling) (one star), b) the sample is somewhat representative (non-random sampling) (one star), and c) selected group of users (no star), d) no description of the sampling strategy (no star). 2) Sample size: a) justified and satisfactory (one star), and b) not justified (no star). Maximum 3 stars.

### Comparability

1) confounding factors: a) the study controls for the most important factor (one star), and b) the study control for any additional factor (one star). Maximum 2 stars.

### Outcome

1) assessment of the outcome: a) independent blind assessment (two stars), b) record linkage (two starts), c) self-report (one star), and d) no description (no star). 2) statistical test: a) the statistical test used to analyse the data is clearly described and appropriate, and the measurement of the association is presented, including confidence intervals and probability level (*p* value) (one star), and b) the statistical test is not appropriate, not described or incomplete (no star). Maximum 6 stars.

We computed the total scores based on the assessment. The total possible stars is 11. The assessment can be found in Appendix B.

### Data synthesis

It was not possible to combine all result and conduct a meta-analysis due to substantial methodological and clinical heterogeneity of the studies.

## Results

We identified 983 papers in the initial search. Papers were then reviewed for relevancy based on their titles or abstracts. Eventually, 29 papers met the inclusion criteria (Fig. 1). Of these papers 27 were cross-sectional, and 2 were case-control. The majority of the selected papers 22 (76 %) were conducted in developed countries. Several studies have specifically addressed a single LOS predictor such as advanced age [11], blood transfusion [12], surgical wound infection [13], hypoactive delirium [14], or serum creatinine [15]. 21 (72 %) assessed LOS in relationship to several preoperative, intraoperative or postoperative variables rather than limiting analysis to one stage of hospital stay. No study has collected data from more than a single institution. A summary of the selected studies is provided in Appendix A.

Multivariate logistic regression was commonly used as a statistical tool in 23 papers. Other statistical analysis carried out were proportional hazard [16], survival analysis [17], case-control [13], regression tree [18], or combination of statistical hypothesis tests.

### Prolonged LOS: lack of uniformed definition

The majority of the studies have dichotomised their LOS into two groups (normal vs. prolonged LOS), hence the use of the logistic regression models. Only four studies have treated LOS as a continuous variable (Appendix A). This might have been the case because LOS data are highly skewed and subject to outliers precluding modelling LOS as normally distributed variable [19]. In addition, it is more meaningful to separate patients into two groups since patients with prolonged LOS are an important subpopulation that impact use of hospital resources. However, we further observed a variation in the selection of the cut-off points that define prolonged LOS. These ranged from 24 h to 7 days.

### The overall objective of identifying predictors of ICU LOS

We categorised studies based on their objectives for identifying predictors of LOS. Two types emerged from our review: 1) general descriptions of predictors (22 papers), and 2) risk prediction for prolonged ICU LOS (7papers). Most studies fell into the first

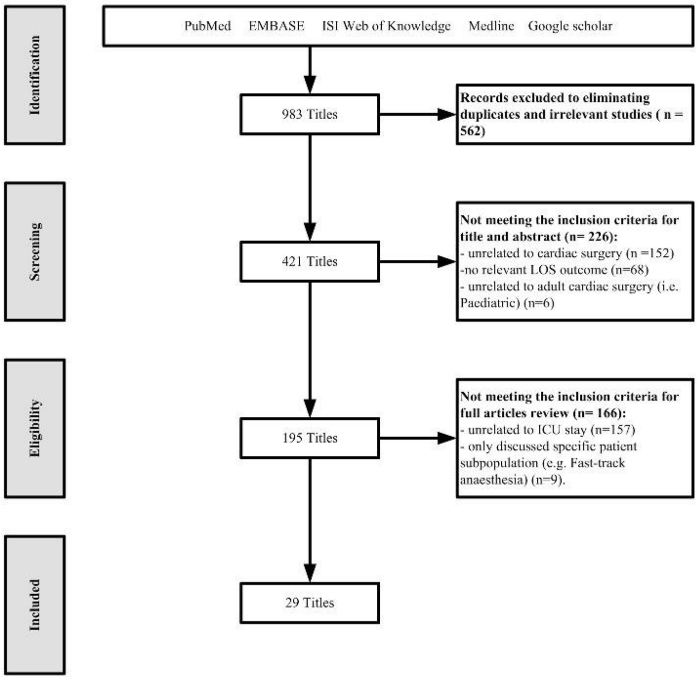


**Fig. 1** Search process flow for articles included in the review

category where predictors are selected among several variables. Studies in the second category attempted to derive predictive models that stratified patients based on their risk for prolonged LOS which potentially can be used to facilitate the selection of optimal patient management strategy. Studies with prediction models had on average 10 predictors which were derived from hospital routinely collected data.

The majority of the reviewed papers didn't report specific real-world application that might be realised from understanding influential predictors. However, two studies reported implementation [20, 21]. With such a small rate, it is difficult to assess the acceptance and usefulness of these studies in improving operational performance of ICU units.

### Independent predictors of ICU LOS

Several studies included factors that are likely to exist early during a hospitalisation. This is especially the case when the aim was designing a predictive model. However, definitions of variables were not commonly discussed with the exception of Augoustides et al., [22] De Cocker et al., [16] Rosenfeld et al., [23] and Widyastuti et al. [24] who reported definitions of variables used in assessment.

Most studies included basic demographic variables such as gender, age, and race. We identified patient fixed variables (e.g. gender, body mass index) to be the most commonly studied variables. Yet, few turned to be independently significant when a multivariate analysis was used. Age was the most commonly reported statistically significant predictor. Only two studies found gender to be a contributing factor of prolonged ICU LOS. Conversely, BMI was independently significant in only two studies and body service area was not independently significant in any of the reviewed studies. As shown in Table 2, comorbidities accounted for a large proportion of risk for prolonged LOS. This is because several studies were designed to predict LOS at time of admission.

Surgical characteristics such as the use of Cardiopulmonary Bypass (CPB) machine [20], bypass time [23–25] and blood transfusion [7, 12, 24] were predictive of ICU LOS. Postoperative complications were

**Table 2** Predictors of ICU LOS after cardiac surgery

| Predictive factors | Reference | Predictive factors | Reference |
|---|---|---|---|
| Patient related factors | | Arrhythmia / Atrial fibrillation | [5, 9, 16, 20, 21, 28, 34, 35] |
| Increased age | [11, 23, 24, 28, 34, 36] [5, 8, 16, 18, 20, 26] | Low Ejection Fraction | [21, 34, 36] [20, 22, 29] |
| Gender | [6, 16] | Left ventricular dysfunction | [17, 37] |
| BMI | [20, 38] | NYHA class III-IV | [6, 16, 25, 34, 36] |
| Body service area | None | Chronic heart failure | [11, 21, 24] |
| Smoking | [20, 39] | Critical preoperative state | [34] |
| Platelet count | [28] | Hypoactive delirium | [14] |
| hyperglycaemia | [35] | Surgical factors | |
| High preoperative serum creatinine | [15, 17, 35] | Non-elective surgery | [16, 17, 20, 23–25, 29, 36, 37] |
| Fat-free mass index | [40] | Type of surgery | [14, 16] |
| Plasma disappearance rate of indocyanine green | [18] | CPB use | [20] |
| Previous cardiac surgery | [5, 24, 36, 37] | Bypass time | [23–25] |
| Comorbidities | | Cross clamp time | [38] |
| Hypertension | [5, 20, 23] | Combined surgery | [34] |
| COPD | [11, 21, 23, 24, 34, 36] | Intra-aortic balloon pump | [16, 24] |
| Diabetes | [20, 39] | Blood transfusion | [7, 12, 24] |
| Insulin-dependent diabetes | [21] | Inotropes support | [7, 16, 25, 28] |
| Hypercholesterolemia | [20] | Triple vessel or left main disease | [36] |
| Recent Myocardial infarction | [36] | Complications | |
| Renal failure/ dysfunction | [11, 21, 22, 29, 36, 41] | Reoperation for bleeding | [26] |
| Unstable Angina | [37] | Pulmonary | None |
| Pulmonary hypertension | [37] | Cardiac | None |
| Angina class IV | [20] | Neurological | [22] |
| Peripheral vascular disease | [20, 24, 36] | Infection | [13] |
| | | Renal complications | None |

*Abbreviation*: *COPD* chronic obstructive pulmonary disease, *BMI* Body Mass Index, *CPB* Cardiopulmonary bypass machine

less commonly discussed. There were only 4 studies [13, 22, 26] that carried out analysis with some post-operative complications included.

We observed some consistency over some factors that have been found to be independently associated with patient stay. For example, the following variables were identified to be independent predictors of ICU LOS in four or more studies (Table 2): increased age, Chronic Obstructive Pulmonary Disease (COPD), renal failure or dysfunction, atrial fibrillation, low ejection fraction, NYHA class III-IV, non-elective surgery, previous cardiac surgery, and inotropes support.

Unlike other studies which neglected the inclusion of patients who died before they were discharged from the ICU, De Cocker et al. utilised Cox Proportional Hazards model which accounted for these patients in the analysis [16]. The rationale for including them was that most of these patients would probably have had extended ICU stays if they stayed alive. Ghotkar and colleagues conducted a sensitivity analysis whereby patients who died were included in a second analysis [20]. The independent risk factors identified originally remained unchanged. Barili et al. [17] developed a model to identify predictors of ICU LOS in patients who were discharged a live from ICU and another model for those patients who died.

## Discussion

### Variation in definitions

Our findings are similar to those reported by Messaoudi et al. who pointed out to the fact that there was a lack of uniformed and standardized definitions regarding ICU length of stay [27]. In most of our reviewed studies, the cut-off criteria was more likely to be arbitrary. Only a single study reported a definition that was based on a clinical consideration. For example, Rosenfeld et al. selected 7 days as a cut-off point because it may indicate a severe complications [23]. The choice of the threshold periods may also be determined by the average stay duration in a particular ICU unit. For instance, when step down units are available, patients can be transferred to these units to free up some ICU beds. In such facilities, patients, on average, will have a shorter ICU LOS.

Few studies have provided definitions of the variables. However, even when the definitions of variables are provided, it is possible that they varied across surgeons even in the same hospital [5]. This might be a common weakness in some of our reviewed studies where data were retrospectively collected.

### Type of surgery

Thirteen studies have included only a single type of surgery in their analysis. Out of these studies, 9 included isolated Coronary Artery Bypass Grafting (CABG) surgery only. However, cardiac ICU beds are shared by all types of cardiac surgical patients. From a resource allocation perspective, these patients compete for the same resources and thus disregarding certain patient types will undermine the usefulness of these studies in resource management.

### The utility of understanding influential factors of ICU LOS

The majority of the studies have identified factors predicting LOS without reference to a particular use in operational or clinical application. Understanding patient variability around resource consumption is an important task that should be undertaken by hospital managers. Continuous surveillance of factors affecting cardiac ICU LOS may allow better design of services and streamline patients more efficiently. However, there is paucity in literature on whether hospitals are integrating these risk factors into resource planning. As stated previously, the majority of the reviewed studies have not demonstrated the applicability of their findings in improving the clinical or operational performance.

Factors contributing to patient ICU LOS variability can be potentially integrated into resource management practices. Broadly speaking, the utility of such knowledge can be applicable to patient management (e.g. aggressive treatment of comorbidities, fast track triage) and resource management (e.g. scheduling surgery, bed allocations, or determining staffing level).

An early recognition of patients at risk of prolonged LOS was the main objective of the prediction models. Our review revealed that these models varied widely on the types of variables included. In addition, all of these models were based on single institution which casts a doubt on their generalisability beyond the local setting where they have been originally derived from. This supports our hypothesis that the practice of ICU LOS prediction is still locally based. Clearly, there is a need for a simple [21] and universal model that takes into consideration differences in patient and surgical characteristics. However, Widyastui et al. argued that a universal model may also be difficult to develop as LOS distributions depend on institutional policies governing ICU discharge [24]. It is worth mentioning that the utility of ICU LOS prediction models in improving patients and resource management has not been investigated in the literature. We aim to address this in a future study.

Based on our analysis of the studies, two options can be pursued when analysing factors predictive of ICU LOS. The first is investigate these factors using available data that are usually routinely collected in most hospitals. Second, there might be a need to evaluate a single common factor (e.g. atrial fibrillation that might be prevalent among the local population) to assess its impact on resource use.

Segmenting patients based on their expected LOS should augment decision making for resource allocation in surgical care. For example, Wagener et al. developed a prediction model that can discriminate between patients who are candidates of fast-track protocol [21]. The goal of instituting a fast track protocol was to minimise the time patients remain in the ICU or bypass it altogether. They further noted that the existing tools were not reliable to identify patients for fast-track protocols and their model was superior to these systems. Another application was suggested by Tribuddharat and colleagues in the form of a prediction tool that can identify patients with prolonged LOS and may provide the anaesthesiologist with enough time to correct risk factors [28]. Targeting risk factors through aggressive treatment regimens prior to surgery may reduce the proportion of patients who require lengthy ICU LOS which can result in several medical, operational and financial benefits. This is the case because many of the risk factors are potentially modifiable. Consequently, aggressive preoperative treatments and workups prior to surgery can mitigate the need for extended LOS [29]. Scheduling patients based on their expected LOS is another way of expanding the applicability of early recognition of factors influential to ICU LOS. For example, patients expected to stay longer in the ICU can be scheduled at the end of the week to take advantage of weekends when no surgical procedures are scheduled [30].

#### Variable selections

Most studies utilised routinely collected data available in most hospitals information systems. These databases include demographic, comorbidities, complications, and surgery detail. Such data are readily available. However, there are several contextual factors that affect ICU LOS that are often overlooked. For example, in hospitals that practice a protocol of fast tracking, the normal duration of stay post cardiac surgery will be less than for hospital that don't implement this system. It will also depend on whether patients can be transferred to a step-down unit which is less resource-intensive than conventional ICUs. Moreover, LOS distributions were found to depend on institutional policies which greatly influence discharge practices [24]. For example, individual physicians' judgement is a factor that is associated with prolonged LOS in the ICU [27, 31]. Additionally, as Cots et al. suggest, the size of the hospital can affect LOS. As such, large urban teaching hospitals had more patients with very high LOS compared to medium and small community hospital [32].

Difference in LOS variability can also be explained by the capacity of the ICU, the level of demand for ICU beds, and the surgeon skills. Therefore, the decision to discharge patients from ICU is mostly based on policy as well as medical criteria [24].

Even though we observed that all reviewed studies have not included variables related to hospital or social settings (i.e. contextual factors), we believe that the hospital routinely collected data are adequate in identifying factors affecting LOS and therefore can be used in assessing resource utilisation in hospital systems. Similarly, for a wider practical application, administrative data can be utilised to describe factors contributing to resource use [33]. This provides an opportunity to consider data commonly collected in most hospitals and improve generalisability of models.

When lack of data is an issue or when the purpose is to predict ICU LOS, researchers should aim for a parsimonious model that explains the largest variation with as few predictors as possible. Equally important, some of our reviewed studies had a sample size that is relatively small (e.g. < 200). With such size, it is possible that these studies missed the inclusion of rare events such as renal failure and stroke which have high impact on ICU LOS. Moreover, in some statistical analysis, low sample size precludes including complete list of potential factors affecting LOS and risk reducing the power of the study.

## Conclusion

Patient and surgical factors are valuable information for predicting LOS in critical care. However, the extent at which these factors are utilised in managing patients is unclear. Studies vary on the type of predictors being selected. Few variables were more common than others. For example, atrial fibrillation/ arrhythmia, increased age, chronic obstructive pulmonary disease (COPD), renal failure/ dysfunction and non-elective surgery status were common predictors.

Identifying risk factors for prolonged LOS should not be treated in isolation of the intended use. That is, the utility of identifying risk factors should be clearly defined. This will facilitate the integration of influential factors into the resource allocation decision making process. This may also allow hospital stakeholders (e.g. bed managers) to engage in case-mix evaluation and thus empirically assess resource needs. More research is needed to link variation around hospital resource use and management strategies designed to optimise patients flow.

The cut-off period for prolonged LOS should be carefully selected taking into consideration clinical judgement as well as past historical data. It might be more accurate to assess LOS as a continuous variable using appropriate statistical methods to adjust for different variables. This will potentially eliminate the arbitrary selection of an endpoint. Similarly, studies examining resource utilisation should clearly define variables as differences in definitions can substantially affect results.

Unique local practices should not be underestimated when investigating factors influencing hospital resource utilisation. Several organisational contexts can impact LOS. However, we acknowledge that it is difficult to account for organisational factors due to the difficultly associated with measuring some of these factors.

Equally, the unique characteristics of patients treated by individual hospitals adds another challenge in predicting LOS across multiple settings. Our review can inform researchers interested in this evaluation to focus on those variables that are commonly reported to be independent contributors to ICU LOS (see Table 2).

#### Limitations

We only reviewed studies published in the English language. This means that studies written in other languages which may meet the inclusion criteria were excluded.

## Appendix A

**Table 3** Studies summary

| RN | First author and year | Country | Number of hospitals | Total patients | Cardiac surgery type | LOS definition | Objective type |
|---|---|---|---|---|---|---|---|
| 1 | Wang, 2012 [34] | China | 1 | 3925 | Valve surgery | Prolonged > 7 days | Prediction model |
| 2 | Atoui, 2008 [29] | Canada | 1 | 426 | CABG, valve, and combined surgery | Prolonged ≥ 2 days | General description of predictors |
| 3 | Abrahamyan 2006 [5] | Armenia | 1 | 391 | Isolated CABG | Prolonged ≥ 3 days | General description of predictors |
| 4 | Augoustides 2006 [22] | USA | 1 | 144 | Thoracic Aortic surgery | Prolonged > 5 days | General description of predictors |
| 5 | Ghotkar 2006 [20] | UK | | 5186 | Isolated CABG | Prolonged > 3 days | Prediction model |
| 6 | Hein 2006 [26] | Germany | 1 | 2683 | CABG, combined, and other | Prolonged > 3 days | General description of predictors |
| 7 | Rosenfeld 2006 [23] | USA | 1 | 9869 | Isolated CABG | Prolonged ≥ 7 days | General description of predictors |
| 8 | Horer 2008 [9] | Germany | 1 | 281 | Atrial septal defect closure | Prolonged > 2 days | General description of predictors |
| 9 | Lei 2009 [25] | China | 1 | 298 | Aortic arch surgery | Prolonged > 5 days | General description of predictors |
| 10 | Widyastuti 2012 [24] | Norway | 1 | 4994 | CABG, Valve, Combined, and other | Prolonged > 2, 5, 7 days | General description of predictors |
| 11 | Wagener 2011 [21] | USA | 1 | 1201 | CABG, valve, Combined, and other | ICU LOS < 2 days ICU LOS > 7 days | Prediction model |
| 12 | Tribuddharat 2014 [28] | Thailand | 1 | 168 | CABG, Valve, and combined | ICU LOS < 42 h | Prediction model |
| 13 | Scott 2005 [11] | USA | 1 | 1746 | CABG | Continuous | General description of predictors |
| 14 | Scott 2008 [12] | USA | 1 | 1746 | CABG | Continuous | General description of predictors |
| 15 | Herman, 2009 [36] | Canada | 1 | 3483 | CABG | Prolonged > 3 days | Prediction model |
| 16 | Graf, 2010 [13] | Germany | 1 | | CABG | Continuous | General description of predictors |
| 17 | Giakoumidakis, 2011 [41] | Greece | 1 | 313 | CABG, valve, and combined | Prolonged ≥ 2 days | General description of predictors |
| 18 | De Cocker, 2011 [16] | Belgium | 1 | 1566 | CABG, valve, combined, and other | Prolonged > 2, 5, 7 days & continuous | Prediction model |
| 19 | Cacciatore, 2012 [6] | Italy | 1 | 250 (≥65 years) | CABG, valve, and combined | Prolonged ≥ 3 days | General description of predictors |
| 20 | Azarfarin, 2014 [7] | Iran | 1 | 280 | CABG, valve, and combined | Prolonged > 4 days | General description of predictors |
| 21 | Nakasuji, 2005 [8] | Japan | 1 | 100 | CABG | Prolonged > 3 days | General description of predictors |
| 22 | Eltheni, 2012 [35] | Greece | 1 | 150 | CABG, valve, combined, and other | Prolonged ≥ 2 days | General description of predictors |
| 23 | Bignami, 2012 [38] | Italy | 1 | 27 | CABG, valve, combined, other | Prolonged > 24 h | General description of predictors |
| 24 | Stransky, 2011 [14] | Germany | 1 | 506 | CABG, valve, combined, other | Continuous | General description of predictors |
| 25 | Weis, 2014 [18] | Germany | 1 | 190 | CABG, valve, combined | Prolonged > 3 days | General description of predictors |
| 26 | Ezeldin, 2013 [15] | Saudi Arabia | 1 | 1033 | CABG, valve | Prolonged > 3 days | General description of predictors |
| 27 | Oliveira, 2013 [39] | Brazil | 1 | 104 | CABG | Prolonged > 3 days | General description of predictors |
| 28 | Venrooij, 2011 [40] | Netherlands | 1 | 325 | CABG, valve, combined | Not specified | General description of predictors |
| 29 | Barili | Italy | 1 | 3861 | CABG, valve, combined, other | Continuous | Prediction model |

## Appendix B

**Table 4** Newcastle-Ottawa modified for cross-sectional studies

| Study | Selection | | | | | | Comparability | | Outcome | | | | | | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Representativeness of the sample | | | | Sample size | | Confounding factors | | Assessment | | | | Statistical test | | |
| | A* | B* | C | D | A* | B | A* | B* | A** | B** | C* | D | A* | B | |
| 1. Abrahamyan, L., et al., Determinants of Morbidity and Intensive Care Unit Stay after Coronary Surgery. Asian Cardiovascular and Thoracic Annals | | + | | | + | | | | | + | | | + | | 5 |
| 2. Atoui, R., et al., Risk factors for prolonged stay in the intensive care unit and on the ward after cardiac surgery. | | + | | | + | | + | + | | | | | + | | 4 |
| 3. Augoustides, J.G., et al., Clinical predictors for prolonged intensive care unit stay in adults undergoing thoracic aortic surgery requiring deep hypothermic circulatory arrest. | | + | | | + | | + | | | + | | | + | | 5 |
| 4. Azarfarin, R., et al., Factors influencing prolonged ICU stay after open heart surgery. | | | | | + | | + | | | + | | | + | | 5 |
| 5. Cacciatore, F., et al., Determinants of prolonged intensive care unit stay after cardiac surgery in the elderly. | + | | | | + | | + | + | | + | | | + | | 7 |
| 6. De Cocker, J., et al., Preoperative prediction of intensive care unit stay following cardiac surgery. | + | | | | + | | + | + | | + | | | + | | 7 |
| 7. Eltheni, R., et al., Predictors of prolonged stay in the intensive care unit following cardiac surgery. | + | | | | + | | + | | | + | | | + | | 6 |
| 8. Ghotkar, S.V., et al., Preoperative calculation of risk for prolonged intensive care unit stay following coronary artery bypass grafting. | + | | | | + | | | | | + | | | + | | 5 |
| 9. Giakoumidakis, K., et al., Risk factors for prolonged stay in cardiac surgery intensive care units. | | + | | | + | | | | + | | + | | + | | 6 |
| 10. Hein, O.V., et al., Prolonged intensive care unit stay in cardiac surgery: risk factors and long-term-survival. | + | | | | + | | + | | | + | | | + | | 6 |
| 11. Herman, C., et al., Predicting prolonged intensive care unit length of stay in patients undergoing coronary artery bypass surgery–development of an entirely preoperative scorecard. | + | | | | + | | + | | | + | | | + | | 6 |
| 12. Horer, J., et al., Risk factors for prolonged intensive care treatment following atrial septal defect closure in adults. | | + | | | | + | | | | + | | | | + | 3 |
| 13. Lei, Q., et al., Preoperative and intraoperative risk factors for prolonged intensive care unit stay after aortic arch surgery. | | + | | | | + | + | | | + | | | + | | 5 |
| 14. Nakasuji, M., M. Matsushita, and A. Asada, Risk factors for prolonged ICU stay in patients following coronary artery bypass grafting with a long duration of cardiopulmonary bypass. | + | | | | | + | | | | + | | | + | | 4 |
| 15. Scott, B.H., F.C. Seifert, and R. Grimson, Blood transfusion is associated with increased resource utilisation, morbidity and mortality in cardiac surgery. | | + | | | + | | | | + | | | | | + | 5 |
| 16. Scott, B.H., et al., Octogenarians undergoing coronary artery bypass graft surgery: resource utilization, postoperative mortality, and morbidity. | | + | | | + | | + | | | + | | | + | | 6 |
| 17. Tribuddharat, S., et al., Development of an open-heart intraoperative risk scoring model for predicting a prolonged intensive care unit stay. | | + | | | | + | + | | | + | | | + | | 5 |
| 18. Wagener, G., et al., The Surgical Procedure Assessment (SPA) score predicts intensive care unit length of stay after cardiac surgery. | | + | | | + | | + | | | + | | | + | | 5 |

**Table 4** Newcastle-Ottawa modified for cross-sectional studies *(Continued)*

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 19. Wang, C., et al., Risk model of prolonged intensive care unit stay in Chinese patients undergoing heart valve surgery. | + | | + | + | | + | + | 6 |
| 20. Widyastuti, Y., et al., Length of intensive care unit stay following cardiac surgery: is it impossible to find a universal prediction model? | + | | + | + | | + | + | 6 |
| 21. Bignami et al. Urinary neutrophil gelatinase-associated lipocalin as an early predictor of prolonged intensive care unit stay after cardiac surgery | | + | + | | | + | + | 5 |
| 22. Venrooij et al. The impact of low preoperative fat-free body mass on infections and length of stay after cardiac surgery: A prospective cohort study | + | | + | + | | + | + | 6 |
| 23. Stransky et al. Hypoactive Delirium After Cardiac Surgery as an Independent Risk Factor for Prolonged Mechanical Ventilation | + | | + | + | | + | + | 6 |
| 24. Ezeldin Relation between serum creatinine and postoperative results of open-heart surgery | + | | + | + | | + | + | 6 |
| 25. Wies et al. Indocyanine green clearance as an outcome prediction tool in cardiac surgery: A prospective study | + | | + | + | + | + | + | 7 |
| 26. Barili et al. An original model to predict Intensive Care Unit length-of stay after cardiac surgery in a competing risk framework | + | | + | + | | + | + | 6 |
| 27. Oliveira E, et al., Risk factors for prolonged hospital stay after isolated coronary artery bypass grafting | + | | + | + | | + | + | 6 |

The number of stars for each item is represented by asterisks*

**Table 5** Newcastle-Ottawa: case-control studies

| Study | Selection | | | | | | | | | | Comparability | | Exposure | | | | | | | | | | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Case definition | | | Representativeness of the cases | | Selection of controls | | | Definition of controls | | Confounding factors | | Ascertainment of exposure | | | | | Same method of ascertainment for case and controls | | Non-response rate | | | |
| | A* | B | C | A* | B | A* | B | C | A* | B | A* | B* | A* | B | C | D | E | A* | B | A* | B | C | |
| 28. Graf, K., et al., Economic aspects of deep sternal wound infections. | | + | | + | | | + | | + | | + | | + | | | | | + | | | + | | 5 |
| 29. Rosenfeld, R., et al., Predictors and outcomes of extended intensive care unit length of stay in patients undergoing coronary artery bypass graft surgery. | | + | | + | | | + | | + | | + | | + | | | | | + | | | + | | 5 |

The number of stars for each item is represented by asterisks*

### Abbreviations
BMI, body mass index; CABG, coronary artery bypass grafting; COPD, chronic obstructive pulmonary disease; CPB, cardiopulmonary bypass machine; ICU, Intensive care unit; LOS, length of stay.

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### Availability of data and material
Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

### Authors' contributions
AA, ME and PA conceived and designed the study. AA drafted the initial manuscript. AA and ME extracted and analysed data. PA made critical revision of the manuscript. All authors read and approved the final manuscript.

### Competing interests
We declare that we have no competing financial, professional or personal interests that might have influenced the performance or presentation of the work described in this manuscript.

### Consent for publication
Not applicable

### Ethics approval and consent to participate
Not applicable

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## Appendix B: Ethical Approval

Sultanate of Oman
Ministry of Health
Directorate General of Royal Hospital

سلطنة عمان
وزارة الصحة
المديرية العامة للمستشفى السلطاني

September 29th, 2013

**To:**
**Mr. Ahmed Al Musharfi**
**PhD Student**
**Imperial College London**

**Subject: Ethical Approval Request for: "Optimising care pathways using patinets' routinely collected data" MESRC# 22/2013**

Thank you for submitting the above mentioned proposal. It is my pleasure to inform you on behalf of Medical Ethics & Scientific Research Committee that your request has been approved, and you can now start your research.

Wish you a productive study.

Best Regards,

For/ **Dr. Seif Al-Abri**
**Chairperson of Medical Ethics & Scientific Research Committee**
**Royal Hospital**

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Sultan Qaboos University
COLLEGE OF MEDICINE
& HEALTH SCIENCES

جامعة السلطان قابوس
كلية الطب
والعلوم الصحية

30th October 2013

To : Dr. Abduallah Al-Asmi
Department of Medicine

Subject: Research Proposal "Optimizing care pathways using routinely collected patient data "(MREC#798)

Thank you for submitting the above mentioned proposal. It is my pleasure to inform you on behalf of the Ethics Committee that your proposal has been approved, and you can now start your research.

Wish you a productive study.

Best Regards,

**Dr Khalid Al Balushi**
Assistant Dean for Postgraduate Studies & Research

P.O. Box: 35
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Al-Khod, Sultanate of Oman
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الخوض - سلطنة عمان
هاتف: ٢٤١٤١١٠٣ (+٩٦٨)؛ فاكس: ٢٤٤١٣٤١٩ (+٩٦٨)

LTANATE OF OMAN
MINISTRY OF HEALTH
DIRECTORATE GENERAL OF ROYAL HOSPITAL

سلطنة عمان
وزارة الصحة
المديرية العامة للمستشفى السلطاني


**MEDICAL RECORDS SERVICES**

MoH/RH/MRS/ 138 /2013
15/09/2013

**Dr Seif Al Abri**
**Chairperson of Medical Ethics & Scientific Research Committee**
**Royal Hospital**

After Compliments,

**Re: Ethical Approval Request for MESRC#22/2013**

Reference to your letter dated 3rd September 2013, we have no objection in conducting research on "Optimizing care pathways use patient's routinely collected data" as long as the individual patients identity is not disclosed, for which the applicant has assured. However, we may have to seek approval of the Hospital Administration as well as Department of Cardiology as this research is much focused on cardiology services.

Thanking you,

15/9/13

**SULTAN SAIF AL RUBAIEY**
Actg. Head, Medical Records

Received on 16/9/13


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Sultanate of Oman
Ministry of Health
Directorate General of Royal Hospital

سلطنة عمان
وزارة الصحة
المديرية العامة للمستشفى السلطاني

September 19th, 2013

**To:**
**Head, Cardiology Department**
**Royal Hospital**

**Subject: Ethical Approval Request for *MESRC#22/2013:***
***"Optimizing care pathways using patients' routinely collected data"***

The MESRC would like to forward you the above mentioned proposal for your view and comments.

Looking forward for your feedback,

Chalid

**Mr. Khaild Al Busaidi**
**Secretary, Medical Ethics & Scientific Research Committee**
**Royal Hospital**

No objection
from Cardiology
department

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**Appendix C: Postop complication definitions: Sultan Qaboos University Hospital**

| | |
|---|---|
| Blood products: RBC | Were red blood cell products transfused postoperatively, Do not include pre-donated blood, cell saver or chest tube recirculated blood. |
| Non-RBC | Were platelets, FFP or cryoprecipitate used. |
| Complication | Did a postoperative complication occur during hospitalization? |
| Reop Bleed | Operative re-intervention for bleeding. |
| Reop valve dysfunction | Operative re-intervention for valve dysfunction. |
| Reop Graft occlusion | Operative re-intervention for coronary graft occlusion. |
| Reop other Cardiac | Operative re-intervention for other cardiac reasons. |
| Reop deep sternal infection | Operative re-intervention for deep sternal infection. |
| Reop Other non-cardiac | Operative re-intervention for non-cardiac reasons |
| Postoperative MI | Diagnosed by finding at least two of the following criteria:<br>a) Enzyme level elevation: either 1) CK-MB>100; or 2) Troponin>2.ougm/ml, or established level at own institution.<br>b) New wall motion abnormalities.<br>c) Serial ECG (at least two) showing Q waves. |
| Heart Block | New heart block requiring implantation of permanent pacemaker. |
| Cardiac Arrest | Either a) VG b) VT with hemodynamic instability c) Asystole. |
| New Atrial Arrhythmia | New onset atrial fibrillation/ flutter requiring treatment. |
| Cardiac Tamponade | Fluid in the pericardial space compromising cardiac filling and requiring intervention. |
| Stroke Permanent | A central neurological deficit persisting for> 72 hours. |
| Stroke Transient | A transient neurological deficit (TIA, RIND, or delirium). |
| Continuous coma >24 hrs | New postoperative coma that persist for at least 24 hours. |
| Vent prolonged >24 hrs | Pulmonary insufficiency requiring ventilator support >24hours. |
| Pulmonary Embolus | Diagnosed by study such as V/Q scan or angiogram. |
| Pneumonia | Diagnosed by positive cultures and C/W clinical findings. |
| Deep sternal infection | Involves muscle, bone and/ or mediastinum. Must have one of the following: a) Wound debridement b) Positive cultures c) Treatment with antibiotics. |
| Thoracotomy infection | Involving Thoracotomy or parasternal site. (Conditions as above). |
| Septicemia | Septicemia (requires positive blood cultures) postoperatively. |
| Aortic dissection | Dissection occurring in any part of the aorta. |
| Acute Limb Ischemia | Any complication producing limb ischemia. |
| Anticoagulation comps | Bleeding, haemorrhage and/ or embolic events related to anticoagulation therapy. |
| GI complications | Postop occurrence of any GI complications, including: a) GI bleeding requiring transfusion b) Pancreatitis requiring nasogastric suction C) Cholecystitis requiring Cholecystectomy or drainage d) Mesenteric ischemia requiring exploration e) Other GI comps. |
| Multisystem failure | Two or more major systems suffer compromised functions. |

## Appendix D: Selected Visual Logic codes

- **Sample Visual Logic code for selecting preoperative patient to minimise CICU LOS:**

VL SECTION: Scenario 1: select patient mix for CICU
* the shift prevents selecting patients during the weekend
Get Shift Status    patient selection for cicu ,  var get shift status patient selection
IF var get shift status patient selection = 1
* only apply this code when the level of CICU is critical
IF CICU beds.Count Contents  <  3
IF preoperative beds.Count Contents  >  0
Select Minimum Label in Object    preoperative beds,  lbl cicu los ,  var min selected
IF lbl surgical patient = 1
IF select prolonged pt.Count Contents  =  0
Move Work Item To    select prolonged pt ,  0

- **Sample Visual Logic code for the selection of patient for the end of the week surgery:**

VL SECTION: Scenario 2 select patients for the end of the week surgery
Get Shift Status    pt select for end of the week ,  var get shift status end of week scenario
IF var get shift status end of week scenario  =  1
IF CICU beds.Count Contents  >  3
IF preoperative beds.Count Contents  >  0
Select Maximum Label in Object    preoperative beds ,  lbl cicu los ,  var max cicu los
IF lbl surgical patient  =  1
IF end of the week.Count Contents  =  0
Move Work Item To    end of the week ,  0

- **Sample Visual Logic code for the selection of patient for the early discharge:**

VL SECTION: Scenario 3: early discharge (CICU and ward)
IF CICU beds.Count Contents  >  3
Select Minimum Label in Object    CICU beds ,  lbl total score cicu ,  var sel min cicu score
SET lbl elapsed los  =  [Simulation Time-lbl cicu entry time]/24
IF lbl surgical patient  =  1
IF lbl total score cicu  <  2
IF lbl elapsed los  >  2
Move Work Item To    Postop beds ,  0
BreakDown    Nonsurgical ,  48
SET var count early discharge CICU  =  var count early discharge CICU+1
IF Postop beds.Count Contents  >  6
Select Minimum Label in Object    Postop beds ,  lbl total score ward ,  var sel min ward score
SET lbl elapsed los  =  [Simulation Time-lbl plos entry time]/24
IF lbl total score ward  <  5
IF lbl elapsed los  >  5
Move Work Item To    discharge surgery ,  0
SET var count early discharge ward  =  var count early discharge ward+1
SET var count early discharge ward  =  var count early discharge ward+1

- **Sample Visual Logic code for the selection of patients for no surgery**

```
VL SECTION: Scenario 4: Don't refer to surgery
SET lbl average score  =  [lbl total score cicu+lbl total score ward]/2
IF lbl surgical patient  =  1
IF lbl average score  >  3.5
SET lbl select no surgery  =  dist select no surgery # set to 10%, 20%, and 30%
IF lbl select no surgery  =  1
Move Work Item To    don't refer to surg ,  0
```