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An Integrated Framework for Staffing and Shift Scheduling in Hospitals

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An Integrated Framework for Staffing and Shift Scheduling in Hospitals

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Abstract

Over the years, one of the main concerns confronting hospital management is optimising the staffing and scheduling decisions. Consequences of inappropriate staffing can adversely impact on hospital performance, patient experience and staff satisfaction alike. A comprehensive review of literature (more than 1300 journal articles) is presented in a new taxonomy of three dimensions; problem contextualisation, solution approach, evaluation perspective and uncertainty. Utilising Operations Research methods, solutions can provide a positive contribution in underpinning staffing and scheduling decisions. However, there are still opportunities to integrate decision levels; incorporate practitioners view in solution architectures; consider staff behaviour impact, and offer comprehensive applied frameworks. Practitioners' perspectives have been collated using an extensive exploratory study in Irish hospitals. A preliminary questionnaire has indicated the need of effective staffing and scheduling decisions before semi-structured interviews have taken place with twenty-five managers (fourteen Directors and eleven head nurses) across eleven major acute Irish hospitals (about 50% of healthcare service deliverers). Thematic analysis has produced five key themes; demand for care, staffing and scheduling issues, organisational aspects, management concern, and technology-enabled. In addition to other factors that can contribute to the problem such as coordination, environment complexity, understaffing, variability and lack of decision support. A multi-method approach including data analytics, modelling and simulation, machine learning, and optimisation has been employed in order to deliver adequate staffing and shift scheduling framework. A comprehensive portfolio of critical factors regarding patients, staff and hospitals are included in the decision. The framework was piloted in the Emergency Department of one of the leading and busiest university hospitals in Dublin (Tallaght Hospital). Solutions resulted from the framework (i.e. new shifts, staff workload balance, increased demands) have showed significant improvement in all key performance measures (e.g. patient waiting time, staff utilisation). Management team of the hospital endorsed the solution framework and are currently discussing enablers to implement the recommendations.

Declaration

I certify that this thesis which I now submit for examination for the award of Doctor of Philosophy (PhD), is entirely my own work and has not been taken from the work of others, save and to the extent that such work has been cited and acknowledged within the text of my work.

This thesis was prepared according to the regulations for graduate study by research of the Dublin Institute of Technology and has not been submitted in whole or in part for another award in any other third level institution.

The work reported on in this thesis conforms to the principles and requirements of the DIT's guidelines for ethics in research. DIT has permission to keep, lend or copy this thesis in whole or in part, on condition that any such use of the material of the thesis be duly acknowledged.

Wael Rashwan, BSc., MSc.

November 2017

This work is dedicated to my wonderful parents, the memory of my grandmother, my lovely wife Nehal, my beautiful girl Marium and my amazing boy Yahia.

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"My Lord, enable me to be grateful for Your favour which You have bestowed upon me and upon my parents and to work righteousness of which You will approve and make righteous for me my offspring. Indeed, I have repented to You, and indeed, I am one of the whom submitting to your will." Quran (46:15)

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List of Abbreviation

AMAU PET	Patient experience time for all patients in AMAU
ADR	the percentage of admission rate
AHP	Analytical Hierarchical Process
AI	Artificial Intelligence
AMAU	Acute Medical Assessment Unit
AMAU ACCESS	Number of medical patients directed to the AMAU
AMP	Acute Medicine Programme
ANOVA	Analysis of Variance
ANP	Advanced Nurse Practitioner
AWR	the percentage of administrative work reduction
B&B	branch and bound
B&C	branch and cut
B&P	Branch and Price
CART	Classification and Regression. Tree
CBR	Case Based Reasoning
CG	column generation
CLD	Causal Loop Diagram
CP	Constraint Programming
DES	discrete-event simulation
DOC	degree of complexity
DOE	Design of Experiments
DP	dynamic programming
DRG	diagnostic-related-group
ED	Emergency Department
ED ADMISSION RATE	Percent of ED patients admitted to inpatient ward

ED PET	Patient experience time for all patients in ED
ED PET ADMITTED	Patient experience time for admitted patients in ED,
ED_PET_DISCHARGED	Patient experience time for discharged patients in ED
EDA	Estimation of Distribution Algorithm
EMP	Emergency Medicine Programme
EPR	electronic patient records
GA	genetic algorithms
GNP	gross national product
GP	general practitioner
HIS	Hospital Information System
HSE	Health Services Executives
ICU	Intensive Care Unit
IMF	International Monetary Fund
ITS	information-technology system
KNN	K-Nearest Neighbour
KPIs	Key Performance Indicators
LOS	Length of Stay
LP RELAXATION	Linear Programming Relaxation
LTB	larger-the-best
M&S	modelling and simulation
MAS	multi-agent system
MIP	Mixed Integer Programming
ML	Machine learning
MLE	the maximum likelihood estimator
MTS	Manchester Triage System
NBO	no burnout
NFC	near field communication
NHPPD	Nursing hours per patient day
NTB	nominal-the-best
OCED	Organisation for Economic Co-operation and Development
OR/MS	Operations Research/Management Science
PCS	primary care
PCS	A patient classification system

PET	Patient Experience Time
PET ALL-AMAU	Patient experience time for all medical patients in AMAU
PSO	particle swarm optimisation
SA	Simulated Annealing
SAHH	simulated annealing hyperheuristic
SD	System dynamics
SD	standard deviation
SHOs	Senior House Officers
SMOTE	synthetic minority over-sampling technique
SMR	Skill-Mix Ratio
SQL	Structured Query Language
SS	Simulated Annealing
SSU	Short Stay Unit
STB	smaller-the-best
TPA	Time per Activity
TS	Tabu Search
VNS	Variable Neighbourhood Search
WBO	with burnout;
WHO	World Health Organisation
WI	Work Intensity

List of Publications

1. Keshtkar, L, **Rashwan, W**, Abo-Hamad, W, Arisha, A " Hybrid Modelling Approach to investigate the impact of boarding patients on unit performance." SIMUL, 2017.

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Chapter 1

Introduction

> The first step in the acquisition of wisdom is silence, the second listening, the third memory, the fourth practice, the fifth teaching others.
>
> *Solomon ibn Gabirol (1021–1070)*

1.1 Introduction

Healthcare systems are complex systems characterised by a high level of uncertainty and dynamism, as well as considerable variability (Henderson et al., 2007). Variability exists in all systems often resulting in enormous impacts on productivity and performance. In the healthcare context, variability results from controllable factors — such as staff capacity and training — and uncontrollable – such as unscheduled patients and treatment time under complex conditions. Variability can be disruptive in any system, to various degrees. Therefore, the need for techniques and sophisticated tools that make it possible to measure, understand and manage variability remains critical for management teams.

1.2 The Irish Healthcare System (Background)

Since 2005, the Health Services Executives (HSE) has replaced the health boards as the body responsible for both the budget and management of Irish healthcare services (HSE, 2007). HSE is the primary health service reform programs in Ireland of over $100,000$ whole-time equivalent staff to deliver all kinds of public health services (HSE, 2015a). 65% are employed directly, and 35% are contracted through agencies funded by HSE. The Health Act 2004 states that HSE's objective is to utilise available resources efficiently in order to improve the health of people (Brady & Donnell, 2009).

One of the critical concerns of HSE is promoting equality regarding patient access to health services. Access to the primary care (PC) system tends to be unsatisfactory as the majority of the population are not qualified for free PC and they have to pay a substantial cost of general practitioner (GP) fees. On the other hand, in the secondary care sector, people can avoid the long waiting for treatment if they can afford private health insurance. Although efforts have been done to change the Irish healthcare system for the better, significant challenges remain. TIrish healthcare system is facing severe challenges including substantial financial pressures; lengthy waiting lists; shortage in capacity; growth of ageing population; and a notable increment in the incidence of chronic illness.

Over the period from 1992 to 2005, Ireland has enjoyed the highest GDP growth rate of 7.09% within the Organisation for Economic Co-operation and Development (OCED) countries. Ireland was also ranked fourth, within OCED countries, regarding the GDP per capita (Chevreul et al., 2010). However, the Irish public sector's infrastructure has struggled to keep pace with the speed of economic growth. Nonetheless, Ireland's gross national product (GNP) fell by nearly 20% between 2008 and 2011 (CSO, 2011, 2012a). Due to the deteriorating economic outline, and the receiving of financial support from the International Monetary Fund (IMF), European Central Bank and the European Commission, significant adjustments to public finance has taken place since 2008 (Figure 1.1). Several budget cuts have been implemented across all public sectors to cope with the impact of financial crisis' (Department of Public Expenditure and Reform, 2017).

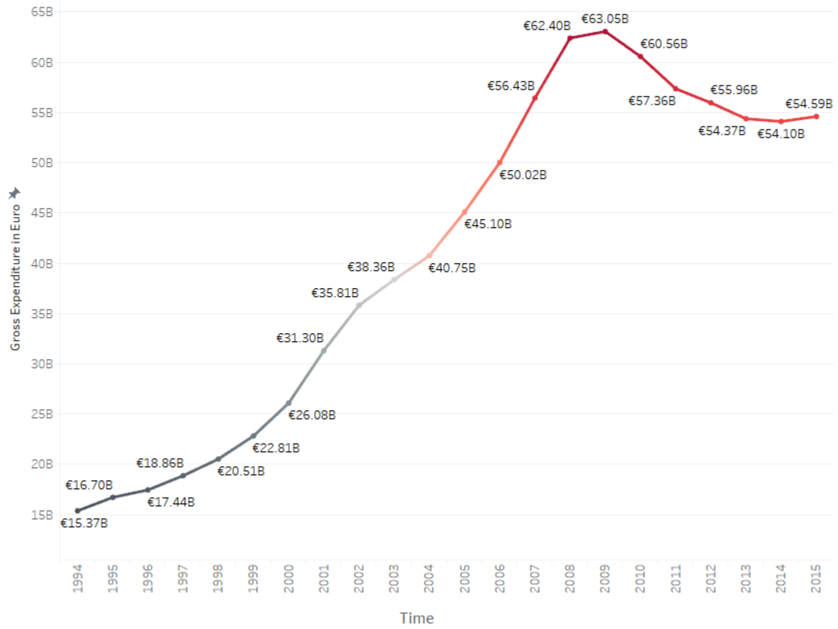


Fig. 1.1 Irish gross expenditure.

Cuts in government expenditures in healthcare sector have been mainly managed through reduced pay for staff, closing beds, and to a lesser extent, increases in the financial burden falling on people. Total number of closed beds in the Irish health service has dropped by nearly 40%, in both acute and long-stay beds (Department of Health, 2010). Bed shortages lead to overcrowding, long waiting times, a rise in elective surgery cancellations and higher mortality rates for elderly patients. Ireland has more to do in the development of primary and community healthcare services, with two-thirds of the population having to pay full costs of their primary care due to a model that favours hospitals over community services (WHO, 2014).

The issue of waiting times for unscheduled medical patients attending the Emergency Department (ED) in Irish hospitals has been a constant concern in the media and public for many years. Overcrowding and failure to cope with growing demand indicate that the current healthcare system is unable to meet public expectations (Gilligan et al., 2007). Increasing number of people on trolleys in hospital corridors comes at a time when there is an increasing expectation for a swift response to a demand for service from the public (Reilly, 2013). Although traditional responses support increasing resources to solve the problems, it can be argued; this approach results in inappropriate investment and expenses without any guarantee of a solution. The problem have to be considered in its entirety before a solution can be found (Ignizio, 2009).

Worldwide, there are around 600 million senior citizens - usually described as those aged 65 years and over (Paul & Hariharan, 2007). There are currently 108 million older adults in Europe: they represent 15% of the continent's population, a proportion that is projected to approach 26% by 2050 (Bensing et al., 2013). Ireland has experienced significant continuous population growth and increasing the demand for care. Older adults currently constitute around 11% of the Irish population. In 2012, almost one-third (33.2%) of total hospital discharges were elderly patients — a figure that had increased annually by 5% on average since 2008. At the same time, they occupied the highest percentage of total bed-days (47.3%), with an increase of 1.9% on the 2011 figure (HRID & ESRI, 2013). Projections show that the elderly will account for 16% of the Irish population by 2021 (Connell & Pringle, 2004). These demographic shifts have led to a significant rise in the need for acute care and long-term care (Wren et al., 2012). Consequentially, the number of frail older people who experience a physical or cognitive decline is growing. Frail people require frequent unplanned transfers to EDs where they need close attention. This trend creates additional demand. In conclusion, this increase in elderly population not only inflates demand but also reduces the workforce supply due to the increasing number of retired people, which results in staff shortages.

During recent years, the Irish healthcare system underwent rapid, comprehensive, and transformative reforms regarding four interdependent pillars: health and well-being, service reform, structure reform, and financial reform (Department of Health, 2012). The ultimate objective is improving patient experience in the context of increasing patient access, improving the efficiency and reducing costs. However, achievement of HSE targets to provide services within a smaller budget range have been significantly hampered by the complexity of the healthcare system, particularly about unscheduled care for medical patients attending Irish hospitals. These changes and restructurings have led to changes in workloads and schedule which have affected staff.

1.3 Research Motivation

The urge of this research is categorised into four dimensions: medical staff shortages, labour intensity, the complexity of staffing decisions, and implications of inappropriate staffing.

1.3.1 Staff Shortage and Safe Staffing

Lack of hospital staff, in particular, nursing staff, represents a critical challenge to decision-makers around the world (Zurn, Dolea, & Stilwell, 2005). Staff shortage is reported in several developed countries such as the United States (Janiszewski Goodin, 2003), Australia (HWA, 2012), UK (Addicott, Maguire, Honeyman, & Jabbal, 2015), Canada (CFNU, 2013), Norway (Durano, 2014), and Ireland (Humphries, Brugha, & McGee, 2012). At the same time, Ireland (Behan, Condon, Milićević, & Shally, 2009), the UK and Australia (HWA, 2012) are experiencing a doctor shortage. Smith, Fisher, & Mercer (2011) have argued that many industrialised countries are facing the steady depletion of nursing staff which will potentially jeopardise healthcare delivery. In the US alone, the shortage of nurses is projected to reach 29% by 2020 (HRSA, 2002). The UK and Ireland have heavily relied on recruiting nurses from overseas to address the shortfall of nursing staff (Buchan, Kingma, Lorenzo, & Nurses, 2005).

Several reasons that are believed to be contributing to this problem; ageing of the professional population, changing in work climate at hospitals, and financial pressures (Janiszewski Goodin, 2003; Murray, 2002). Reductions in hospital staffing levels cause several problems for management. These include discontinuity of care, long waiting time, increasing cost, high workload, and extended time spent organising cover (Buchan & Seccombe, 1995). Since healthcare services require the physical presence of medical personnel and patients, this creates an inevitable sensitivity to demand-capacity gaps. Acknowledging that the service buffer is not a valid option either economically or strategically, the management of healthcare services are forced to find solutions to demand uncertainty, which in turn creates a workload pressure on the hospital staff. This often causes unintended consequences to their health and safety (Portoghese, Galletta, Coppola, Finco, & Campagna, 2014).

HSE is currently experiencing critical staff shortages. Between 2007 and 2014, there has been 13% reduction in healthcare staff (Health Service Executive, 2014). This challenge results in increased working hours and lowers budget allocations (Health Service Executive, 2014). Waiting lists to see consultants are unacceptably long, and it may take three years after GP referral in some Specialities.

1.3.2 Labour Intensive

Hospitals are labour intensive where its services are characterised by being not inventorial; intangible; high degree of customer contact and customisation; the service produced and consumed simultaneously in the presence of the client (Li & Benton, 2003). Since health services require the physical presence of medical personnel and patients, this creates inevitable sensitivity to demand-capacity gaps. Also, health service processes differ from manufacturing processes since the servers (staff) and items being processed (patients) are both humans—with different perceptions, expectations, and characteristics. At the same time, delivering health services are heavily dependent upon the staff who drive both cost and quality (Ganguly, Lawrence, & Prather, 2014). Therefore, the convergence of multiple factors has stimulated the need for an integrative approach to address the challenges embedded in the healthcare system. Given the fact that Human Capital in healthcare organisations represents the backbone of their budget and knowledge assets, staff planning is a priority. An integrated approach necessitates considering not only the physical characteristics but also the behavioural elements of the healthcare system.

1.3.3 Complexity of Hospital Staffing and Scheduling Process

The process of hospital staffing and scheduling has become incredibly complex due to the workload variability. Also, the staffing requirements are frequently changing in the very short-term in terms of the size and the skill-mix of the required employees (Norrish & Rundall, 2001). Internal factors contributing to the issue includes the organisational structure of the hospital, department characteristics, interdepartmental cooperation and coordination, and flexible policies. External factors that increase the complexity of staffing issues are demand profile and patient needs, regulations and rules adopted by hospital policy, union regulations, contracts for different staff categories, and state legislation that mandate the staffing and scheduling practices. Above all, mandatory rules and flexible policies differ from one hospital to another (Carter & Lapierre, 2001) - often considerably - which makes it difficult for one method to address all cases (Rousseau, Pesant, Gendreau, Pesant, & Gendreau, 2002).

1.3.4 Consequences of inappropriate Staffing

Over the years, economic factors were the driving motive to underpin staffing and scheduling decisions (Michael J. Brusco & Jacobs, 1995). Today, other factors have been considered such as workload balance and staff preferences (Van den Bergh, Beliën, De Bruecker, Demeulemeester, & De Boeck, 2013). Understaffing carries risks that damage the quality of care and hospital performance suffer from several ramifications (Alistair Clark, Moule, Topping, & Serpell, 2015). A trade-off among multiple perspectives, e.g., fairness, cost and morale have to be considered. Several studies have identified an association between staff scheduling and staff morale (Hegney, Plank, & Parker, 2006). Ineffective schedules (Dunn, Wilson, & Esterman, 2005), work pressure (Aiken, Sloane, Bruyneel, Van den Heede, & Sermeus, 2013), working long hours (Bae & Fabry, 2013; Rogers, 2008), and unfair shifts (Dunn et al., 2005; Wilson, 2002) are significant factors that lead to a decline in morale. A direct correlation between appropriate staffing size and lower hospital-related mortality is reported in the literature (Kane, Shamliyan, Mueller, Duval, & Wilt, 2007; Rothberg, Abraham, Lindenauer, & Rose, 2005). Cost increases indirectly due to high staff turnovers (Hayes & Bonnet, 2010; Jones, 2005), absenteeism (Silvestro & Silvestro, 2008), and over-staffing. Therefore, optimising a staff schedule can play a fundamental role in enhancing the performance of healthcare organisations regarding cost, quality of care along with staff and patient satisfaction.

Nevertheless, the response from the senior management to high workload pressure to increase staff capacity is slow and inflexible (Oliva & Sterman, 2010). Two possible reactions can result from staff in order to reduce the work pressure:

1. working harder, and this will swiftly lead to a burnout in a shorter time or

2. reducing the time allocated to the patient and equally the quality (Kalisch, Landstrom, & Hinshaw, 2009). In response to the increasing workload, doctors and nurses working intensively.

1.4 OR/MS Methods

Healthcare systems are human-based systems that involve multiple stakeholders interacting with each other in complex manners. Due to the stochastic nature of healthcare systems, and the complex dynamics and interactions of their inputs, activities and outputs health care providers need tools which can enable them to comprehend the complexity and enhance their understanding of their systems.

Operations Research/Management Science (OR/MS) has contributed significantly to understanding the different levels of complexity of healthcare processes, including the variability and uncertainty of activities. Over the past 50 years, OR/MS researchers have worked closely with healthcare professionals in the management of the healthcare systems, seeking to offer a diverse portfolio of solutions to address the current issues at different decision levels. Modelling is always the first phase of most of these studies, regardless of the algorithm or framework applied as a solution.

Simulation is a valuable tool to assist healthcare managers in making their decisions (Jacobson, Hall, & Swisher, 2006). A simulation allows patient flows, layouts, staffing, procedures, and equipment allocations to be tested so that optimal departmental control strategies can be developed. Simulation has been proven to be a useful tool for process modelling and improvement (Harper, 2002). Healthcare managers can apply simulation for assessing a system's current performance, predicting the impact of operational changes, and examining the trade-offs between system variables (Wierzbicki, 2007). Furthermore, simulation has been used to map patients flow in the healthcare system and identify bottlenecks and areas of potential service improvement through a possible reorganisation of existing resources. Furthermore, simulation is well-suited to tackle problems in emergency departments (EDs) (Abo-Hamad & Arisha, 2013), where resources are scarce, and patients arrive at irregular times, and data mining can be efficiently combined with simulation for better results (Ceglowski, Churilov, & Wasserthiel, 2006).

Simulation models are a valuable predictive tool that enables management to capture the dynamics of human and process interactions, uncertainty and the complex aspects of a problem. However, it is not suitable for determining optimal decisions. This limitation can be tackled through optimisation methods. Optimisation has proven to be a useful tool that supports hospital management's efforts to cut cost, reduce waste, improve quality and increase efficiency (Sainfort, Blake, & Rardin, 2005). Furthermore, optimisation has been used to identify areas of improvement through optimal scheduling of resources. Several examples are reported such as operating theatre and anaesthesia (Pham & Klinkert, 2008); surgical case mix (Blake & Carter, 2002); staffing (Wright et al., 2010); staff scheduling (Carter & Lapierre, 2001); and speciality clinics appointment scheduling (Kolisch & Sickinger, 2007). Optimisation is also well-suited to tackling planning and scheduling problems, where resources are scarce, and an immense number of constraints and conflicting objectives exist (Belien et al., 2008).

Applying OR/MS methods to healthcare problems has shown definitive results demonstrating clear, and positive operational improvement. Therefore, this study aims to utilise OR/MS methods to develop an integrated framework that hospital administration can utilise practically and reflectively. It is envisaged that the research adopts simulation and optimisation for better staffing and shift scheduling.

1.5 Research Questions and Objectives

The purpose of this study is to examine the development of an integrated decision support framework for managing medical staffing and shift scheduling in hospital systems. To develop such a framework, an understanding of the requirements is crucial. System and decision analysis can achieve this. The proposed integrated framework incorporates complementary approaches to tackle real-world-world staffing and shift scheduling problems: Data Analytics, Modelling and Simulation, Machine learning, and Optimisation. The principal research question of this study is:

The central research question is divided into four sub-questions:

How can hospitals effectively match staffing patterns (i.e. nurses and doctors) to meet patients' demands?

1. RQ1: What are the existing models, frameworks, solution methods, and best practices used in staffing/scheduling of hospital staff?
2. RQ2: What are the key factors of management in staff planning activities?
3. RQ3: How can human behaviour be modelled to impact the output of planning process?
4. RQ4: What should an integrated solution for staffing and schedule look like in order to be applicable for managers?

To address the research question and in turn achieve the aim of this research, the primary objective is to:

Develop an integrated decision framework for staffing and shift scheduling in hospitals.

Based on this central objective, the specific objectives have been detailed and summarised in Table 1.1.

1.6 Thesis Outline

The thesis is organised to address the research questions (Figure 1.2). Chapter 2 provides the literature review for the current models and methods of staffing and scheduling. Chapter 3 describes the research methodology adopted. A detailed study design is illustrated to address the primary research question. Chapter 4, then, presents an exploratory study that uses interviews to gain insights from hospital managers. This chapter and chapter 2 inform how to design and develop of the integrated framework in chapter 5. The empirical validation of the framework is accomplished by using a case study strategy in the Emergency Department in an Irish hospital in chapter 6. Finally, chapter 7 concludes the thesis and outlines the research limitations and future work.

Table 1.1 Mapping research questions to research objectives.

Research Questions	**Research Objectives**
*RQ*1: What are the existing models, frameworks, solution methods, and best practices used in staffing and scheduling hospital staff?	*RO*1*: To identify and gain an in-depth understanding of current models, frameworks, and solution methods that are applied for effective planning and scheduling medical hospital staff.*
*RQ*2: What are the key factors of management in staff planning activities (implications, regulations, and others?)	*RO*2*a: Explore the management perceptions of staffing and scheduling practices in Irish hospitals, highlighting the challenges they are facing.*
	*RO*2*b: To identify the key elements for developing an integrated framework for medical staff planning.* *O*2*c: To develop an integrated framework for medical staffing and shift scheduling decisions.*
*RQ*3: How can human behaviour be modelled to impact the output of planning process?	*RO*3*: Assess the implications of incorporating adaptive staff behaviour on the quality the staff related decisions.*
*RQ*4: What should an integrated solution for staffing and schedule look like in order to be applicable for managers?	*RO*4*: To evaluate and validate the proposed framework.*

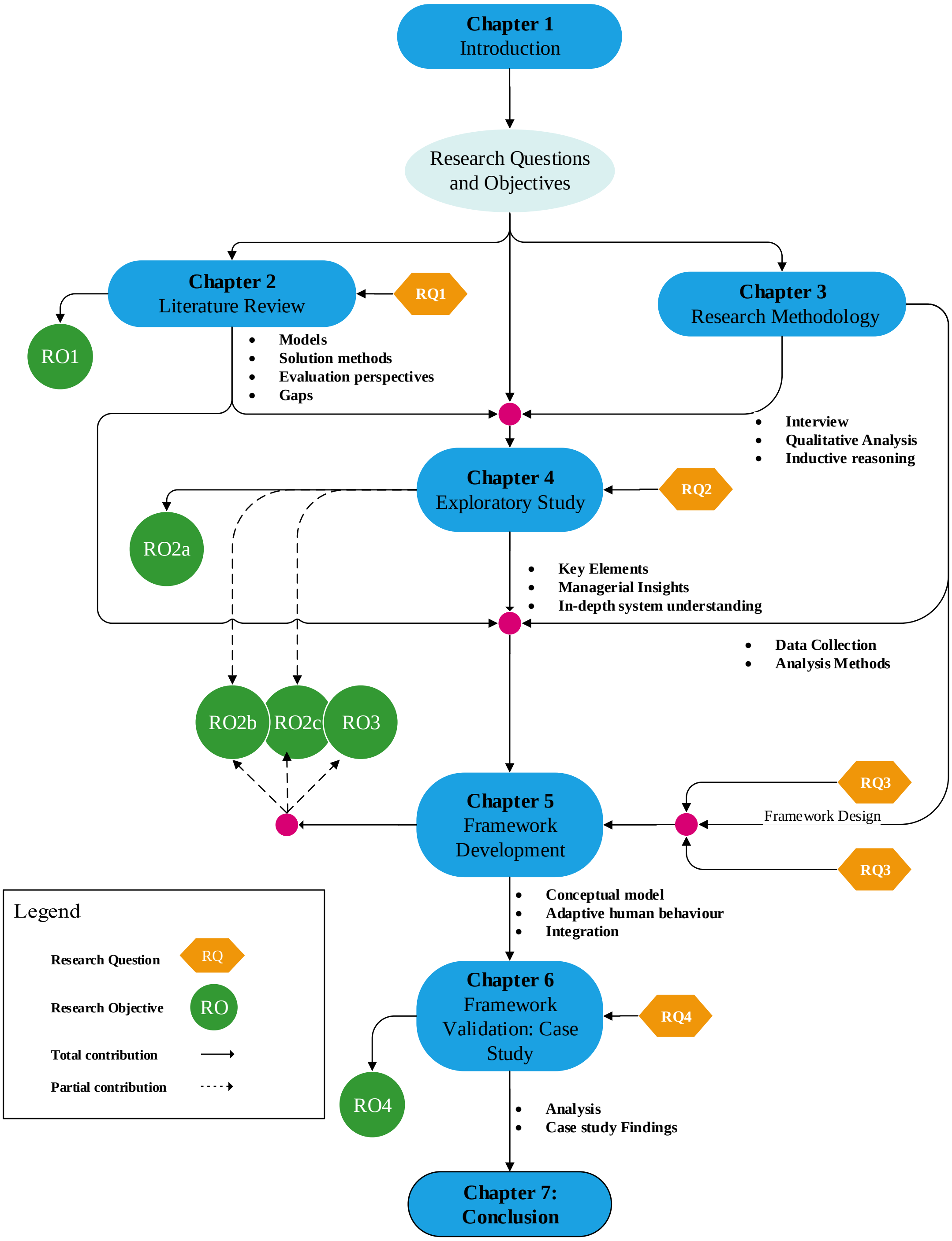


Fig. 1.2 Thesis outline.

Chapter 2

Literature Review

If I have seen a little further, it is by standing on the shoulders of Giants.

Isaac Newton (1643–1727)

2.1 Introduction

Among hospital capacity management challenges, personnel staffing and scheduling decisions have been increasingly highlighted to their impact on staff morale (Hegney et al., 2006), patient's outcomes (Trinkoff et al., 2011), and cost (Hayes et al., 2012). Given the fact that human capital is the backbone of hospital systems and their knowledge assets and it controls both cost and quality. Hospital staffing and scheduling decisions are getting more sophisticated because of increasing demand, budget limitations, shortage of qualified medical staff, changes in people's expectations, and growing complexities within the system. This chapter provides a comprehensive review of operations research/management science (OR/MS) methods that are used for staffing and scheduling of medical staff in hospital settings. This chapter aims to address the first research sub-question:

What are the existing models, frameworks, solution methods, and best practices used in staffing and scheduling hospital staff?

This research question is based on the assumption that OR/MS methods can help hospital management to address complex decision-making problems, which is a valid assumption based on evidence from the literature. The chapter also emphasises both the technical knowledge and managerial implications of staffing and scheduling decisions. It also highlights the benefits that hospital management can gain from using OR/MS methods to address this complex problem. This comprehensive review covers a broad range of publications aiming:

1. To thoroughly examine the previous models, frameworks and staffing and scheduling process.

2. To provide a comprehensive review of the current state of the art to identify methods that have recently been applied to hospital staffing and scheduling problems with a particular focus on integrated decisions.

3. To identify the research gaps and the important research directions which require further research efforts.

To achieve these objectives, a research plan is devised to outline the scope of the review; the methodology engaged and selection criteria for the publications. In total, this study reviewed more than 1300 manuscripts (of which 226 articles are cited in the reference list). European Journal of Operational Research, Annals of Operations Research and Health Care Management Science are the top three journals regarding the number of publications (Figure 2.1). Broadly, the analysis of journal publications by continent reveals that Europe is the highest contributor (38%), followed by North America (30%), Asia (13%), Africa (1%), South America (1%), and not reported (18%). The majority of the studies (68%), are undertaken in Europe and North America. Of the European articles, 45 and 26 of the studies alone were conducted in the UK and Belgium respectively. While articles from North America, 73 were from the US and 13 were from Canada. Despite the urge for effective methods to manage and optimise the limited resources in developing countries in Africa and South America, the medical staff scheduling issue has gained a moderate attention from researchers there.

The distribution of articles reveals a constant growth in studying medical staff and planning problems. Projection on the increase in the publication is expected as a result of cost-cutting practices that demand efficient scheduling of resources within healthcare facilities (Figure 2.2).

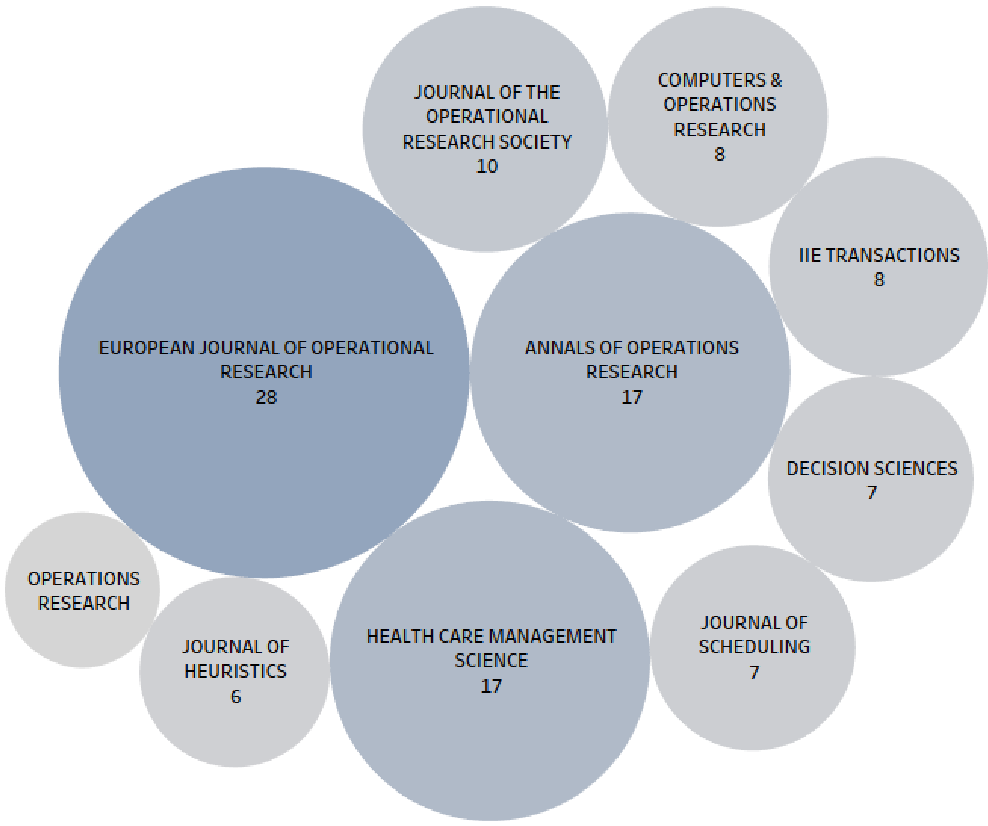


Fig. 2.1 Distribution of articles by journals.

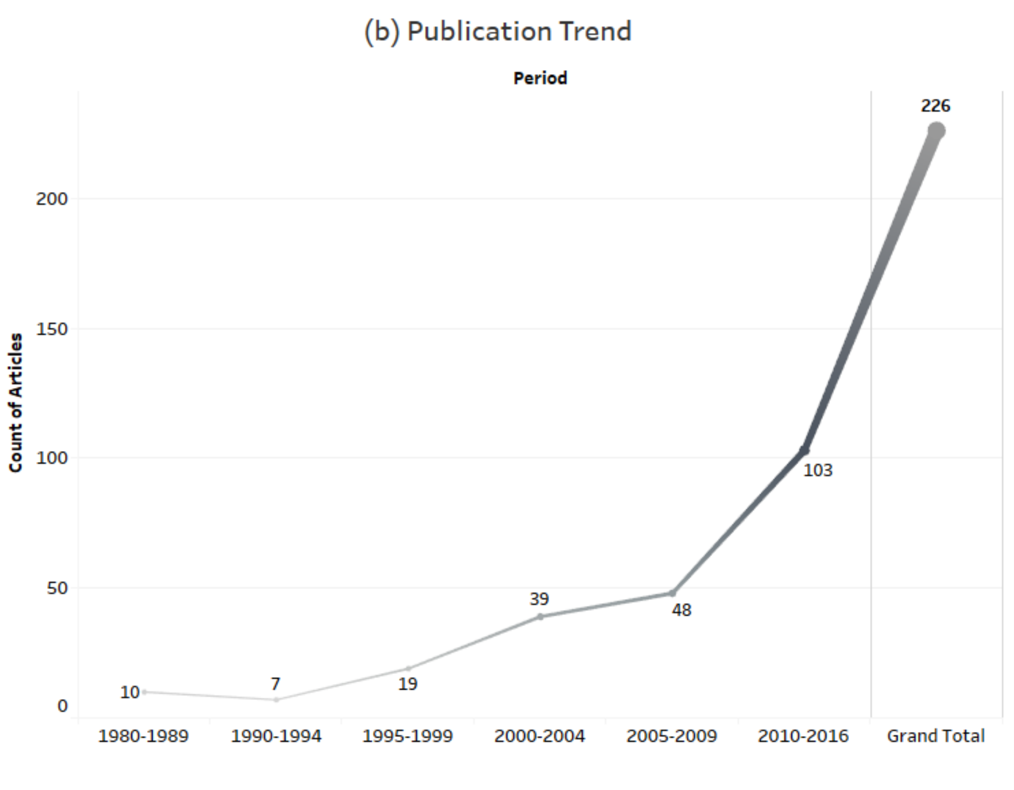


Fig. 2.2 Trend of publications.

2.2 Problem Contextualisation

Within the literature regarding workforce planning, several studies have contextualised the staff planning and scheduling decisions in multiple interdependent stages. In 1973, Abernathy, Baloff, Hershey, and Wandel (1973) introduced a three-stage staffing framework. The first stage is related to the policy decisions, which includes operating procedures, and staff control process. Staff planning is covered in the second stage, which concerns with decisions such as hiring, firing, training, and reallocation. Finally, the third stage discusses short-term scheduling of the available staff. In this framework, the actions taken at lower levels are constrained by decisions at higher levels. In 1982, Tien and Kamiyama (1982) divided the process into five phases: physical staff requirements; aggregate personnel needs; recreation blocks; recreation/work schedules; and shift schedule. Stage 1 and 2 represent the staffing problem; it primarily satisfies the requirements principally to meet the service level or budgeting constraints. The scheduling stages, stage four and five, consider the individual staff well-being and preferences. Similarly, in 1999, Campbell (1999) presents a three-levels decision-making framework: planning, scheduling and allocation. The planning phase determines the staff requirements. The scheduling phase assigns off-days, work days and shifts to the individuals. The allocation phase –referred to rescheduling or re-rostering– deals with the real-time adjustment of personnel to accommodate for demand fluctuations and unplanned staff's absences. Another major study outlines a six-module framework to classify staff scheduling and to roster: demand modelling; days-off schedule; shift scheduling; a line of work construction; task assignment; and employees assignment (Ernst, Jiang, Krishnamoorthy, & Sier, 2004). Module one addresses the demand forecast to determine staff requirements per period and per shift distinguishing between three broad demand incidents: task-based, flexible, and shift-based demand. Modules two, three, and four deals with the three types of scheduling problems that appear in the healthcare system namely days-off allocation, shift scheduling and tour scheduling problems (Morris & Showalter, 1983). Days-off allocation problem arises when staff's work is different from the facility's working week (i.e. continuous system). The shift schedule deals with selecting from a large pool of shifts to satisfy the demand over some planning horizon. Tour scheduling (line of work construction) combines both shift schedule and days off schedule to build feasible work patterns over the planning time horizon. Task assignment allocates jobs (e.g. patients) to staff (e.g. nurses).

The quality of staffing decisions depends on the reliability of workload estimation (Duffield, Roche, & Merrick, 2006). Workload analysis determines the amount of work (e.g.

hours)—directly or indirectly—to be provided by a given unit to meet the patient's needs considering timeout (e.g. breaks and days off) and patient outcome measures (O'Brien-Pallas et al., 2004). It aims to provide a basis for expressing the patient volume of care from a service regarding standardised unit of activity or productivity. Standards can be developed to match the workload to the similar staff requirements (de Vries, 1987). Broadly, quantifying the workload can be categorised into two types: activity and dependency based. Activity-based identifies the care activities/tasks and estimates their time (De Souza & Jericó, 2013). In contrast, dependency-based is a patient classification system that classifies on acuity and dependencies (DeGroot, 1994). Measuring the staff workload is a daunting task especially when where the work environment becomes more complex, challenging and stressful place. Increasingly, the definition of health workload, in particular for nursing workload, is a controversial concept (Morris, MacNeela, Scott, Treacy, & Hyde, 2007), with no agreed definition or objective quantification of the workload.

In a systematic review of the classification system, Williams & Crouch (S. Williams & Crouch, 2006) find that the majority of the patient classification system (PCS) is designed for hospitalised patients. They are not suitable for measuring workloads of other units such as the Emergency Department (ED). Comparing to nursing workload measurement, the literature on the development of physician workload is limited (Conlon & Tharani, 2008). Physician roles and workloads have been defined as clinical activities which include direct and indirect patient contact, and nonclinical activities involving education, administration, meeting, and research (Dubinsky, 2012).

Figure 2.3: Staffing and scheduling decision models.The models addressing medical staffing and scheduling can be categorised into two categories: single- and multi-stage models (Figure 2.3). The former class includes studies that examined one stage of the problem while the latter class consider the integration between the different stages.

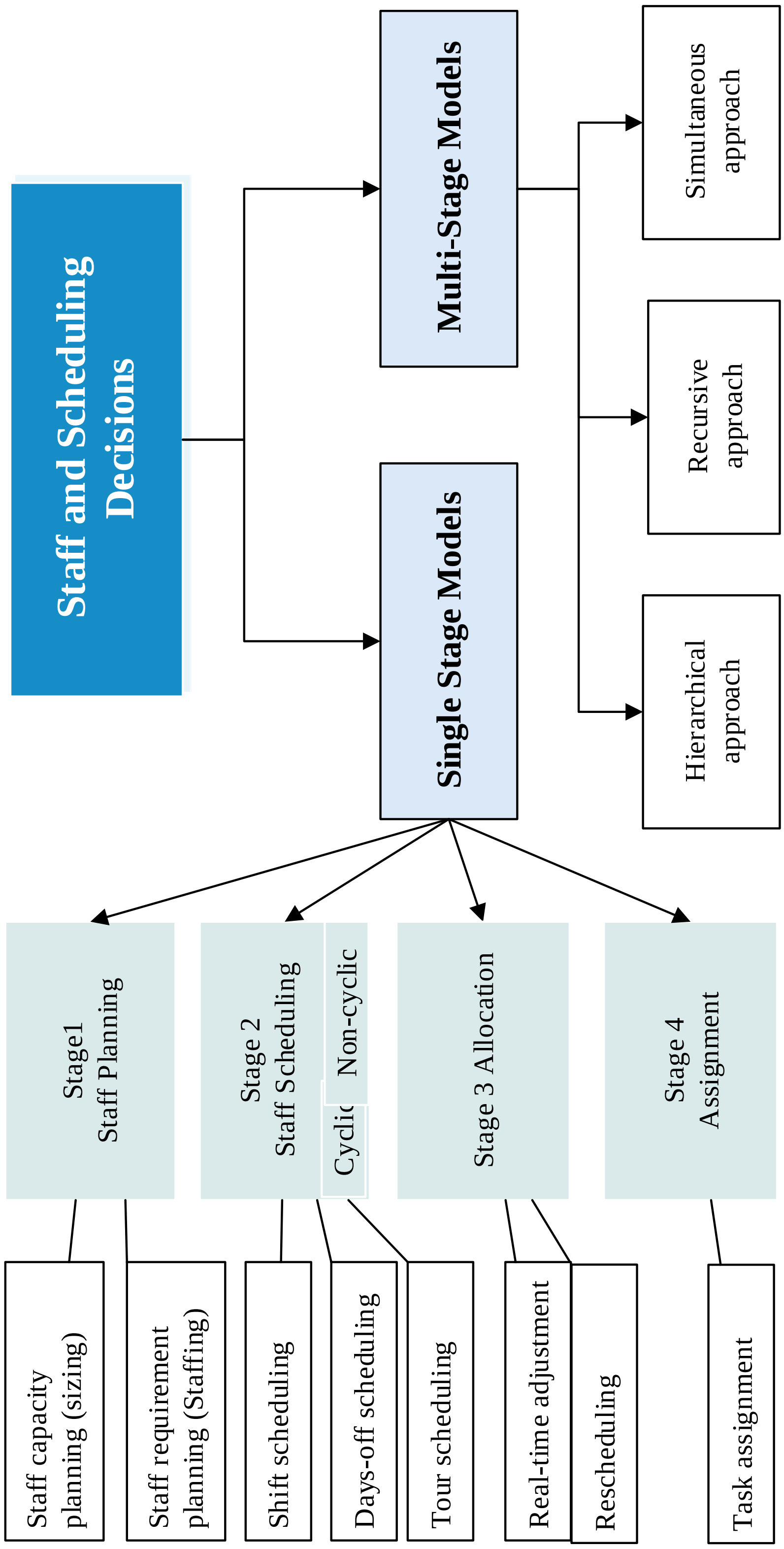


Fig. 2.3 Staffing and scheduling decision models.

2.3 Single-stage Models

Single stage models include studies that address one staffing and scheduling stage. They are divided into four stages: planning, scheduling, rescheduling and assignment. The following section summarises the literature in this class.

2.3.1 Staff Planning Stage

Staff planning is concerned with matching projected workforce and skills required within the organisational activities (Bowey, 1977). To effectively plan, there are two decision problems to look out: staff sizing and levelling decisions (Wright et al., 2006). Staff sizing, (staff budgeting or staff capacity planning), is a long-term plan spanning from few months to a year. This is when management decides the overall size and skills of the workforce, making the essential hiring and training decisions (Venkataraman & Brusco, 1996). Staff sizing can also include decisions regarding how much aggregate staff should be assigned to each unit. Also decisions regarding the projected usage of the supplemental staff capacities such as overtime, part-time, subcontracting and cross-training besides to the regular staff (Mincsovics & Dellaert, 2010). Decisions at this level determine the adequate staff capacity considering the annual budgetary constraints (J. Henderson, Krajewski, & Showalter, 1982). These decisions can be performed at hospital level or departmental level according to organisational structure.

Staffing problem (staff requirement planning), incorporates workload models to decide the appropriate staffing levels to satisfy time-varying demand with a given service level (Izady & Worthington, 2012). It concerns the efficient matching of staff resources with the time-variant demand for multi-service centres (Abernathy et al., 1973). Staffing can be volume-based staffing (i.e. traditionally based on the number of patients) or acuity-based staffing, which is more accurate and flexible (Barton, 2013).

Publications of medical staff planning over time has increased (Figure 2.4). Most of the staff planning literature (Table A.1; Appendix A) has examined single resource staffing (n=23; 64%) with particular attention to nurses (n=18; 50%) as nursing staff constitutes the most significant percentage of the operating cost in most hospitals. Physician planning occurs less frequently than nurse plan (n=5; 14%). Thirteen articles have addressed multiple resources. Regarding applications, the single unit got most of the attention (24; 67%) with emphasis on ED staffing, while four articles (11%) have investigated multiple units of hospital staffing decisions and four studies have a hospital level application.

The nurse-to-patient ratio previously was the predominant staffing method; that represented the number of patients to be cared by a nurse in a particular care unit. Nevertheless the evidence of whether the minimum nurse-to-patient ratio in acute hospitals will benefit nurses and patient care (Coffman, Seago, & Spetz, 2002). This type of staffing has been the subject of many discussions in the literature. Other common staffing methods used in hospitals include; case mix or diagnostic-related-group (DRG) (Duffield et al., 2006), Nursing hours per patient day (NHPPD) (Duffield et al., 2006; Holcomb, Hoffart, & Fox, 2002) and patient classification system (PCS) (Williams & Crouch, 2006)). These methods tend to use the average as a workload indicator, but this has been criticised for limitations when it comes to handling the variable workload with staff skill-mix (Buchan, 2004).

A study at a British hospital has shown different patient-to-nurse ratio could be applied in an attempt to determine the optimal number of nurses given the necessary skill mix and shift demands using average values (Harper, Powell, & Williams, 2009). While this study has also considered cost factor, it failed to estimate resource needs under demand fluctuations accurately. In the US, the effectiveness of ratio policies—as mandated by California Bill AB 394—have been explored within a single medical unit considering the probability of excessive delay as a measure of performance (Véricourt, & Jennings, 2011). Findings have confirmed that fixed nurse-to-ratio cannot provide consistent quality of care across units of

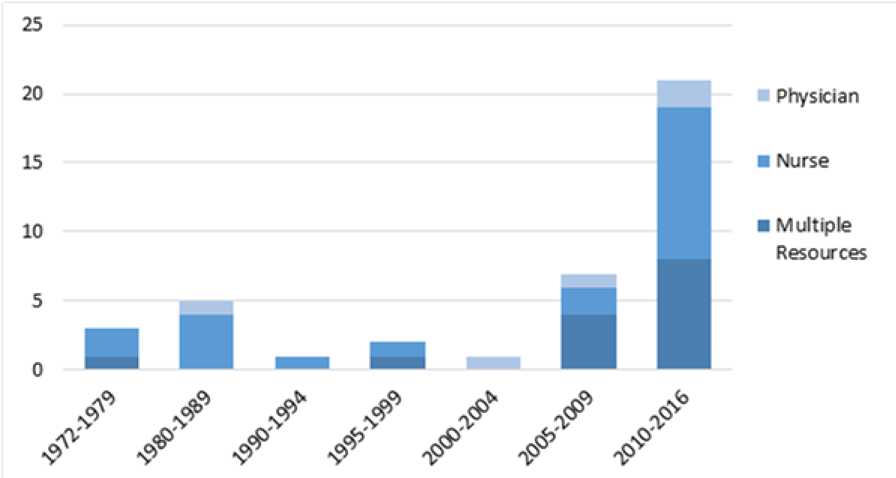


Fig. 2.4 Staff planning publications trend per staff type.

different sizes. Staffing policies have to deviate from the fixed ratios according to factors, which account for the total number of patients present in the unit. Unit size (beds), nursing care intensity, bed utilisation, and average length-of-stay are significant factors that should be taken into account when staffing to have a consistent and timely response to patients (Yankovic & Green, 2011).

Flexible resources are among the practices that can help hospitals cope fluctuations in workloads while maintaining safe staffing. Introducing task flexibility is a valid alternative in short and long-term periods as the workforce become leaner and provides a capacity cushion that helps to manage time-varying demand and reduce costs (Li & King, 1999). It is critical for float pool nurses be cross-trained for different units, the cross-training of float nurses is more efficient than cross-training of unit nurses (Wright et al., 2010). In a multi-unit system, two types of flexibility (i.e. demand and staff) are used to coordinate beds and nurses to meet stochastic demand (Gnanlet & Gilland, 2009) considering the centralised and decentralised decision-making. Centralised decision-making – setting beds and staffing decision together – has more significant benefits than decentralised (sequential decisions) due to suboptimal sequential decisions. In contrast, the issue of productivity variations, between regular and cross-trained nurses, and its impact on the optimal staffing decisions have been addressed by Gnanlet & Gilland (2014) considering three cross-training policies under centralised and decentralised decision-making. The optimal number of cross-trained staff declined, as fewer cross-trained staff are sufficient to obtain the benefit of staffing flexibility beyond a productivity threshold level.

Management can use part-time staff as an instrument for work redesign through reallocation of staff activities to ensure the workflow continuity against uncertainty, inflexibility, and complexity of coordination (Van Merode, Molema, & Goldschmidt, 2004). Introducing part-time policies, for managing discontinuity of flow, provides a mechanism for improving system design and hence the performance but may require changing the design of work and tasks (Molema et al., 2007). The higher availability of part-time nursing staff is associated with higher job satisfaction which results from the higher flexibility of part-time staff policy but on the expenses of the quality of care (Maenhout & Vanhoucke, 2013b).

The use of overtime and temporary staff have raised many questions regarding the cost, quality of care and employee's dissatisfaction. On-call over-time lowers the cost by reducing the reliance on the outside agency workers but the expenses of the quality of healthcare and staff morale (Campbell, 2012). Although cross-training and cross utilisation can improve the team agility and system robustness to accommodate workload variations, it can be costly, time-consuming to implement, limited to employees learning capacity and can lead to ambiguity regarding work responsibilities. Cross-utilised nurses have often struggled to deliver the same quality or productivity level as regular nurses (Maenhout & Vanhoucke, 2013b).

2.3.2 Staff Scheduling Decisions

The term 'schedule' is used as a generic term to cover specific types of problems, in particular, staff rostering. Wren (1996) has made a distinction between scheduling and rostering activities, asserting that scheduling is the minimisation of the total allocation cost of resources to objects being placed in space-time subject to a set of hard and soft constraints. A hard constraint must be satisfied without any violation such as coverage constraint (Aickelin & Burke, 2009; Glass & Knight, 2010; Goodman, Dowsland, & Thompson, 2007), while soft constraint can be relaxed such as staff preferences (Ásgeirsson, 2012; Azaiez & Al Sharif, 2005; Burak Bilgin et al., 2012). Information about the staffing requirements, possible shifts and days patterns are required for staff scheduling. Once shifts have been produced, they are placed on a roster to show which shifts are allocated to which workers. Rostering processes deal with assigning the employees to schedules that are defined in the scheduling problem considering the staff preferences, management policies, union and contractual constraints. In the literature, the term rostering is ill-defined and may be deemed as a particular case of scheduling (Burke, De Causmaecker, Berghe, & Van Landeghem, 2004). For this research, the terms staff scheduling and staff rostering are often used reciprocally and are treated as a synonym, and the first expression is adopted. Practical staff scheduling problems are a complex combinatorial problem that involves a large number of decision variables and a broad set of constraints which leads to NP-complete problems (Winstanley, 2004). Being sophisticated and highly constrained, scheduling problem has attracted the attention of various research communities (Baeklund, 2014; Burke & Curtois, 2014; Cheang, Li, Lim, & Rodrigues, 2003).

Three types of scheduling problems emerge in the healthcare systems. Namely shift, days off and tour scheduling problems (Morris & Showalter, 1983) (Figure 2.5). Shift scheduling deals with selecting work shifts that satisfy the demand over some planning horizon (Brunner, Bard, & Kolisch, 2009; Siferd & Benton, 1994). It involves designing the work stretches of time to allocate workers on a daily basis, to determine which shift will be performed on each day of the planning horizon. Days-off allocation problem appears when staff work is different from the facilities working week (Lin, Kang, Liu, & Deng, 2014). It addresses how rest days are interspersed with workdays. It determines both rest and working days for

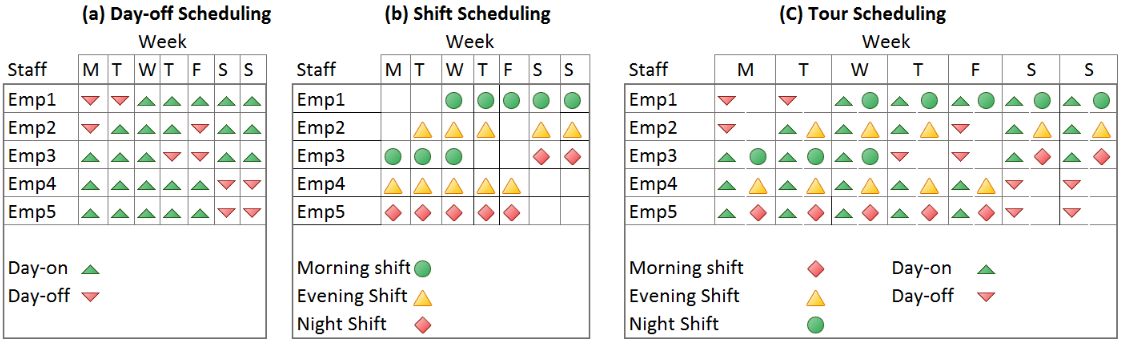


Fig. 2.5 Visualisation of the three types of staff scheduling problem.

each employee simultaneously. The tour schedule is typically for the organisation that works around the clock (e.g., hospitals) that combines both shift schedule and days off schedule and uses the results to build feasible work patterns over the planning horizon (Isken, 2004).

Management trade-offs among five qualities to constructing a good schedule (Broos Maenhout & Vanhoucke, 2013b; Warner, 1976). Operational efficiency includes labour cost and productivity (Figure 2.6). Cost is the primary objective to ensure that the resources are allocated efficiently without any waste (e.g. overstaffing). Coverage constraint maintains the service level, continuity of care and providing the minimum staff levels required to meet the patient needs. Staff satisfaction—regarding fairness and equality—becomes a vital determinant of a schedule of high quality besides accounting for staff preferences. Flexibility enables managers to adapt to environmental changes while stability aims to minimise the schedule modifications that impose a managerial burden and staff dissatisfaction.

Two main strategies are adopted in the scheduling literature to develop staff schedule: cyclic (i.e. rolling/rotational) and noncyclic (i.e. discretionary) schedule. The cyclic staff schedule obeys strict patterns to meet demands (Bartholdi, Orlin, & Ratliff, 1979), where each employee member (team) would rotate equally (Millar & Kiragu, 1998). The cyclic schedule is regularly used as long as the workload per shift resides approximately constant from a planning horizon to another (Isken, 2004; Purnomo & Bard, 2007). Cyclicity guarantees even coverage, fairness, stability and less effort (Lau, 1996). However, the schedule quality

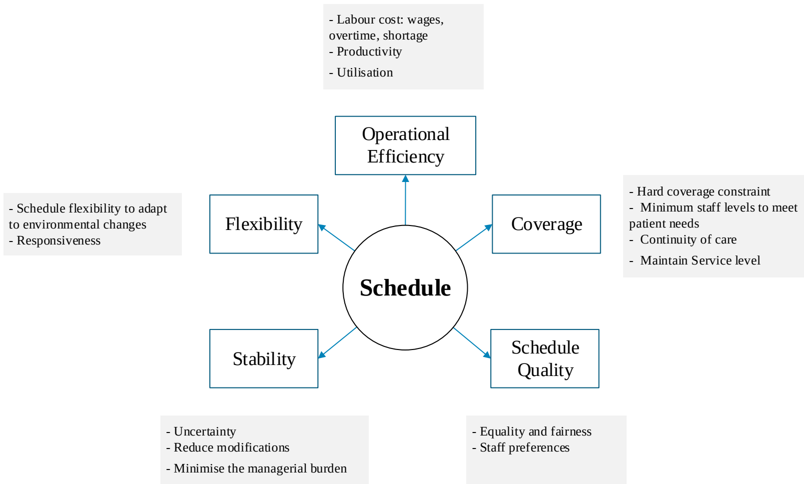


Fig. 2.6 Qualities of efficient and effective staff schedule.

is low regarding the staff satisfaction, and it is inflexible and rigid to absorb changes arising from personal or hospital settings (Burke, Curtois, Qu, & Berghe, 2008).

On the other hand, the non-cyclic scheduling addresses the shortcoming of cyclic schedule by generating a new schedule every planning period (e.g. few weeks). Considerable attention is paid to noncyclic scheduling due to its flexibility (Dohn & Mason, 2013; Hadwan, Ayob, Sabar, & Qu, 2013; M'Hallah & Alkhabbaz, 2013). A shift could be fixed (Ikegami & Niwa, 2003) or flexible (Brunner, Bard, & Kolisch, 2011) with different start and finish time, length or breaks for each staff member and on each day. When the schedule enables the staff to have some or full control over their working hours— such as flexible shift, it is called a flexible schedule (Brunner et al., 2011; Robin et al., 2005). In hospital systems, scheduling flexibility strategy is essential to account for variability, reduce staffing costs, improve the work environment and encourage stability of workforce (Brunner et al., 2009). However, it also brings an extra layer of complexity into the scheduling process (Robbins, 2011). A rather extreme mode of preference scheduling is self-scheduling - transfers responsibility of producing a schedule to employees (Bailyn, Collins, & Song, 2007; De Grano, Medeiros, & Eitel, 2009; van der Veen, Hurink, Schutten, & Uijland, 2016). Despite the high flexibility of self-scheduling strategy, it usually suffers from over/under-staffing as well as a violation of most of the constraints. Rönnberg & Larsson (2010) have automated nurse self-scheduling using shift voting system. Other studies investigated a mixture between self-scheduling and preference scheduling (Ásgeirsson, 2012; De Grano et al., 2009; Kaplansky & Meisels, 2007). Findings imply that self-scheduling could be difficult to be implemented efficiently. Negotiation power and the size of the unit can influence the success/failure of self-scheduling approach (Bard & Purnomo, 2005). Silvestro and Silvestro (2000) have reported difficulties in implementing self-scheduling in medium to large units having more than 35 staff members.

Several studies have considered employees' skills, such as the ability to perform specific tasks, in the scheduling process (De Bruecker et al., 2015). Staff members can be distinguished by skill categories that reflect their level of experience, qualifications and training obtained. The skill group constraint represents the minimum/maximum number of employees of particular grade that is required to cover a particular shift type in a given day during the planning horizon. Strictly disjunctive skill categories do not allow for substitution among the different grades. Several studies adopted the hierarchal substitutions of skills where the higher grade employee can replace the lower grade (Aickelin & Burke, 2009; Aickelin & Dowsland, 2004; Bard & Purnomo, 2005a; Beddoe & Petrovic, 2006). Assigning alternative skill categories to persons are used for substitution (Burke et al., 2008).

Nurse scheduling is the most addressed problem, which involves producing a periodic (weekly, fortnightly, or monthly) schedule for nursing staff, subject to a variety of constraints such as legal regulations, personnel policies, nurses' preferences, and many other requirements that may be hospital-specific restrictions. The primary aim is to obtain a satisfactory schedule for all nurses subject to constraints (De Causmaecker & Vanden Berghe, 2011). Mainly, most of the nurse scheduling models adopt non-cyclic strategies to cope with the dynamic nature of nursing activities. Unlike nurse scheduling, physician schedules seem to have more flexibility according to personal preferences (Carter & Lapierre, 2001). Relatively few studies on healthcare staff scheduling have addressed physician scheduling compared to nurse scheduling. Demand fluctuations, complex work agreements, the flexibility of doctors' shifts and on-call requirements, are among the reasons why doctors' schedule, which is more hospital-centric than nurse scheduling, differs from nurse rostering problems (Brunner et al., 2009; Carter & Lapierre, 2001). Brunner et al. (2009) introduce a flexible physician shift for scheduling problems using an implicit formulation that highlights the importance of flexibility in dynamic working environments, while Ferrand et al. (2011) model cyclic schedules to gain high predictability and stable work patterns. White & White (2003) study the scheduling of hospital ward rounds according to physicians' specialities to construct monthly rosters.

The problem of residents' work scheduling differing from that of doctors in the sense that residents are students in a training programme as well as being providers of medical services (Topaloglu & Ozkarahan, 2011). Cohn et al. (2009) address the annual on-call schedules for medical residents specialising in psychiatry in three hospitals for taking into account the relative importance of their differing (and perhaps conflicting) goals. Considering residents' preferences, Güler et al. (2013) examine the scheduling of residents' night and weekend shifts to produce a schedule that satisfies the coverage constraints of both Intensive care Unit (ICUs) and Operating Rooms (ORs). Majority of the on-call rosters, either for physicians or residents, is based on a cyclic strategy to promote greater job satisfaction through emphasising fairness among medical staff and their preferences (Gendreau, Ferland, & Gendron, 2007; Stolletz & Brunner, 2012).

2.3.3 Staff Allocation Decisions

Most of the staff rescheduling and real-time team adjustment literature focused on nurses. Medical staff allocation (12 publications) has been summarised subject to policies, objectives, features, orientation, country, team type, formulation, and size (Table 2.1).

Rescheduling (Rerostering). Staff Schedule is usually a deterministic roster that defines lines of work for the staff members. Since hospitals have dynamic environments, any unexpected events that disrupt a predetermined schedule can lead to modification or reconstruction of the schedule (Maenhout & Vanhoucke, 2011).

In the literature, this process is known as staff rescheduling - a reactive approach to respond to unexpected disruptions (e.g. sick leave, absence, maternity/paternity leaves, missing skills, and even sudden demand increase) (Alistair Clark et al., 2015). These events violate some constraints in the existing schedule. Staff rescheduling can be practised on the medium-term or a real-time ('ad-hoc') planning horizon (Maenhout & Vanhoucke, 2013). It works on the assumption that source of disruption is resolved before it acts on rebuilding the schedule so that the new version is as close as possible to the original schedule (i.e. minimise dissimilarities between the repaired and original plan) (Pato & Moz, 2008). Staff rescheduling can be done to manage understaffing (Maenhout & Vanhoucke, 2011), reduce staffing cost (Maenhout & Vanhoucke, 2013), or increase staff satisfaction (Clark & Walker, 2011).

Real-time adjustment decisions. Staff managers often attempt to make a real-time adjustment to the staff schedule subject to the demand changes (Norrish & Rundall, 2001). If demand falls, reducing a unit staff capacity can be implemented by, for instance, assigning staff to a voluntary or mandated day-off, or temporarily assigning nursing staff to a unit with high-level workload or lower staffing levels (Bard & Purnomo, 2005). Due to changes in demand frequently occur in the very short-term, staff re-allocation decisions in response to these changes entail decisions over a short horizon—typically at the beginning of a shift (Siferd & Benton, 1994).

Table 2.1 Rescheduling, real-time staff allocation decisions.

Study	Prob.	Size	Policies	Features	Unit	Orientation	Ctry.	Form.	P.P	Objectives
[1]	ALC		Float Staff	Multiple skills- Category	MU; IC	Problem Solving	US	NL; MIP	BoS	Maintain equity between nursing units; Min severity index.
[2]	ALC			Patient acuity	SU; IC	Theory	US	NLP	BoS	Project number of nurses for next shift
[3]	ALC		cross-training; staff agency; Float Staff		MU; IC	Managerial Perspective and Insights & Policy Analysis; Theory	US	NLP	BoS	Utility Function
[4]	RSC		No nurse pool	Multiple skills- Category	IC	Case Study; Computational Algorithmic; Formulation	PT	MIP		Min Dissimilarities between new and old roster
[5] [6]	ALOC	40 - 120	call nurse off-duty; Staff Agency; Float Staff; Part-time staff	Multiple skills-Category; Reactive-Disruption	H	Problem Solving	US	MIP	1D	Min Penalty Cost; Min Staffing Cost (overtime, floating; agency), and min number of shortage
[7] [8]	RSC	19	No nurse pool	Reactive- Disruption	IC	Computational Algorithmic; New Scheduling Methods	PT	MO	1D to 28D	Min Dissimilarities between new and old roster; compliance with soft constraints
[9]	RSC	20; 30; 40	Part-time; Full-time; Day-only	Reactive- Disruption; single-skill		Formulation		MIP	4W; 6W; 8W	Min disruption penalties; satisfy nurses preference; fairness.
([10]	RSC	30	Unplanned Absence; Unplanned Turnover	Multiple skills- Category		Gain Understanding & Identify areas of improvement;	UK		1D to 28D	Fairness; Overstaffing; Penalty Cost; Satisfaction of staff preferences; Understaffing
[11]	RSC			Reactive- Disruption		Computational Algorithmic & New Scheduling Methods	BE; UK		1D to 28D	Min Dissimilarities between new and old roster; workload balance; min cost of additional cost
[12]	RSC	30	Disruption; rescheduling strategies and characteristics.	Disruption factors; Multiple skills-Category; Reactive-Disruption	IC	Managerial Perspective and Insights & Policy Analysis	BE; UK		1D to 28D	Min Dissimilarities between new and old roster; Min Extra Nurses; Min Overtime

ALC: Allocation; RSC: Rescheduling; N: Nurse; FN: Float Nurse; IC: Intensive Care; MU: Multiple-units; SU: Single-Unit; WR: Ward; H: Hospital; Ctry.: Country; US: United States; PT: Portugal; JP: Japan; UK: United Kingdom; BE: Belgium; P.P: Planning Period; Form.: Formulation; MIP:mixed integer programming; MIQP: mixed integer quadratic programming; CSP: constraint satisfaction problem; NLP: Nonlinear programming; MO: multi-objective; D: Day; W: Week.
[1] (Trivedi & Warner, 1976), [2] (Siferd & Benton, 1994), [3] (Campbell, 1999), [4] (Moz & Pato, 2003), [5] (Bard & Purnomo, 2005b), [6] (Bard & Purnomo, 2005c), [7] (Pato & Moz, 2008), [8] (Moz, Vaz Pato, & Pato, 2007), [9] (Clark & Walker, 2011), [10] Maenhout & Vanhoucke, 2011), [11] (Maenhout & Vanhoucke, 2013a), [12] (Maenhout & Vanhoucke, 2013d).

Real-time staff adjustment seems to be an ordinary matter to most units in hospitals. However, research efforts are limited in this space. A study on real-time adjustment has adapted convex shortage cost function to examine the validity of allocating float nurses to cope with this demand changes (Trivedi & Warner, 1976). Similarly, a generalised assignment model address the fractional worker capabilities (Campbell, 1999). The central emphasis of the allocation model is to gain insights into the value of cross-training and cross-utilisation to face the demand variations. Siferd and Benton (1994) define a patient's acuity of care mathematically, as the number of nurses needed by one patient during a shift. They have then shown the number of nurses required during a shift using a multiplicative model of average patient acuity. For a hospital level, a reactive methodology to modify the nursing schedule to respond to shift-by-shift staff shortage (Bard & Purnomo, 2005). Different alternatives are examined including decisions regarding mandatory overtime, floating, on-call, agency nurses in case of lack of staff, cancelling nurse shift and reallocating nurses for excess capacity units.

Real-time staff adjustment decisions can be a costly option with limitations on staffing preferences (Clark & Walker, 2011). From patient safety and experience perspective, the constant staff adjustment can sometimes result in inappropriate skill mix due to lack of familiarity and knowledge of float nursing/agency staff (Norrish & Rundall, 2001).

2.3.4 Assignment Decisions

Typically, the assignment problem is the fundamental mathematical formulation for the nurse-to-patient assignment (Allen, 2015). The quality of nurse assignment decisions mainly depends on the accuracy of the workload assessment systems (Mullinax & Lawley, 2002). Nurse-to-patient assignment problem aims to allocate patients to the available set of nurses considering patients' characteristics (e.g. acuity level) that drive the workload. It typically performed at the beginning or during the shift (Punnakitikashem, Rosenberger, Buckley

Behan, & Behan, 2008). The most important consideration is the balancing workload distribution among nursing staff, which is the responsibility of the head nurse (Acar, 2010). Due to the high variability of patients' needs, volume-based workload assignments can be unfair to some of the staff (Liang & Turkcan, 2015). It often fails to account for acuity levels of patients and hence an unbalanced distribution of workload among staff is flagged (de Vericourt et al., 2011). A detailed analysis of nine leading publications in the area of task assignment is presented in Table 2.2.

In a neonatal intensive care of a major university hospital, Mullinax & Lawley (Mullinax & Lawley, 2002) examine assigning nurses to patients while balancing workload among nurses. They looked at factor evaluation acuity system and validated it by experts panel (Jeri Bigbee, James Collins, 1992). Patients' severity was used as an indicator for the required time for care; then the assignment model has utilised patient acuity scores to help in assigning the right nurse. Another study has proposed methods to update the assignments periodically during a shift to account for dynamic changes in the patient census (Sir et al., 2015). The purpose of the study is to improve the assignment decisions by combining the objective factors (e.g. patient acuity metrics from patient classification system) and subjective factors (e.g. nurse perceptions of the workload from a survey). This individualised workload balancing model can also help improve nurses' working conditions. In an oncology unit, Liang & Turkcan (2015) proposed a multi-objective model for nurses assigned to a trade-off between total patient waiting time, total staff overtime, and cost of additional nurses. Although the time of patient's care is stochastic and can significantly vary according to many factors, most of the existing models proposed in the optimisation literature are deterministic (Punnakitikashem et al., 2013). For example, the staff assignments usually consider patient care requirements without attaining other activities (e.g. non-patient care, indirect workload, training, administration, meeting, and research (Myny et al., 2011) that can delay the job at hand (Punnakitikashem et al., 2008).

Table 2.2 Task assignment publications

Study	Staff	Acuity	Features	Unit	Orientation	Ctry.	Form.	P.P	Uncertain	Objective
(Ernst, Lasdon, Ostrander, & Divell, 1973)	D-T		Room location	OR	Problem Solving	USA	MIP	D		Cost
(Sundaramoorthi, Chen, Rosenberger, Kim, & Buckley-Behan, 2010)	N-P	Acuity level is given	Nurse Location; acuity levels in each room; assignment policies; multiple nurse type	SDU	Problem Solving	USA	SIM	D	Transition Probabilities; location; time of direct care	Min Excess work-load
(Punnakitikashem et al., 2008) (Punnakitikashem, et. al, 2013)	N-P	Random work-load; no PCS	direct and indirect workload; Multiple skills; patient uncertainty; a fixed number of patients	SDU	Formulation; Problem Solving	USA	SP; MIP	D	workload	Equitable work-load
(Liang & Turkcan, 2015)	N-P	Acuity levels are pre-assigned	single-unit; multiple skills; Allow excess work-load	ONC	Problem Solving	USA	MO; MIP			Min total Excess work-load; Min waiting Patient time; Min Overtime
(Mullinax & Lawley, 2002)	N-P	Develop Acuity system	Multiple skills- Category; location (zone)	NICU	Case Study; Problem Solving	USA	MIP	BoS		Fairness; Equitable work-load
(Sir, Dundar, Steege, & Pasupathy, 2015)		N-P	PCS and surveyed acuity (perceived acuity)	Fixed staff;	ONC; OR	USA	MO; MIP	BoS		Min perceived work-load; Equitable work-load
(Ku, Pinheiro, & Beck, 2014) (Schaus, Van Hentenryck, & Régin, 2009)	N-P	Acuity per patient group	Multiple skills- Category; location (zone); fixed staff	NICU	Computational Algorithms	CA	CSP; MIQP	BoS		Min standard deviation of nurses' work-load

Ctry, publication country; Form., formulation; Sol., Solution Approach, P.P, Planning Period; D-T, doctor-to-task; N-P, nurse-to-patient; OR, operating room; SDU, surgical and medical unit; ONC, oncology; NICU, Neonatal Intensive care unit; USA, United States of America; FR; France; CA, Canada; MIP,mixed integer programming; MIQP, mixed integer quadratic programming; CSP, constraint satisfaction problem; SIM, simulation; MO, multi-objectives; SP, stochastic programming; D, Daily; BoS, beginning of the shift; Min: minimise.

2.4 Multi-stage Models

Staff planning and scheduling is an iterative process that requires interactions among all stages to maintain feasibility and ensure optimality (Aickelin, Burke, & Li, 2007). The operational decisions are influenced by decisions taken at a higher strategic level (Tien & Kamiyama, 1982; Warner, 1976). The integration between staffing and scheduling decision have to accommodate for forecast error in the staffing decisions and also reduce its implications on the scheduling decisions. Also, efficient scheduling decisions often lead to better aggregate staff planning and hence a more accurate costing model. It can be argued that the under/overstaffing occur regularly in hospitals as a result of disjoint and independent decisions at different planning and operational stages (Li, Chen, & Cai, 2007). Adequate staffing decisions require monitoring the impact of these decisions on the key performance indicators. The research found in the interaction between two or more planning stages can be categorised into three categories: hierarchical, recursive, simultaneous approaches (Figure 2.7). Review of the published articles indicates that most of the staffing and scheduling efforts have used single-stage models, and only a few publications have attempted to combine multiple planning stages (Kim & Mehrotra, 2015). Table 2.3 presents a detailed classification of fourteen articles that introduced a multi-stage model.

2.4.1 Hierarchical Approaches

Hierarchical models tend to combine two or more decision levels sequentially where the optimal solution in the higher level (e.g. staffing), restricts the lower level problem (e.g. scheduling). For example, the nurse shortage problem is examined using two sequential stages (Wright et al., 2010). Stage one uses a scheduling model to assign nurses to shift for the five-week planning period. The second stage utilises a staff adjustment model to account for forecast errors by allocating supplemental staff at the beginning of a shift. This study has

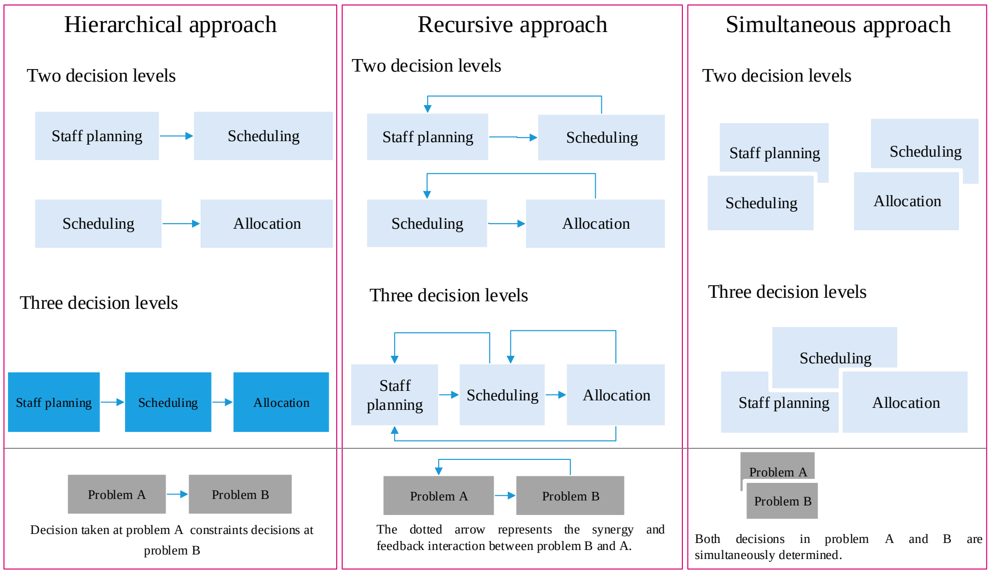


Fig. 2.7 A schematic representation of the integrated approaches.

found that coordination and information sharing between the two stages enables lower cost and more desirable schedules.

Although medical staff (e.g. doctors, nurses, and consultants) are sort of dependants on each other, most of the reported research has studied a single resource type. In ED, a study has considered staffing and scheduling of multiple resources but one at a time (Sinreich & Jabali, 2007). This study had focused on determining the required staff levels that best serve patient demands and then an appropriate work shift schedule was developed. Likewise, Izady & Worthington (2012) have determined staffing and scheduling for multiple ED staff sequentially.

Hierarchical approaches that sequentially treat the staffing and scheduling are criticised because they may end up in sub-optimal solutions. The inefficiencies arising from performing staffing and shift scheduling routines separately may produce suboptimal decisions (Komarudin, Guerry, De Feyter, & Berghe, 2013).

Table 2.3 Classification of multi-stage models.

Study	Stages	Staff	Policies	Features	Depart-ment	Orient-ation	Integ-ration	Form-ulation	P.P	Stoch.	objective
[1]	Scheduling; Staffing	N	Days-off patterns; demand disaggregation; Max % of overtime; Max % of part-time staff; Part-time staff; Staffing Mix	Single Skill	Unit	Managerial Perspective and Insights/Policy Analysis	Recursive	MIP	2W; 6M		Cost
[2]	Planning; staffing; Scheduling	N	Discharge; Float/locum staff; Hiring; Training; fixed staff; variable controlled staff; part-time staff	Multi-department	Hospital	Framework	Recursive	MIP SP	1Y; 1M	demand	Cost
[3]	Scheduling; Staffing; Work-load	N; D	Downsizing	single-unit	ED	Deal with daily fluctuations; Managerial Perspective and Insights/Policy Analysis	Hierarchical	LP; Sim	1D	arrival; service time	Overstaffing; Understaffing
[4]	Real-time Scheduling/daily adjustment problem; Staff Scheduling	lN	cross-training; coordination; Staff Agency; flexibility; Float Staff; Overtime; Travel Nurses; Nurse-to-patient Ratio	Multiple skills-Category; Staff Shortage	MSU	Managerial Perspective and Insights/Policy Analysis	Simultaneous	MIP MO	5W; BOS		Min dissimilarities; Min undesirable shifts and weekends; cost; Satisfaction
[5]	Scheduling; Staffing	N; D; S; T		single-unit	ED	Case Study; Problem Solving	Hierarchical	QN; Sim; MIP; OL		demand	Overstaffing; sojourn time target; Understaffing
[6]	Scheduling; Staffing	N	Float Staff; Overtime; Part-time; Permanent Staff; temp staff	Centralisation; Multi-department	Ward	Managerial Perspective and Insights/Policy Analysis	Simultaneous	MIP	28D		Cost; Fairness; Min Extra Nurses; Overstaffing; Satisfaction; Understaffing

[7]	Staff Assignment; Staff adjustment	Het-N	Staff Agency; Float Staff; Unscheduled hold-over overtime	Multiple skills; Multiple units; Reactive-Disruption	MSU	Managerial Perspective and Insights/Policy Analysis;	Simultaneous	BO SP	BOS	workload	Excess Workload; Cost
[8]	Staff Scheduling; Staffing	Het-N	scheduling policies; staffing policies; Nurse-to-patient Ratio	allow Secondary Skill; Multiple skills	Ward	Framework	Recursive	MIP	13W; 4W		
[9]	Staffing; Scheduling; adjustment	Hom-Nurse	Add/Cancel shifts; Nurse-to-patient Ratio	Single Skill; single-unit	Unit	Computational Algorithmic; New Scheduling Methods	Recursive	MIP SP	12W; 18W; 1W; 1D	Demand.	Cost; Overstaffing; Understaffing
[10]	Staffing; Scheduling	Het-N	cross-training; Cross-Utilisation; flexibility; Nurse-to-patient Ratio; Unscheduled hold-over overtime (extend hours from prior shift)	Multiple departments; centralisation	MSU	Managerial Perspective and Insights/Policy Analysis	Simultaneous	MO MIP	1W	Patient Arrival	Cost; Overtime; Satisfaction of staff preferences; Staffing Cost
[11]	Staffing; Scheduling	Radiologist	Staffing and scheduling policies	Multiple departments	Radiology	Case Study; Problem Solving	Hierarchical	MIP; GP	1M	Demand	Staff satisfaction (schedule desirability); Min number of required staff;

[1](Venkataraman & Brusco, 1996)
[2] (Abernathy et al., 1973)
[3] (Sinreich & Jabali, 2007)
[4] (P. D. Wright et al., 2010)
[5] (D. Wright et al., 2006)
[6] (Izady & Worthington, 2012)
[7] (Broos Maenhout & Vanhoucke, 2013c)
[8] (Punnakitikashem et al., 2013)
[9] (Broos Maenhout & Vanhoucke, 2013b)
[10] (Komarudin et al., 2013)
[11] (Kim & Mehrotra, 2015)
[12] (P. D. Wright & Mahar, 2013)
[13] (Chen, Lin, & Peng, 2016)

2.4.2 Recursive Approach

Recursive or interactive methods allow interactively between two or more decision levels which enable a learning propagation from lower to a higher level (Abernathy et al., 1973). The synergy and feedback loop between the stages can improve the quality of the actions at all stages and hence overcome the bounded rationality of the decision maker (Abernathy et al., 1973; Li et al., 2007). This approach emphasises that the process of staffing and scheduling can be an iterative process instead of a linear one. A recursive study by Abernathy et al. (1973) has described an iterative three-stage framework for aggregate nursing-staffing planning: policy decisions, staff planning and scheduling. A recursive integrated system can also enable the identification of interrelationships between staffing and scheduling policies (Venkataraman & Brusco, 1996). On the other hand, Roster Quality Staffing (RQS) problem has been discussed by Komarudin et al. (2013) using a three-step interactive methodology to support hospitals in assessing the appropriateness of the personnel structure. This method enforces adjustment to the staffing profile in an attempt to improve the available roster quality. Kim & Mehrotra (2015) use a two-stage model for integrating the staffing, scheduling and adjustment decisions under demand uncertainty for a single unit. Stage one, the here-and-now, is to attain initial staffing and schedule, while stage two, the wait-and-see, is to reconcile this schedule at a time closer to the actual date of demand realisation.

2.4.3 Simultaneous Approach

This method implements two or more stages simultaneously in one model. The way of integration is controversial due to the computational complexity of simultaneous integration (Ernst et al., 2004) and sub-optimality of sequential combination (Özcan, 2009). An integrative approach that link nurse staffing and tour scheduling problem is used to evaluate nurse-to-patient ratio and other policies (Wright et al., 2006). This study uses the mean arrival and service time to determine the staffing levels, which do not reflect the patients' acuity and the actual workload. To evaluate the benefits of simultaneously integrated decisions, Maenhout & Vanhoucke (2013b) propose an integrated methodology based on MIP. The model aims to allocate different staff nurses over multiple departments according to a set of hospital and ward policies. Substantial improvements regarding cost, personnel job satisfaction and effectiveness are obtained. This model has also been utilised to investigate the impact of organisational structures (e.g. degree of centralisation) and processes (e.g. staffing and scheduling practices) on the resulting quality of care (dependent variable) for a real-life situation in a Belgian university hospital (Maenhout & Vanhoucke, 2013c). The experiments confirmed that the integration and centralisation could lead to a better global outcome for the hospital over decentralised and non-integrated decision support systems. This view is backed up by Wright & Mahar (2013) where they presented a centralised nurse schedule that can reduce both scheduling and overtime costs. Another study has integrated the real-time nurse adjustment and nurse-to-patient assignment problems to provide better care for patients, the balanced workload for nurses and enhance budget control for hospitals (Punnakitikashem et al., 2013). Although the integration of interrelated decisions increases the problem's complexity, it often leads to a better global optimal solution (Maenhout & Vanhoucke, 2013c).

2.5 Solution Approaches

Optimisation solution methods are presented in six categories (Figure 2.8), namely analytical methods (e.g. queuing theory and newsvendor model), simulation-optimisation, exact/decomposition (e.g. branch and bound, and branch and price), artificial intelligence/multi-agent system, heuristics/metaheuristics and hybrid/ hyperheuristic methods. The following perspectives are considered in the analysis of related categories:

1. **Theory:** Papers that mainly focus on problem formulation; modelling; and framework.

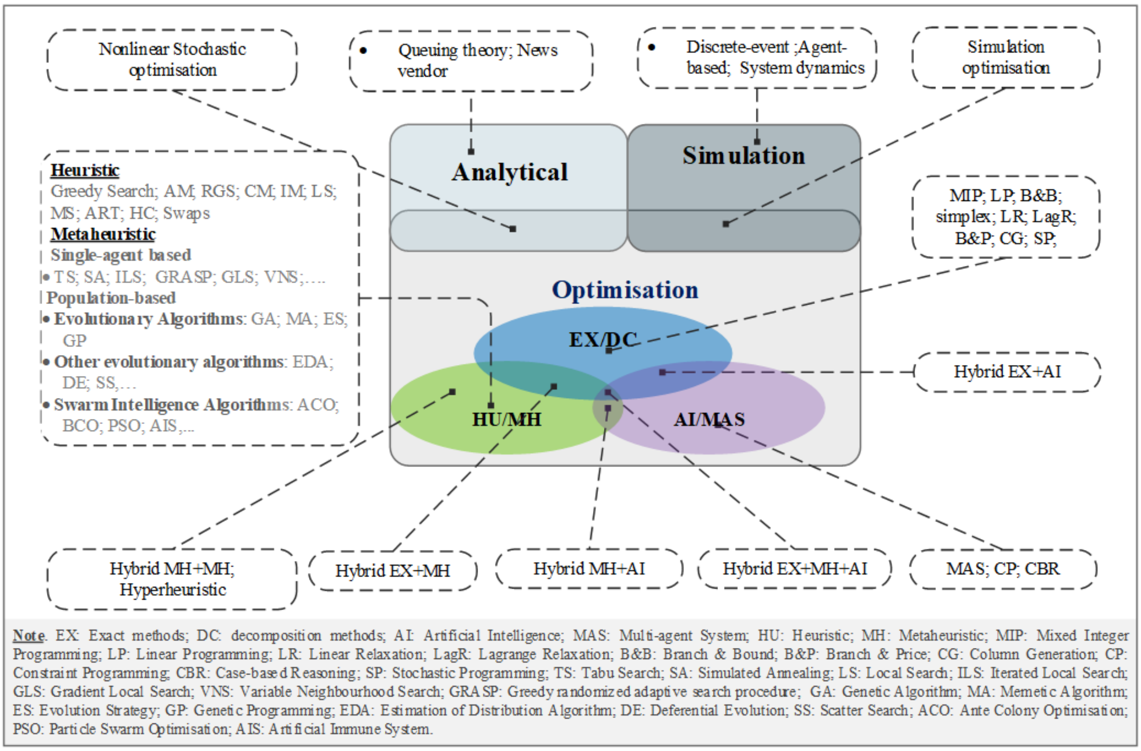


Fig. 2.8 Classification of Solution approaches.

2. **Managerial Perspective:** Papers that aims to gain understanding; evaluate staffing policies; provides case study; or solve a problem.

3. **Computational Algorithmic:** Papers that focus on mainly on new solution methods and provides computational algorithms that may include comparisons to other approaches and techniques.

To date, various optimisation methods have been employed to underpin the different problem stages (Figure 2.9). From the analysis of the articles, it is evident that the exact and metaheuristic methods have been extensively applied in solving hospital staff scheduling problems and dominating the majority of the literature. Among the reviewed articles, at least 36% (n=90) of the papers have applied exact methods (e.g. branch & bound or branch & cut) or decomposition methods (e.g. branch & price) to solve hospital staff scheduling problems, where the majority have addressed staff scheduling/rostering (n=57). In contrast,

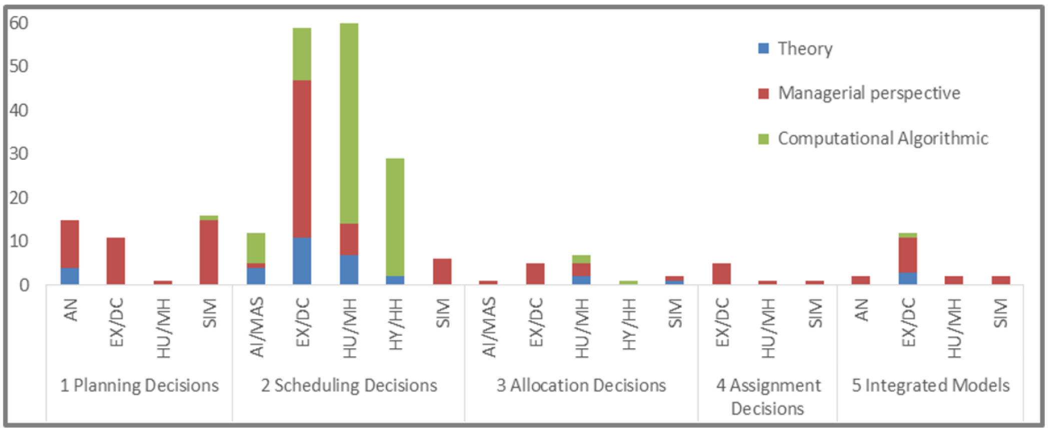


Fig. 2.9 Distribution of solution methods.

the analytical methods (e.g. queuing theory), simulation and simulation optimisation methods were dominant in the literature for addressing staffing and planning decision where more attention has been paid to the uncertainty factors such as patient arrivals and workload variability. A detailed classification of the publications can be seen in (Table A.2; Appendix A).

Publications have mostly focused on the managerial implications of the decisions. However, the scheduling stage has been more concerned with devising new scheduling algorithms to tackle hard problems. At the same time, there is a relatively low level of the theoretical studies on the model's structure and complexity. Quite surprisingly only Osogami and Imai (2001), Brucker et al. (2011) and Smet et al. (2016) approach understanding theoretical complexity structure of scheduling models. Osogami & Imai (2001) prove the difficulty of staff rostering problem with constraints on the number of assignments of particular shifts and with constraints on consecutive days worked and days off. While Brucker et al. (2011) address complexity issues by identifying polynomial solvable and NP-hard for special cases based on a generalised mathematical model. Also, Smet et al. (2016) identified new personnel rostering problems based on minimum cost network flow formulations that can solve in a polynomial-time. Theoretical insights allow for new formulations that make the problem or sub-problems computationally tractable.

2.5.1 Analytical Methods (AN)

The majority of the publications that applied analytical methods category have addressed staffing planning from a managerial perspective, with few focusing on theoretical aspects of the problem (Table A.2; Appendix A). Time-varying queues are among the most common methods applied for hospital staffing to accommodate demand fluctuations over short time periods (Green, Kolesar, & Whitt, 2007; Zeltyn et al., 2011). A Lagged SIPP queuing model for a single station can be applied to examine the efficient allocation of homogenous ED staff (Green, Giglio, & Green, 2006), while a closed queuing framework is more suitable to set ward nurse (de Vericourt et al., 2011). Similar approaches have been employed for staff requirements planning such as time-varying Erlang-R queuing model (Yom-Tov & Mandelbaum, 2014), square root staffing rule (Izady & Worthington, 2012), two-dimensional queuing model to guide nurse staffing decisions (Yankovic & Green, 2011), an exact analytical stochastic method based on hourly census predictions (Kortbeek, Braaksma, Burger, Bakker, & Boucherie, 2015), and a stochastic closed-form expression determine the optimal proportion of cross-trained nurses in a two-unit assuming full flexibility (Gnanlet & Gilland, 2014).

2.5.2 Simulation (SIM) Methods

Although the queuing theory has widely been used for staff planning, it is often criticised due to its limitations in accommodating the complexity of hospital systems. Alternatively, several studies have employed a simulation-optimisation method in order to overcome the shortcomings of analytical methods (Marmor, 2010). Most simulation-optimisation studies have emphasis on the managerial implications of hospital staff planning (Brenner et al., 2010; Feng, Wu, & Chen, 2015; Harper et al., 2009), scheduling (Badri & Hollingsworth, 1993; Dittus, Klein, DeBrota, Dame, & Fitzgerald, 1996), allocation (Inman, Blumenfeld, & Ko, 2005), and assignment (Sundaramoorthi et al., 2010) (Table A.2; Appendix A). For staff planning, several studies that applied simulation-optimisation methods have been carried out on ED staff planning. Some examples of previous research include: a simulation framework to support the short-term prediction of staff required (physicians and nurses) (Zeltyn et al., 2011), using ILP and a heuristic iterative algorithm to solve this ILP model considering once resource at a time (Sinreich & Jabali, 2007) and evaluating the assumption and validity of staffing model (EL-Rifai, Garaix, Augusto, & Xie, 2014). Also, simulation-optimisation is used to perform a sensitivity analysis expressing the expected LOS and the average time to be seen by a doctor for urgent patients as a function of the staffing budget (Ghanes et al., 2015). In ED, Cabrera, Taboada and Iglesias (2011) provide an agent-based model to obtain the optimal staff configuration (i.e., doctors, nurse, admin). Instead of using simulation as a function evaluation, a metamodel based simulation and Design of Experiments (DOE) is developed to find the optimal level of resources (staff and beds) that minimises the LOS in ED (Zeinali, Mahootchi, & Sepehri, 2015). Recently, a stochastic multi-objective simulation-optimisation model is proposed to examine multiple staff types that minimise the expected LOS and expected medical waste cost (Feng et al., 2015). In addition to ED staffing, simulation-based methods were applied to staff planning of homogenous ICU nurse levels (Griffiths, Price-Lloyd, Smithies, & Williams, 2005), investigating part-time surgeons policies for endoscopy department (Molema et al., 2007) and nurse staffing in in-patient care (Harper et al., 2009).

2.5.3 Exact/Decomposition (EX/DEC) Methods

Two-thirds of the articles for hospital staffing have an interest in scheduling decisions (n=59; 67%), followed by integrated models (n=11; 12%), planning (n=10; 11%), allocation (n=5; 5.5%), and assignment (n=4; 4.5%) (Table A.2; Appendix A). Regarding the study scope, it appears that the majority of papers have focused on a managerial perspective (n=63; 70%) rather than theory (n=15; 13%) and computational algorithmic (n=13; 15%). Among the exact/decomposition methods are the Simplex algorithm and its variants (e.g., interior point, and primal simplex), branch and bound (B&B) and its variants (e.g., branch and cut (B&C), branch and price (B&P), and cutting plane), dynamic programming (DP), and Lagrangian relaxation based methods.

All models are formulated as a mixed integer program. Branch and Bound (B&B) is a traditional algorithm for optimal staffing and scheduling decisions. As for Linear MIP, B&B tends to solve the LP relaxation problem by ignoring the integrity constraints of the decision variables. Then, heuristic rounding procedures are applied to the LP-relaxed solution to obtain an integer solution – only if the LP-relaxed solution is not an integer.

B&B algorithms are guaranteed to get an optimal solution to any problem within a problem-dependent computational time. However, most of the real-world problems are NP-hard; no polynomial-time algorithm can efficiently solve them. To overcome this issue, The B&B method can be applied to stage one of the solution, and a complementary method can be enacted at stage two. For problems with a large number of variables, in particular, staff rostering problems, several authors have reported branch and price (B&P) method (Dohn & Mason, 2013). B&P combines B&B and column generation (CG) to solve a Dantzig-Wolfe decomposition to the optimal or near-optimal solution (Barnhart & Johnson, 1998). The problem is decomposed into two sub-problems: Master sub-problem (i.e. a relaxed version of the original problem with a subset of variables) and Pricing sub-problem (i.e. new entering variables). A decomposition approach based on B&P has been considered to solve large-scale problems such as nurse tour preferences scheduling (Burke & Curtois, 2014), cyclic nurse scheduling (Purnomo & Bard, 2007), physician scheduling with flexible shifts (Brunner et al., 2011), resident scheduling (Beliën & Demeulemeester, 2007), and integrating nurse planning and scheduling (Maenhout & Vanhoucke, 2013c). Other decomposition methods that are employed include Branch and Cut (Bruni & Detti, 2014; Kim & Mehrotra, 2015), Lagrange-relaxation (Bard & Purnomo, 2007) and bender-decomposition (Punnakitikashem et al., 2008).

Examples of problems addressed in literature; nurse planning (Brusco & Showalter, 1993; van der Veen, Hans, Veltman, Berrevoets, & Berden, 2014; Wang, Gupta, & Potthoff, 2009), multiple staff planning (Bretthauer & Cǒté, 1998), nurse scheduling (Azaiez & Al Sharif, 2005; Glass & Knight, 2010; Millar & Kiragu, 1998; Smet et al., 2016; Topaloglu & Ozkarahan, 2004), physician scheduling (Brunner et al., 2009; Ferrand et al., 2011; Gunawan & Lau, 2013; Stolletz & Brunner, 2012), resident scheduling (Ovchinnikov & Milner, 2008; Smalley & Keskinocak, 2014; Topaloglu, 2009), real-time nurse allocation (Bard & Purnomo, 2005c; Brusco, 2008), nurse to patient assignment (Sir et al., 2015), integrated nurse staffing and scheduling (Komarudin et al., 2013; Maenhout & Vanhoucke, 2013b), and the coordination between nurse scheduling and allocation (Wright et al., 2010).

2.5.4 Artificial Intelligence/ Multi-agent system (AI/MAS) Methods

Most of the articles that reported AI or MAS have investigated nurse scheduling. Few critiques on using black-box optimisation methods (i.e. metaheuristics and mathematical programming for self-scheduling) are reported in the literature. The main two reasons appear to be the difficulties in incorporating human expertise, and the lack of ability to see exactly the changes and choices made. Staff members usually perceive the schedules that are created manually from the preliminary schedule as fair. For example, the global constraints approach is presented by Simonis (2007) to model and solve a large-scale real-world nurse rostering problem. Bayesian optimisation and learning classifier systems can also contribute in solving the nurse scheduling problem (Li & Aickelin, 2004). The idea is to use information from past solutions to implement explicit learning. Case-Based Reasoning (CBR) is presented by Beddoe and Petrovic (2007) to develop a personnel roster. Offline feature selection and weighting method can improve CBR's classification accuracy as well as reduce the number of attributes to be considered (Beddoe & Petrovic, 2006). Neural networks have also been proposed to identify the quality of the generated solution, showing for highly constrained problems, that pattern recognition could speed up the search process significantly (Jingpeng Li, Burke, & Qu, 2010). Some studies have discussed scheduling as naturally a distributed problem. For instance, a cooperative distributed intelligent agents is proposed for nurse scheduling (Winstanley, 2004), where the nurse agents communicate with a logic constraint programming agent to solve the overall problem. A competitive agent-based negotiation, called competitive nurse rostering (CNR), is introduced to solve nurse rostering (Chiaramonte & Chiaramonte, 2008). Each nurse competes for days off by trading shifts in an auction. AI/MAS methods are not hampered by the highly constrained complexity of mathematical programming approaches thus allowing for the inclusion of more preference considerations.

2.5.5 Heuristic/Metaheuristics (HU/MH) Methods

Another method of obtaining a near optimal solution is heuristics and metaheuristics algorithms. The significant development of metaheuristic can be explained by the increase in the processing power of computers and the development of parallel architectures (Boussaïd, Lepagnot, & Siarry, 2013). Metaheuristics mostly share the following characteristics: nature-inspired; use of stochastic components; derivative-free; and have several parameters to be tuned. The primary challenge is to balance between two different criteria: firstly, diversification to explore the search space and secondly, intensification to exploit the promising solution regions. The NP-hard characteristic of the staff scheduling problem (Bartholdi III, 1981) has stimulated the attention of researchers over the years to devise new algorithms that can provide high-quality solutions within a reasonable timeframe. This is evident from the analysis of the literature where most of HU/MH methods have emphasised on computational algorithmic category (n=48) with 45 of them have examined the scheduling problem, in particular, nurse scheduling problems (Table 2.4).

Table 2.4 Heuristics and Metaheuristics methods distribution.

HU/MH methods	n	References
Heuristics	18	(Brucker, Burke, Curtois, Qu, & Vanden Berghe, 2008; Campbell, 1999; Carrasco, 2010; Constantino et al., 2014; De Causmaecker & Vanden Berghe, 2003; Eiselt & Laporte, 1987; Franz & Miller, 1993; Legrain, Bouarab, & Lahrichi, 2015; Mullinax & Lawley, 2002; Osogami & Imai, 2001; Ozkarahan & Bailey, 1988; Pierskalla & Rath, 1976; Sherali, Ramahi, & Saifee, 2002; Sinreich & Jabali, 2007; Sinreich, Jabali, & Dellaert, 2012; Smalley, Keskinocak, & Vats, 2015; Christos Valouxis, Gogos, Goulas, Alefragis, & Housos, 2012; Wong, Xu, & Chin, 2014)
Metaheuristics		
Single-agent based search	17	(Bellanti, Carello, Della Croce, & Tadei, 2004; Burak Bilgin et al., 2012; Brucker et al., 2011; Burke, Causmaecker, Petrovic, & Berghe, 2006; Burke, Curtois, Qu, & Berghe, 2013; Burke et al., 2012; Burke, Causmaecker, Petrovic, & Berghe, 2004; Burke, Curtois, van Draat, van Ommeren, & Post, 2010; Carter & Lapierre, 2001; Dowsland & Thompson, 2000; Ferland et al., 2001; Goodman et al., 2007; Ikegami & Niwa, 2003; Lu, Hao, Lü, & Hao, 2012; Nonobe & Ibaraki, 1998; Parr & Thompson, 2007; Tassopoulos, Solos, & Beligiannis, 2015)
Multi-agent based search		
Evolutionary Algorithms	14	(Aickelin & Dowsland, 2000, 2004; Aickelin & White, 2004; Feng et al., 2015; Guo, Wu, Li, Song, & Rong, 2014; Li et al., 2009; Maass et al., 2015; Maenhout & Vanhoucke, 2008, 2011, 2013d; Ohki, Uneme, & Kawano, 2010; Pato & Moz, 2008; Puente et al., 2009; Tsai & Li, 2009)
Other Evolutionary Algorithms	1	(Aickelin et al., 2007)
Swarm Intelligence Algorithms	5	(Altamirano, Riff, Araya, & Trilling, 2012; Buyukozkan & Sarucan, 2014; Maenhout & Vanhoucke, 2013a; Wu et al., 2015; Yin, Chao, & Chiang, 2011)
Others	4	(Aickelin & Burke, 2009; Gascon, Villeneuve, Michelon, & Ferland, 2000; Hadwan et al., 2013; Li, Burke, Curtois, Petrovic, & Qu, 2012)
Total	59	

Many scientists have proposed various methods of single-agent metaheuristics that start with a single complete solution (generated randomly or by a greedy approach) and then seek to improve the current solution iteratively. Some studies have shown that Tabu Search (TS) based algorithms search solution space efficiently before producing a good solution in a reasonable computation time (Ikegami & Niwa, 2003; C Valouxis & Housos, 2000).

Other single-agent metaheuristics algorithms that have been proposed for nurse scheduling are Simulated Annealing (SA) (Burke, Li, & Qu, 2012; Parr & Thompson, 2007), Iterative Local Search (ILS) (Li, Aickelin, & Burke, 2009), Greedy Randomized Adaptive Search Procedure (GRASP) (Goodman et al., 2007), and Variable Neighbourhood Search (VNS) (Burke, Li, & Qu, 2010). On the other hand, multi-agent based search methods or population-based metaheuristics deal in every iteration of the algorithm providing a set solutions rather than a single solution. A number of studies have reported population-based metaheuristics for solving scheduling, including evolutionary algorithms such as genetic algorithms (GA) (Aickelin & Dowsland, 2004; Pato & Moz, 2008; Puente et al., 2009), swarm intelligence algorithms such as particle swarm optimisation (PSO) (Wu, Yeh, & Lee, 2015), artificial immune system (Maenhout & Vanhoucke, 2013a), and bee colony optimisation (Buyukozkan & Sarucan, 2014). Other evolutionary algorithms such as Estimation of Distribution Algorithm (EDA) (Aickelin et al., 2007), and Scatter Search (SS) method (Burke, Curtois, Qu, & Berghe, 2010) are also proposed.

2.5.6 Hybrid/Hyperheuristic (HY/HH) Methods

Hybrid optimisation was developed in order to exploit the complementary characteristics of various optimisation strategies from different domains. Several authors have explored the hybridisation between exact and metaheuristic methods (Figure 2.10) including: combining of the B&B with LS (Meyer & Hofe, 2001), a hybrid IP and TS (Aickelin & Dowsland, 2000), and IP and VNS (Burke, Li, et al., 2010). Hybridisation between exact and AI methods are also explored in the literature; for example, a hybrid constraint programming (CP) based Column Generation (CG) for nurse scheduling (He & Qu, 2012) and resident scheduling problem (Seyda Topaloglu & Ozkarahan, 2011). Many articles investigate hybrid algorithms based metaheuristic and AI methods; combination of CP and LS (Li, Lim, & Rodrigues, 2003), CP and ILS (Stølevik & Nordlander, 2011), and CBR and memetic algorithms (Gareth

Beddoe, Petrovic, & Li, 2008). To raise the generalisation level of an optimisation algorithm, hyperheuristic frameworks have also been proposed for nurse timetabling problems including simulated annealing hyperheuristic (SAHH) (Bai, Burke, Kendall, Li, & McCollum, 2010), TS hyperheuristic framework (Burke, Kendall, & Soubeiga, 2004). Hyperheuristic algorithms describe heuristics that choose between heuristics in the context of the combinatorial problem, which emphasise on the generalisability of algorithms that can potentially be applied to many related problems without much effort of adaptation (Burke, Kendall, et al., 2004). Unlike to metaheuristics, hyperheuristic operates on a search space defined by a lower-level heuristics or metaheuristics instead of acting directly on the problem search space. In summation, HY/HH algorithms represent the most efficient algorithms for many classical and hard real-world problems. Apparently, a considerable number of hybrid methods have proposed to solve a variety of scheduling problems.

2.5.7 Stochastic Models

Hospital managers are concerned with matching staff supply to the predicted demand under the inevitable uncertainty. One source of demand variability is the unscheduled arrival of patients with a diverse range of severity. Another source of variability originating from supply-side is staff absenteeism and availability of resources. Deterministic models that assume average values under/over-estimate resources requirements and fail to account for fluctuations in demand (Harper et al., 2009). Limited studies have examined uncertainty surrounding decision making and optimisation processes (except for planning stage (Green et al., 2007)). Such a trend can mainly be explained by the fact that stochastic combinatorial optimisation models are extremely hard to solve.

A classification of the studies that incorporated stochastic element(s) across the different staff stages is shown in Table A.3; Appendix A. It appears that stochastic models address all staffing and scheduling stages, but planning decisions occur more frequently. Regarding

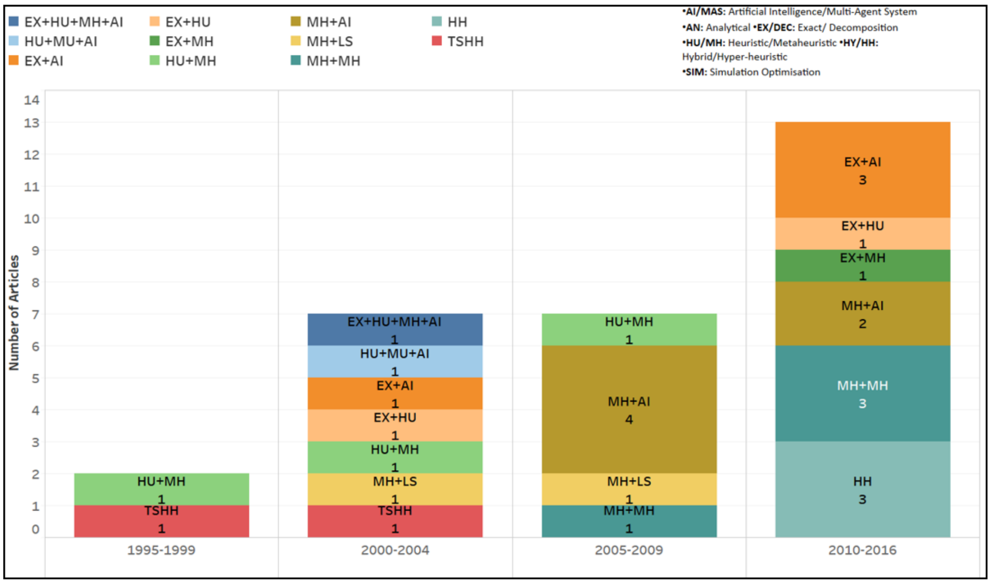


Fig. 2.10 Hybrid/hyperheuristic methods.

stochastic parameters, the majority of articles have considered the uncertainty of demand arrival, service time, and routeing probabilities. Few papers have incorporated the randomness associated with patient acuity and staff absenteeism. Regarding the distribution of stochastic models across the solution approach (Table A.4; Appendix A), simulation and analytical (queues) methods are the most frequently applied method to handle stochastic parameters when it compared to other methods.

2.5.8 Software Package

The solution process mainly depends on mathematical formulations. Frequently, these models are solved exactly using commercial software packages (e.g., ILOG CPLEX and LINDO) or non-commercial solvers (e.g., OR-COIN) to obtain the optimal solution (Figure 2.11). It is found that 44% of the reviewed articles used a commercial solver to get a complete or partial solution, while in some cases to compare with other methods. Of the total, the most frequently used software package is CPLEX (21%) followed by LINGO (5%) and XPRESS (4%).

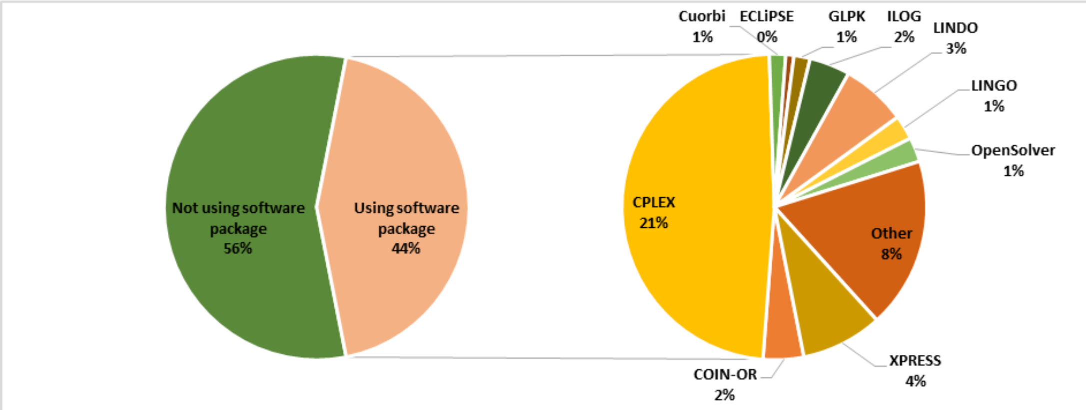


Fig. 2.11 Software packages distribution.

2.6 Evaluation Perspective

Performance appraisal is an integral part of any planning processes. To evaluate alternatives for medical staff planning and scheduling decisions, measures are classified into four perspectives; efficiency performance perspective, effectiveness performance perspective, staff satisfaction perspective, and Patient Experience perspective (Figure 2.12). Reviewed articles have shown that most of the studies preferred efficiency and effectiveness perspectives to staff and patient satisfaction (Figure 2.13). A summary of the classification of the evaluation perspectives is presented in Table A.5; Appendix A.

Efficiency. This broad perspective focuses mainly on the technical efficiency of healthcare services. Hospital management aims to be cost-efficient regarding medical staff by matching the planned staff size with the forecasted demand (Maenhout & Vanhoucke, 2013c). Various objectives are reported in the literature seeking to improve processes or organisation efficiency. Most of these objectives have emphasised on costing by minimising the number of required staff, staffing cost, float and cross-training cost, outsourcing cost, overtime cost, part-time and casual labour cost, overtime cost, overstaffing and penalty costs (Table A.5; Appendix A). Cost-efficiency is the traditional dominant performance perspective focusing on maximising resources utilisation as much as possible. On the other hand, flow efficiency focuses on the patient whose needs are satisfied through the process of activities.

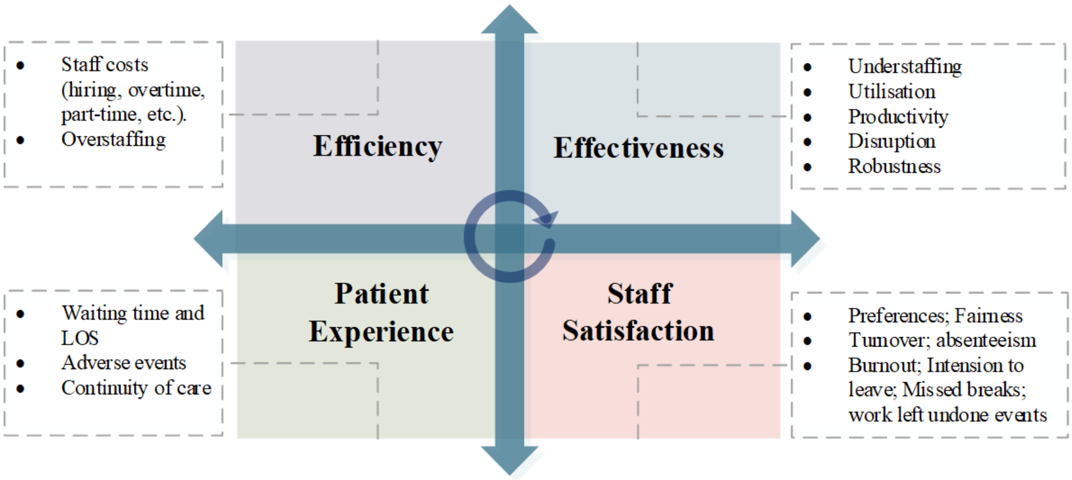


Fig. 2.12 The four evaluation perspectives.

Effectiveness. These evaluation criteria are concerned with providing a high-quality service by minimising understaffing, schedule disruptions, maximising staff utilisation and schedule robustness (Table A.5; Appendix A).

Staff Satisfaction. Intuitively, the satisfaction level of its providers (e.g., nurses and physicians) significantly influences the quality of healthcare delivery. Dissatisfaction of staff can lead to costly and risky consequences that might hinder patient and staff safety (Hegney et al., 2006). The contributing factors to staff dissatisfaction include an inefficient schedule (Dunn et al., 2005), work pressure (Aiken et al., 2013), long working hours (Bae & Fabry, 2013), and unfair shift allocations (Dunn et al., 2005). Currently, most of the hospitals are keen to try solutions that will incorporate staff's preferences and workload balance into scheduling models to increase the level of satisfaction of their employees.

Patient Experience. Ineffective staff planning and scheduling can adversely impact on patient experience by increased waiting time. This will result in extra costs and pressures on staff. The longer the patients stay in the hospital unnecessarily, the higher the associated risks. This category focuses on maximising patient satisfaction through minimising patients' waiting time and cancellation rate and incorporating patient preferences.

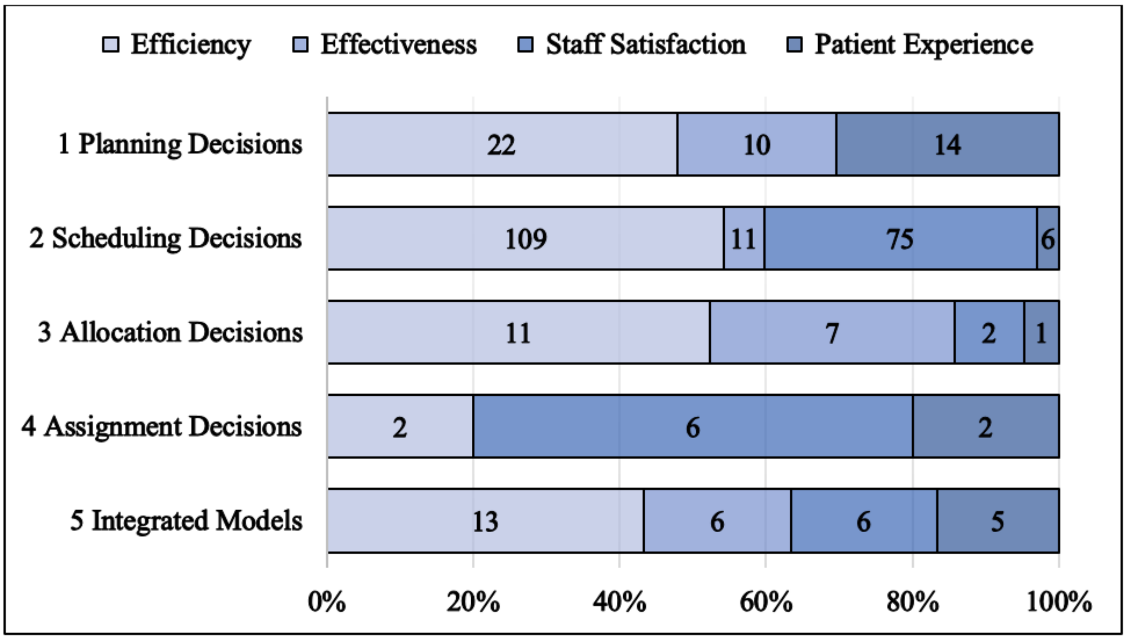


Fig. 2.13 Distribution of the articles according to performance criteria.

2.7 Discussion

Studying the social, economic and operational benefits associated with applying OR/MS to staffing and scheduling problems has proven to be a fast-growing research area due to the critical nature of the topic. This growing interest a result of the following;

1. The rising cost of healthcare.
2. Patients' expectations are getting higher regarding the services quality, access and timing of duty.
3. There is an urge to balance the mounting demand with capacity. This includes skill sets and training.
4. Staff expectations and work environments have become crucial for decisions.
5. Advances in technology have an impact on both operational and strategic decisions.

Adequate staffing and scheduling of medical staff can help hospital management to respond better to these challenges (Otegbeye, Scriber, Ducoin, & Glasofer, 2015).

Integration. The predominant studies have revolved around investigating problem-specific models with stringent boundaries, a vertical separation between decisions levels, and a paucity of horizontal integration. Most of the research efforts have focused on modelling a specific problem in a single unit in the hospital. Such models often set questionable and restrictive assumptions regarding the upstream and downstream resources (e.g. using aggregate averages). Ultimately, addressing staff planning and scheduling decisions in isolation of interrelated activities have deemed ineffective. Similarly, there is a focus on single-staff type scheduling (i.e. nurses or physicians) except few attempts to combine multiple staff types or resources. Thus, in a dynamic hospital environment, it is essential to consider the mutual interactions between the different staff types and resources in order to facilitate coordination between various resources.

Regarding the vertical integration between the four scheduling stages (i.e. staff planning, scheduling, allocation, and assignment), relatively few publications appreciate the importance of such integration at different resolution levels (e.g. strategic, tactical, and operational). For instance, sub-optimal staffing decisions can lead to under/over-staffed shifts (i.e. on the operations). Understaffing is associated with substantial and sustained excess workload, increasing the risk of burnout and staff turnover, thereby compromising the quality of care. In turn, it has negative consequences on both staff satisfaction and patient experience. On the other hand, overstaffing can cause inefficiencies. Overstaffing improves the patient experience (e.g. little waiting time) in favour of higher cost, while, understaffing increase waiting time and resulting mistakes may occur from the high workload. Therefore, achieving efficient operational performance entails the alignment between the different stages in order to avoid the suboptimal decisions. In this regard, the recursive integration of staffing and scheduling are commonly used in the literature, while the simultaneous integration between different stages is uncommon as well as the models that integrate more than two stages. Similarly, the challenge of integrating the four stages have not received any research attention yet. These limitations can be partially explained by the computational complexity associated with the simultaneous integration of two or more stages for real-world problems (Ernst et al., 2004). Potential research opportunities are evident in the area of incorporating both horizontally integrated models (i.e. combining multiple resources across multiple units) and vertically integrated models. To address this challenge, a holistic framework ought to be adopted to underpin the problem in its totality, considering the interdependency between hospital units, the mutual synergy of various resources, and the dynamic interactions between decisions are fundamental determinants of the effectiveness of decisions.

Selection of the evaluation perspective. There are four different angles for evaluation metrics: efficiency, effectiveness, staff satisfaction, and patient experience. They present themselves in the hospital/unit performance (efficiency and effectiveness), medical employees, and patients. Most of the studies have underpinned the problem from a single evaluation perspective. Efficiency and the effectiveness are the most commonly used aspects. Over the recent years, it seems that the economic factors are the main driving force underpinning the staffing and scheduling decisions due to financial constraints and budget cuts. As a result, staff utilisation and efficient use of the available resources have an impact on management decisions. These decisions as expected will have an impact not only on the unit/hospital performance but also on both staff morale and patient experience. Regarding staff morale, shift systems are often associated with a variety of psychosocial and physiological issues that can affect the health of employees. Workload balance of medical staff has always been an urging matter for hospital management. Medical staff in particular often suffer 'burnout' due to the complexity of staff scheduling and high workload. The burnout of staff can lead to mistakes in diagnosis, operational difficulties, and failure to achieving hospital performance targets and most importantly deterioration in patients' outcomes. As for patient experience, in the past several years, patient-centered care has gained ground in all hospital management forums. Inadequate hospital staffing can only lead to patients suffering from adverse events and medical errors. Therefore, the four perspectives of evaluation have to be an integral part of the decision process. This should realise the implications of staff satisfaction and their behaviour on the productivity and quality of services without compromising both efficiency and effectiveness.

Method selection. The analysis of solution methods has showed that there are some methods more applicable than others to address particular stages of staffing and scheduling problems. For example, staff planning stages are more likely to use analytical (queues), and simulation models have addressed the Emergency Department, which is an intense, dynamic and stochastic work environment with a variety of patient's categories. Simulation can model such complex environments. However, for scheduling, it is recognised as an NP-hard problem with solutions varied between primarily exact, metaheuristic, artificial intelligence, and hybrid methods. The exact methods were proposed to obtain the optimal solution to a small to medium size problems within a problem-dependent computational time. For large-scale problems, decomposition and approximate methods can be customised based on traditional techniques (e.g., B&P, B&B and DP) for solving a relaxed problem iteratively. However, accumulated knowledge from solving one problem is, to a large degree, not extendable to new challenges. Heuristic/metaheuristic and hybrid methods are extensively used to address large-scale scheduling issues. One critique of these methods is they are susceptible to the parameters, and they entail a broad range of settings tuning. Most of the studies have mentioned little about the tuning process. Trial and error guided by some rule of thumb are a characteristic parameter tuning procedure. Comparatively, the article that addressed the allocation, assignment or even integrated models is biased to use the exact/decomposition methods. An explanation of the original scope of these studies is the managerial implications and the evaluation of the alternatives. This may be used to develop an evident-based framework for selecting the appropriate methods for underpinning a distinct problem in the hospital context. Nevertheless, choosing an optimisation method to use has become exponentially challenging with the growth of analytical and smart models. Users often struggle to decide, and for this reason, modellers have to embark on this task. Clear justification and clear guidance on the decision of the selection of a particular optimiser to resolve a scheduling solution are still an issue to both practitioners and academics. Besides the mathematical complexity of the methods and the lack of understanding lead to losing the confidence in the outcomes. These can create implementation rigidity and inflexibility for adopting these methods in the context of healthcare.

Solution robustness. Solution robustness of staffing and scheduling decisions in hospitals setting has not yet been adequately researched. The optimisation models in the literature, and in particular staff scheduling, tend to be deterministic. However, resources scheduling is vulnerable to continued changes. Small variations or slight changes in data should not affect the schedule; unless it becomes unstable (i.e., fragile solution). Despite the extent usefulness of robust scheduling, it received a modest attention. There is a need to integrate predictive and proactive models that anticipate the expected variation and plan accordingly to unforeseen events. The stochastic models of staff planning and scheduling describe either reactive or proactive model but not both.

2.8 Conclusion

One of the significant issues facing hospitals is how to optimise medical staff planning decisions. OR/MS research community has reported various and interdisciplinary methods for underpinning the challenges of medical staffing and scheduling. An extensive review of literature coupled with a comprehensive analysis has resulted in a new four-dimension classification subject to problem contextualisation, solution approach, evaluation perspective and uncertainty. There is a growing trend acknowledging the potential impact of existing models, but a set of dominant characteristics were found: a vertical separation between decision levels; unrealistic assumptions; paucity horizontally integrated models; deterministic is still more dominant; reliance on empirical case study methodologies; a dearth of pragmatic frameworks that incorporate the practitioners view.

Regarding the problem of contextualisation, the literature has addressed the topic using either single-stage models—that focus on a single-stage including planning, scheduling, allocation, assignment decisions—and integrated models, whose approaches can be categorised into three categories: hierarchical, recursive, and contemporary. The majority of articles have substantially addressed a single decision stage, in which the papers are mainly concentrated on nurse scheduling, whereas few papers are focused on the real-time decisions, i.e. allocation and assignment stages. For integrated models, only a limited number of publications have attempted to amalgamate multiple stages to examine the implications of the interactions. The emphasis is on incorporating two stages, particularly planning and scheduling stages. Despite the importance of integrating the interrelated decisions, there is a paucity of models that can combine three stages or more in a single model. Furthermore, there is a disregard to account for mutual interactions and strong interdependencies between the different resources types and to acknowledge the implications of coordination on the optimal decisions. Notably, there is a presence of mostly single-unit applications, setting stringent boundaries regarding interconnected units.

In terms of solution methods, over the years, this topic has been at the centre of attention of the OR/MS research. To date, various optimisation methods have been employed, but they primarily use exact/decomposition, heuristics/metaheuristic, hybrid, and simulation techniques, and (to a lesser extent) artificial intelligence or analytical methods. It appears the majority of articles that are from a managerial perspective are more likely to be investigated using analytical, simulation, or exact methods. On the other hand, variety of algorithms have been introduced to solve scheduling stage, where metaheuristics and hybrid methods are more frequently to be applied. Over time, the interest in hybrid methodologies has gathered momentum, exploiting the complementary characteristics of different optimisation strategies to address large-scale problems. However, selecting an optimisation method to use has become more challenging. Users often struggle to choose the appropriate method. Clear guidance to choose a particular optimiser to resolve a scheduling solution is still an issue to both practitioners and academics.

Chapter 3

Research Methodology

If we knew what we were doing it
would not be called research, would it?

Albert Einstein

3.1 Introduction

Conducting any research entails a well-defined research methodology that stands on scientific principles (Eldabi, Irani, Paul, & Love, 2002). Research methodology refers to a systematic scientific process, the various steps that the researcher adopted to solve or to scrutinise a research problem along with the logic behind it (Saunders, Lewis, & Thornhill, 2016). It may be perceived as a discipline of investigating how research is conducted scientifically. So far, there is no agreement upon 'perfect' methodology within the research community (Tsoukas & Knudsen, 2003). However, designing an appropriate research methodology depends mainly on the research objective(s) and the philosophical assumptions of the researcher. This chapter will present the research methodology to address the main research question of this study:

How can hospitals effectively match staffing patterns (i.e. nurses and doctors) to meet patients' demands?

An overview of the research methodology of the study is presented in Figure 3.1. The chapter discusses research philosophy in the literature and highlights the main research paradigms and approaches relevant to the study. The paradigmatic stance of the research is then explained along with its associated research methods.

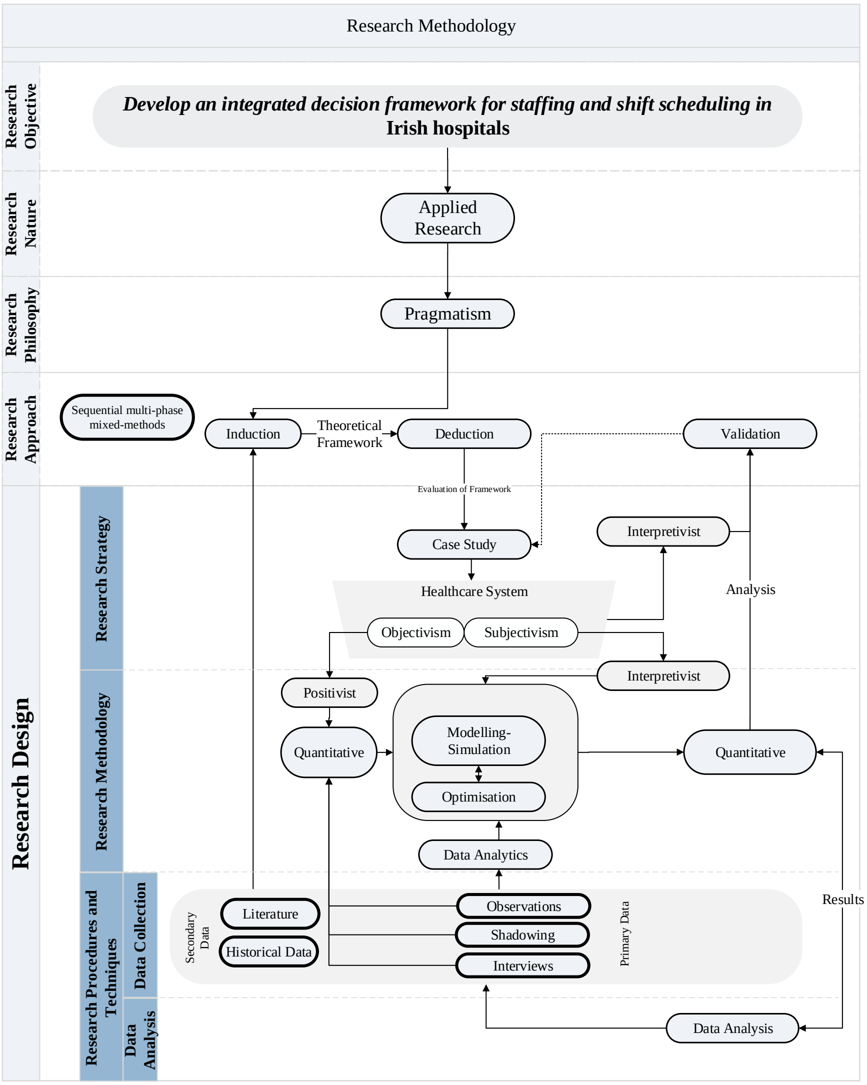


Fig. 3.1 The employed research methodology process.

The research design is composed of three distinct research modes, and each mode has its sub-objectives, administration procedure, and techniques employed in order to achieve the ultimate research goal. Finally, ethical issues and the measures taken to address them are clarified.

3.2 Research Philosophy and Paradigm

Hospital structures are complex social systems, which characterised as labour intensive with a diversity of technical skills. The work in these institutions are so specialised and staffed with a variety of technical and professional personnel. Social structure emerges from the relationships and the interactions between hospital staff and patients who are the client and product at the same time.

Due to the bounded rationality of a human being, all social scientists address their subject through explicit or implicit postulates about the nature of the social entity and the way in which it may be examined (Myers & Avison, 1997). Burrell and Morgan (1979) categories the philosophical assumptions into two dimensions: the nature of science and nature of sociology. The former is delineated by four sets of philosophical assumptions concerning ontology (reality), epistemology (knowledge), human nature, and methodology. Two primary intellectual traditions and their four sets of underlying assumptions are depicted in Figure 3.2.

3.2.1 Nature of Science

The ontological stance describes the reality of research objects (e.g. organisations, management, and individuals) under investigation (Burrell & Morgan, 1979). It differentiates between whether the 'reality' to be investigated is 'external' to the researcher who called 'objectivist' or 'internal' construct—concepts formed in mind—which called 'subjectivist'

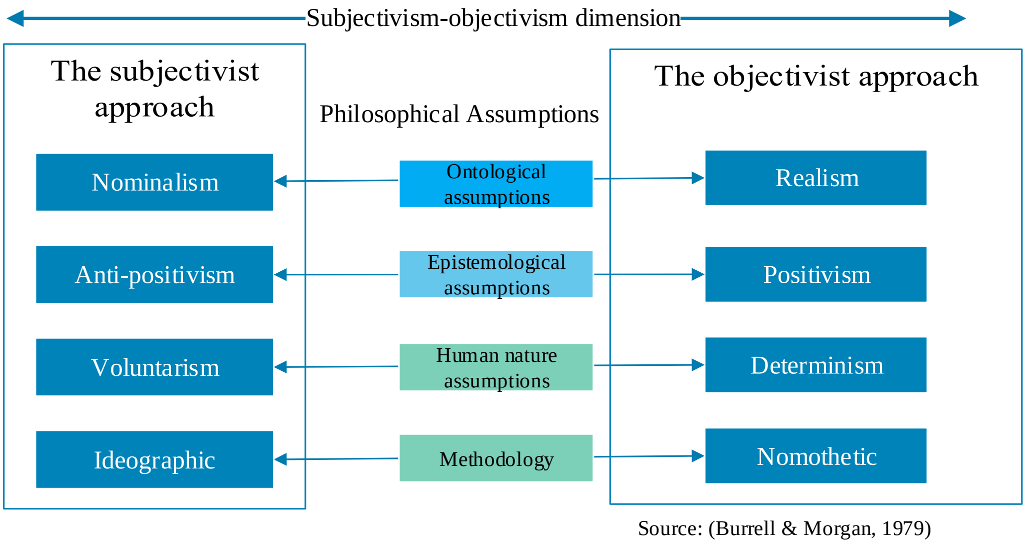


Fig. 3.2 The philosophical assumptions.

(Saunders et al., 2016). Business and management research philosophies are scattered along a multidimensional set of continua (Niglas 2010) between these two opposing extremes. The epistemological assumptions are predicated upon the view of the nature of the obtained knowledge and how to communicate knowledge to others (Burrell & Morgan, 1979). Objectivists adopt the observer role when viewing the knowledge as hard, tangible and objective. Interpretivists view social system as personal, subjective, soft, transcendental and unique. Objectivist and interpretivist are considered the most extreme positions of the epistemological assumptions. Objectivist relies on quantitative approaches for understanding a social setting by identifying the causal relationships between constructs to explain the subject under investigation (Cavaye, 1996), while interpretivist describes the social system from the participation perspective (Eldabi et al., 2002).

Human nature describes the relationship between people and the environment, which is conceptually separate from the ontological and epistemological assumptions. One extreme perspective, *determinism*, believes individuals have no control over their actions, which is predetermined (i.e. mechanistic and deterministic) (Paul Keys, 1991). This extreme perspective assumes that external circumstances restrict human beings. *Voluntarism*, in contrast, view the man as the founder, controller, and master of their environment. There is a great philosophical debate between the advocates of determinism (determinist view) on the one hand and voluntarism (voluntarist view) on the other (Burrell & Morgan, 1979).

Ontological, epistemological assumptions regarding human nature have substantial consequences on the methodology that is adopted to investigate and acquire knowledge about the subject under study. The interactions between the three sets of philosophical assumptions result in a range of possible choices. The methodological debate split between two major theories: nomothetic and ideographic (Hegde, 2015).

Ontological debate. Objectivism is an ontological stance that asserts that the reality of the investigated social reality is the absolute external fact that is independent of social actors (Bryman, 2012). Objectivists study social phenomena in the same way as naturalists. In this sense, Objectivism embraces realism—the most extreme position which postulates that the social entities to be like physical objects of the natural world (Stacey, 2011). There are two fundamental forms of realism: empirical and critical realism. Empirical realism—also referred to as naïve realism—is one of the main forms of realism in which the realists assume a perfect correspondence between reality and the term that is used to describe it (only one social reality experienced by all actors). On the other hand, ***subjectivism***—also known as ***constructivism*** —is an extreme ontological position that incorporates the assumptions of art and humanities. Subjectivism grasps **nominalism**—also called conventionalism—that assert that the social actors determine the entity under investigation and their meanings. Realists believe in multiple realities, where each perceives and experiences reality differently.

Epistemological debate. Positivism is an extreme epistemological assumption postulating that the knowledge about social reality can be procured by applying the methods of natural sciences. Positivism adopts a scientific position to research and aims to develop generalised findings from experimentation and structured observations of reality (Hussey

& Hussey, 1997). When applied in the context of social science, the positivist searches for causal relationships and regularities between constructs to explain and predict the social reality. The positivist paradigm assumes the researcher objectively obtains data while remaining external to the research process and independent of the subject of study, similar to the way a physical scientist would investigate physics or chemistry (Remenyi, Williams, Money, & Swartz, 1998). The outcomes of positivist research are replicable factual generalisations about social phenomena (Easterby-Smith, & Lowe, 2002). In the 20^{th} century, positivism faced substantial dispute and critiques by **antipositivists**; they firmly argued that social activities have to be examined through interpretive methods based upon interpreting the meaning and purpose that people attach to their personal actions (Bhattacherjee, 2012). For antipositivists, the social world is fundamentally relativistic because they are created by individuals in certain contexts and can be experienced by the persons who have directly involved their activities (Crotty, 1998). Interpretive research stresses the role of human beings as social actors where a researcher obtains knowledge by entering the social world of research subjects to understand the phenomena being studied from their point of view in a personal and empathetic manner (Holden & Lynch, 2004). The outcomes of interpretive research offer an understanding of the social phenomenon under investigation, and therefore cannot be generalised to other contexts (Burrell & Morgan, 1979). Antipositivists firmly tend to reject the objective knowledge and the utility of searching for laws or regularities in the social world.

3.2.2 Nature of Society

The next dimension, nature of society, distinguishes between two extreme schools: regulation and radical. Sociology of regulation schools refer to the position that the researcher concerns to provide an explanation that stresses on the unity and cohesiveness of the society under study. Most of business and management research, in addition to this study, can be classed as regulation research that seeks to suggest how organisational affairs may be improved within the framework of how things are done at present rather than radically challenging the current position (Saunders et al., 2016). Second, radical change school stands in the stark contrast to the regulatory view of the society, where it primarily tries to provide explanations for the radical change, modes domination, structural contradictions and deep-seated structural conflict. These lateral views are the foundation of distinguished, and often totally opposing, schools of thought – a reasonable prospect of society is the basis of modernism whereas a radical change perspective underlies post-modernism.

3.2.3 Pragmatism Paradigm

Over the years, scholars of business and management have had long debates regarding the importance of the multiplicity of research methodologies (Saunders et al., 2016). Pluralists argued that no proper single research methodology be intrinsically better than other methodology and sees the diversity of the field enriches business and management (Tsoukas, 1994). Others, unification, support the endorsed unification of management research under a unified research philosophy, paradigm, and methodology.

As a philosophical doctrine, pragmatism has descended from Charles Peirce (1839-1914) (Ormerod, 2006), but articulated and developed by James, Dewey, Mead and others (Barton, 1994). The pragmatic method can be advocated as a perspective of the dualism that has been debated over the years which attempt to take a pragmatic or pluralist position to improve the communication among researchers from different paradigms. In the second half of the 19-century, pragmatism appeared in the USA, which predicated on the way that people behaved in practice (Ormerod, 2006). Regarding ontology, pragmatism views truth as external, contemporary and continuously changing (Saunders et al., 2016). Epistemology in pragmatism considers observable phenomenon and subjective meaning, (or both of them) as adequate knowledge where the research questions determine it. This paradigm is appropriate to applied research. Qualitative, quantitative or mixed methods are also suitable for data collection under the umbrella of this philosophy (Saunders et al., 2016). It emphasises on the practical outcome of the research and rejects the "forced selection" between research paradigms (Tashakkori & Teddlie, 1998). It is based on using "what works" and argues that it is possible to adopt more than one philosophy within the same research project to achieve research objectives (Howe, 1988). This flexibility enables researchers to apply whichever philosophical or methodological approach they find appropriate if it would have an effective contribution to addressing their research question (Saunders et al., 2016). Tashakkori and Teddlie (1998) describe pragmatism as "study in the different ways in which you deem appropriate, and use the results in ways that can bring about positive consequences within your value system." They note that pragmatism is becoming a popular research philosophy because it facilitates the use of mixed method approaches and offers an alternative to what they refer to as "paradigm" wars.

3.2.4 Philosophical Assumptions of OR/MS

The pragmatism philosophy has come to the field of OR/MS through the work of the pioneering thinkers Churchman (1971) and Ackoff (1979, 1981). Churchman introduces the concept of "inquiring system", a system that produces knowledge (Figure 3.3). Accordingly, a scientific discipline can be organised as a three-levels of inquiring systems:

1. *An implementation inquiring system,* which represents the practical layer of the discipline.

2. *A science inquiring system*, which depicts that science level of the discipline where the scientific methodology is developed and shaped. This layer can be distinguished by Kuhn's (Kuhn, 1970) level of "normal science".

3. *An epistemology inquiring system*, which is the epistemological layer of the discipline where "extraordinary science”, such as innovation, creativity and the paradigm, is conceived.

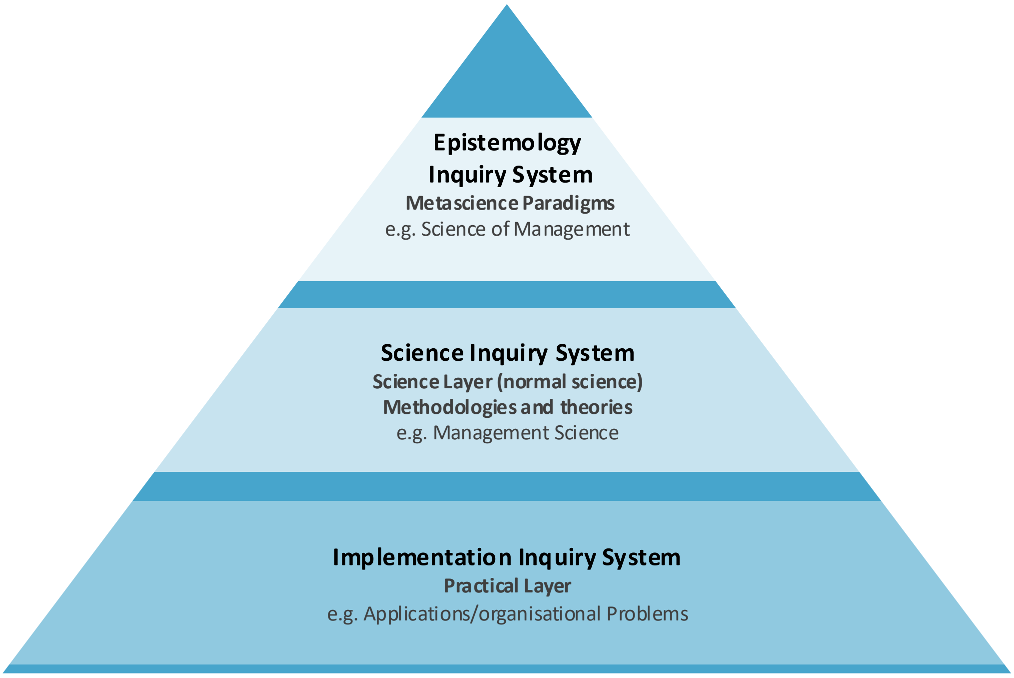


Fig. 3.3 Inquiry system.

According to this hierarchy, Churchman made a distinction between the “*sciences of management*” and the “*management science*” by creating the “X of X”, a self-reflexive loop. *The science of management*, (X), a metascience which is carried out in the epistemology inquiring system, whereas *management science*, (the X of X) devoted to the application of the *science of management* to the solution of organisational problems. Management science is mostly carried out in the so-called "*science inquiring system*" where management science experts and scientists study organisational problems and later implement the chosen solutions at ”the practice level” or implementation inquiring system. Many reasons justify the suitability of pragmatism to OR/MS studies (Table 3.1).

Table 3.1 Reasons for the suitability of pragmatism paradigm for OR/MS[a].

- Pragmatism fits how problem-solvers behave in practice. In Practice, most of the researchers resolve issues by comparing the outcomes that could result from different courses of actions rather than appealing to a generalised set of abstract principles.
- Pragmatism fits how problem-solvers behave in practice. In Practice, most of the researchers resolve issues by - Pragmatism advocates experimental approaches. In OR/MS, most researchers are attempting to utilise scientific methods to their activities.
- Pragmatism focuses on the uncertainty and changing nature of the findings. Pragmatist views that science is fallible changing, and subject to social context accords. IN OR/MS, researchers blend the methods from natural and social science to build a context-dependent science and local science. Its emphasis is on testing the uncertain truth experimentally.
- Pragmatism realises the individual psychological nature of meaning and thinking, where the soft OR support these ideas.
Pragmatism underpins the morality, politics, and social interests. Within OR, advocates criticised other approaches for failing to consider issues of conflict and power. Pragmatism is flexible enough to accommodate other philosophical positions.
- The pragmatism philosophy supports several of OR/MS approaches. For instance, multi-criteria decision making (MCDM) is a venue of emphasising on the outcomes and consequences of courses of actions, which is advocated by pragmatists. Other examples that support pragmatists including mathematical programming as logic machines, simulation for experimentation, system dynamics for whole system view and probability and statistical theories for allowing the statements to be made about the fallibility of predictions.

[a] Source: adapted from (Ormerod, 2006)

Advance knowledge (Maxcy, 2003; Watson, 1990). Management science—including operations research (OR), information systems (IS), and system thinking have emphasised data collection, analysis, and developing simulation and mathematical formulation to test out hypotheses (Mingers, 2006). Management science has been dominated by empiricism philosophy where the quantitative methods and statistical analysis were the primary research methods. More details regarding the philosophical assumptions debates of OR/MS is provided in Appendix B-1.

3.2.5 Research Paradigm Adopted

This research aims to develop knowledge regarding integrated decision support systems for staff planning in a hospital context. This can be achieved by reviewing and exploring the available theories and frameworks and then developing a framework underpinning the observed gaps. The hospital systems are complex systems with human interactions and social relationships among the system elements. This research has attempted to avoid what may be delineated as methodological monism (using a single research method). Instead, the pluralist approach is adopted as each method has something unique and valuable if used appropriately (Tashakkori & Teddlie, 1998). This research project includes elements of both the positivist and interpretivist approaches that should be both relevant to the research question:

How can hospitals effectively match staffing patterns (i.e. nurses and doctors) to meet patients' demands?

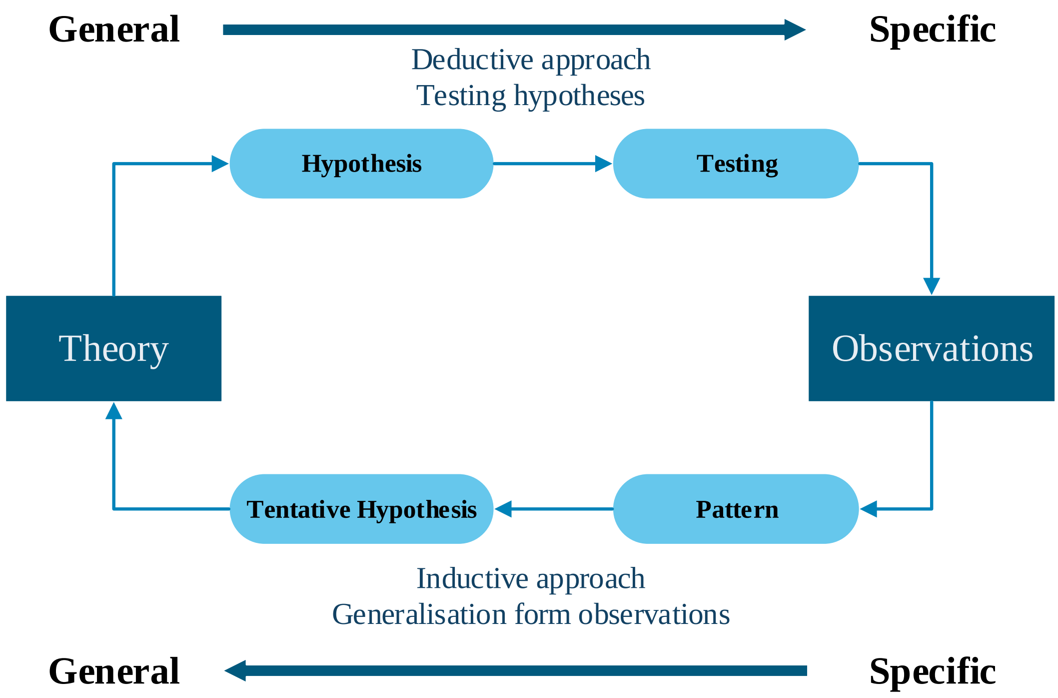
The interpretivist philosophy is required for the understanding, e.g. how managers make decisions regarding medical staff in the context of Irish hospitals and what are the challenges that they are facing. The positivist view, quantitative approach, is selected to develop an analytical solution which will be elaborated in the research strategies.

Given the multifaceted nature of this research, the pragmatic paradigm was adopted as the foundation philosophy to answer the research questions completely and comprehensively. As pointed out in Table 3.1 pragmatism paradigm is the most suitable paradigm for the OR/MS studies. Also, pragmatism enables the researcher to engage in satisfying research objectives by utilising different paradigms and their associated approaches at various stages of the research. It also allows the identification and implementation of the best-suited research methods and tools at each stage, resulting in an efficient research process which would yield relevant and valid results. Moreover, alternating between varying epistemological positions under a single pragmatic paradigm allows the use of mixed methods including both qualitative and quantitative techniques in data collection and analysis. Benefits of such combination for this research include triangulation and complementary of findings, in addition to a rigorous process for framework development.

3.3 Research Approach

After deciding the research paradigm of this study, this section specifies the research approach of this study. The main three reasons this should be addressed was discussed by Easterby-Smith, Thorpe, & Jackson (2008). First, the choice of research approach reflects upon the research design which is not restricted by merely specifying the data collection methods and data analysis. Second, the chosen approach will guide the selection of research strategy answering the research question. Third, research constraints such as a deficiency in the literature, or insufficient theories or hypothesis compel the research to investigate different approaches which then requires knowledge of the latter.

Broadly, two types of the argument of high importance to research are deduction and induction approaches (Cooper & Schindler, 2014). A deduction is a form of argument that purports to be conclusive—the conclusion must by necessity follows from the premises (reasons) given. As a result, a conclusion that results from deduction should be already "contained in" its premises. In deductive research, the goal of the researcher is to test concepts and patterns known from theory using new empirical data (Bhattacherjee, 2012). The deductive approach belongs to positivism. It is described as a "top-down" approach (Figure 3.4). It starts with a theory or hypothesis and narrows this by forming a hypothesis in operational terms, testing them, then examining the output to strengthen the theory or modify it and apply the same cycle repeatedly (Robson, 1993).



Source: adapted from (Trochim Donnelly,2001)

Fig. 3.4 Inductive and deductive reasoning.

The central aspect of the deductive approach is its capability to explain causal relationships between variables (Saunders et al., 2016), the use of a highly structured methodology which assists the replication (Gill & Johnson, 2002). Concepts require operationalisation which means the ability of the entities to be measured quantitatively to be generalised statistically with a suitable sample size.

On the other hand, in inductive research, the goal of a researcher is to infer theoretical concepts and patterns from observed data (Bhattacherjee, 2012). The inductive approach is seen as a "bottom-up" approach (Figure 3.4). Social science researchers criticised the deductive approach because of its concept of focusing on the cause-effect relation between variables regardless of the human interpretation of their social world (Saunders et al., 2016). Focusing on the context of the phenomenon as one of the inductive approach aspects allows for a smaller number of samples to be sufficient to gain outcomes. In this approach, different qualitative methods can be applied, and the researcher acts as a part of the research. A comparison between deductive and inductive approaches is provided in Appendix B-2.

Induction and deduction can be used together in research reasoning (Figure 3.5). This study mixes between both inductive and inductive approaches. The research goal is to develop an integrated framework to help hospital managers to improve staffing and shift scheduling decisions. Focusing on understanding the problem and incorporating the adaptive staff behaviour is applied through the inductive approach while formulating the framework to address the problem followed the deductive approach. The inductive approach was adopted in the early stages of the study to explore challenges regarding staffing and scheduling in hospitals. This was applied through interviews with physicians, nurses and consultants.

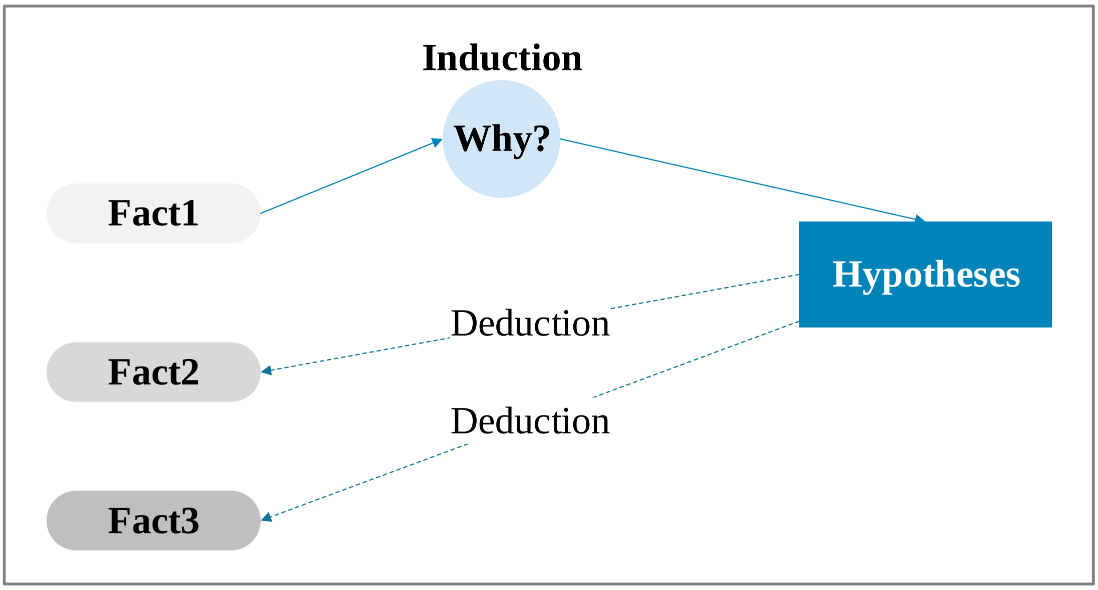


Fig. 3.5 Mixing induction and induction approach.

As a part of the literature review, the highlighted issues by the interviews were investigated for the available potential solutions. The conceptual framework is considered as the catalyst of the literature findings and the proposed solution. The deductive approach is then suitable to evaluate, confirm and verify the theoretical framework.

3.4 Research Design

Aligned with the pragmatic paradigm, this section outlines the fundamentals of how this study is conducted. This section will chart the research design and ensure that the empirical elements of this thesis are realised. The research design is the detailed work plan that describes what should be done to complete the research project and to ensure that the obtained evidence is addressing the research question clearly (Saunders et al., 2016). Research design specifies the research strategy, data collection methods, time frame, researcher role, data analysis, limitations and ethics (Robson, 1993). The details of these design components of this research are discussed in this section.

3.4.1 Research Purpose

Research purpose is the method of form adopted to answer the research question. It can be categorised into descriptive, exploratory, explanatory, evaluative or a combination of these. An exploratory study focuses on discovering what is happening and thus generates more insights which guide the following stage of the investigation (Robson, 1993). Adoption of this scheme is helpful when the problem is not clearly identified and requires more investigation. Several ways exist to conduct exploratory research which includes literature investigation, interviewing, or focus groups (Saunders et al., 2016). This type of research is flexible and adaptable to change regarding direction. An exploratory research can be further extended by a descriptive study to obtain a clear picture of the phenomena or problem under investigation before collecting actual data. Explanatory research focuses on establishing a causal relationship between the studied variables of the phenomenon (Saunders et al., 2016).

In business and management, an evaluative study concerning with assessing the effectiveness of an organisational or business strategy, policy, programme, initiative or process which can be related to other organisation or business (Saunders et al., 2016). In this way, evaluative research allows you assess performance and to compare this. Study design can combine more than one purpose which is often achieved through adopting the mixed method.

3.4.2 Choice of Research Methodology

Conducting a research project entails selecting between three methodological approaches as indicated in Figure 3.6: Quantitative, qualitative, and mixed methods (Williams, 2011). One distinction between qualitative and quantitative research is the type of data required to address the research question. Quantitative methods deal with numerical data and involve statistical techniques, qualitative methods manipulate textual data (e.g. narrative), while mixed methods combine both elements: numerical and textual.

3.4.2.1 Quantitative Methods

The quantitative approach is often related to positivism paradigm and utilises predetermined and highly structured data collection techniques. In a quantitative approach, the surveying and experimentation theme predominate, and the data is used to measure reality objectively with the isolation of the researcher from the research (Creswell, 2003). Research studies following a quantitative approach tend to collect data in a quantifiable form and then apply mathematical models for analysis (Creswell, 2003). That suits the natural sciences where the deductive approach is followed through proposing a hypothesis or starting with a theory and then confirming or validating them through data collection and observations. Quantitative research can be conducted through various strategies: survey, experiment, and structured observation.

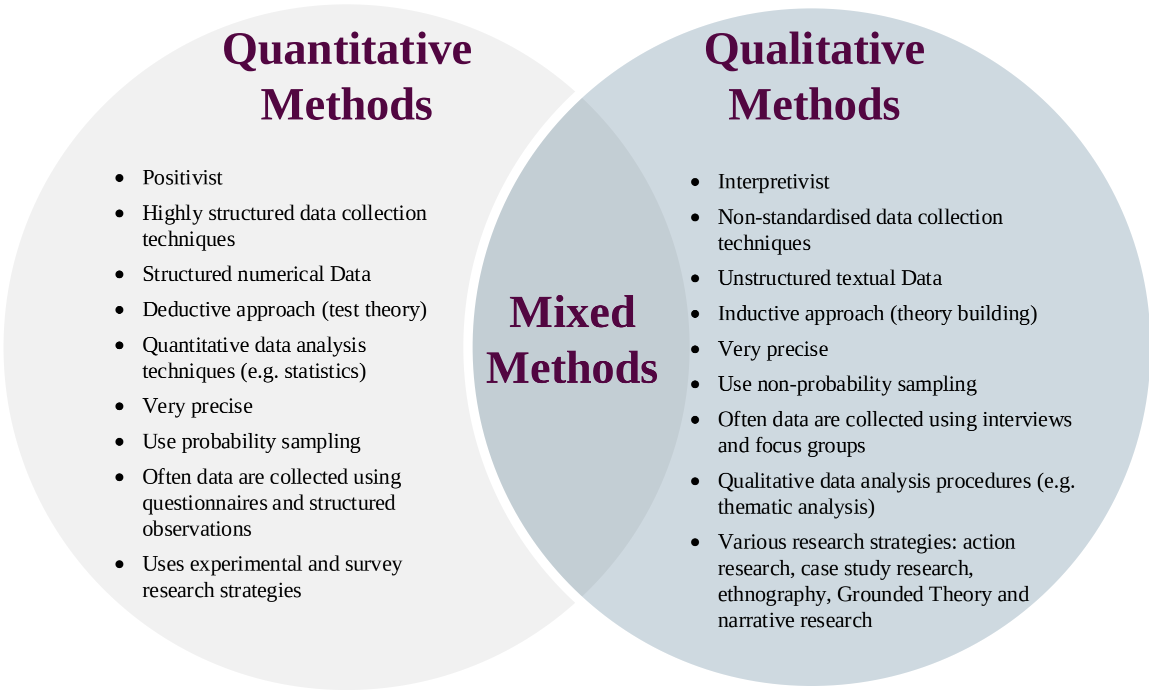


Fig. 3.6 Methodological approaches.

3.4.2.2 Qualitative Method

On the other hand, qualitative research is associated with the interpretivist paradigm that emphasises explanation and interpretation of social phenomenon from the researchers perspective (Creswell, 2003). The strength of qualitative data is its focus "*on naturally occurring, ordinary events in natural setting", which allows the researcher to gain insight into the effects of '*real life*' phenomena (Creswell & Clark, 2011). Also, qualitative data provides a richness or holism to the research that provides an in-depth description that is vivid and context specific. Qualitative research embraces the inductive approach for building theories from observations (Saunders et al., 2016). The main strategies to conduct qualitative research are a case study, ethnography, phenomenological, grounded theory and content analysis (Leedy & Ormrod, 2001). Interviews and focus groups are commonly used for collecting qualitative data which are in the form of textual format.

3.4.2.3 Mixed Methods

From the perspective of a pragmatist paradigm, a pluralistic and integrative view suggests that quantitative and qualitative methods should not be perceived as opposites but rather as complementary, and, therefore, should be mixed in research projects (Onwuegbuzie et al., 2004). The integration of qualitative and quantitative methods through mixed methods has become increasingly popular in management research in recent years due to its numerous benefits (Tashakkori & Teddlie, 1998). Taking a pragmatic position facilitates the communication among researchers from different paradigms. It helps to identify how research approaches can be mixed in ways that offer the best opportunities for answering the research question(s) (Creswell, 2009). Mixed methods incorporate methods of collecting and analysing both numerical and narrative data in a single research study (Creswell, 2003; Tashakkori & Teddlie, 1998). The aim of mixed methods is a complementary strength of utilisation of more than one method and minimises the weaknesses of mono qualitative/quantitative approaches (Johnson Onwuegbuzie et al., 2004).

However, a disputed weakness of mixed methods in being time-consuming requires researchers to learn both quantitative and qualitative research skills, quantising the qualitative data in some cases leads to loss of the flexibility and depth (Johnson Onwuegbuzie et al., 2004). Qualitative and quantitative phases in mixed method approaches are combined either sequentially or concurrently (van Griensven, Moore, & Hall, 2014). If the phenomenon is not well understood and requires more investigation, a quantitative phase follows the qualitative phase to create what is called an exploratory study. However, if the qualitative phase follows the quantitative phase, this adds depth explanation to the phenomenon and creates what is called an explanatory study (Creswell & Clark, 2011).

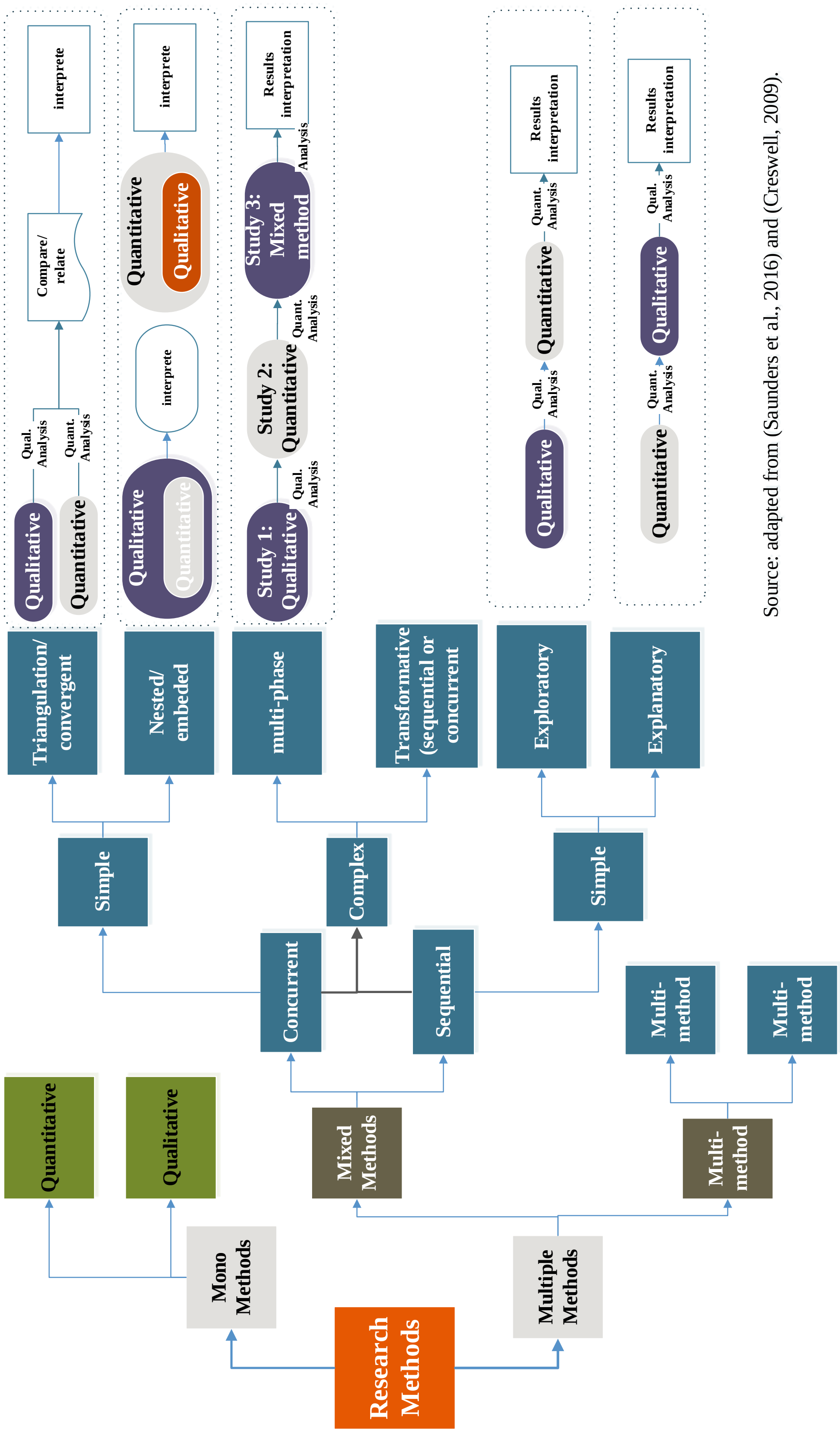
The ways in which quantitative and qualitative research may be combined have resulted in the identification of a number of variations of mixed methods research (Creswell, 2009) as indicated in Figure 3.7.

1. Concurrent mixed methods: In this design, the researcher collects both qualitative and quantitative data at the same time (single-phase) and then combine them to interpret the overall results. Concurrent nested or embedded mixed methods are used when one method supports the other

2. Sequential mixed methods: In this design, the data collected and analysed over multiple phases where the investigator will follow the use of one method with the intent to enhance and expand the initial set of findings. For two-phase research design, two alternative research strategies can emerge sequential explanatory mixed methods, when quantitative is followed by qualitative. Or sequential exploratory mixed methods, in this case, the qualitative is followed by quantitative.

3. Transformative mixed methods procedures are those in which the "*researcher uses a theoretical lens as an overarching perspective within a design that contains both quantitative and qualitative data. This lens provides a framework for topics of interest, methods for collecting data, and outcomes or changes anticipated by the study.*"

4. Multi-phase design: can emerge from multiple projects conducted over time with a common purpose. This design is a complex that utilises the simple or basic designs which appear when a researcher investigate a topic through phases or separate studies. The phases/studies can mix a combination of sequential, concurrent, or both designs to underpin large projects. Table 3.2 outlines a number of reasons for the advantages of using a mixed methods design.



Source: adapted from (Saunders et al., 2016) and (Creswell, 2009).

Fig. 3.7 Research method selection.

Table 3.2 Reasons for using mixed methods[b].

Reason	**Details**
Triangulation	- Convergence and corroboration of results from different methods to increase the validity of findings.
Complementarity	- When the single method is not sufficient. Elaboration and clarification of results from one method with the results from the other to improve interpretability and meaningfulness.
Development	- Utilisation of the results from one method to help develops or inform the other method to enhance the validity of constructs.
Initiation	- Discovery of contradiction by comparing data from one method with data from the other to increase the strength of results and their interpretation by analysing them from the different perspectives.
Expansion	- Extension of the breadth and depth of research by using different methods for various stages of inquiry.
Interpretation	- One method may be used to help to explain relationships between variables emerging from the other.
Confidence	- Using mixed methods leads to greater confidence in the conclusion.
Facilitation	- One method may result in the discovery of new insights which inform and are followed up using the other method.

[b] Source: adapted from (Greene, Caracelli, & Graham, 1989; Saunders et al., 2016)

3.5 Research Plan/ Strategy

In this study, mixed methods approach is best suited to satisfy the research objectives. Furthermore, using a mixed methodological approach has been noted recently as a trend in management research to provide multidimensional insights into many management research problems. The nature of this research project is a combination of exploratory, descriptive and evaluative and explanatory purposes. This can be achieved using mixed methods in the research design to facilitate some combined purposes. Moving from a pragmatist paradigm, the research design adopted in this study is a hybrid multiphase approach to address the research question. The design is a three-phase that combines nested and concurrent mixed methods designs (Figure 3.8).

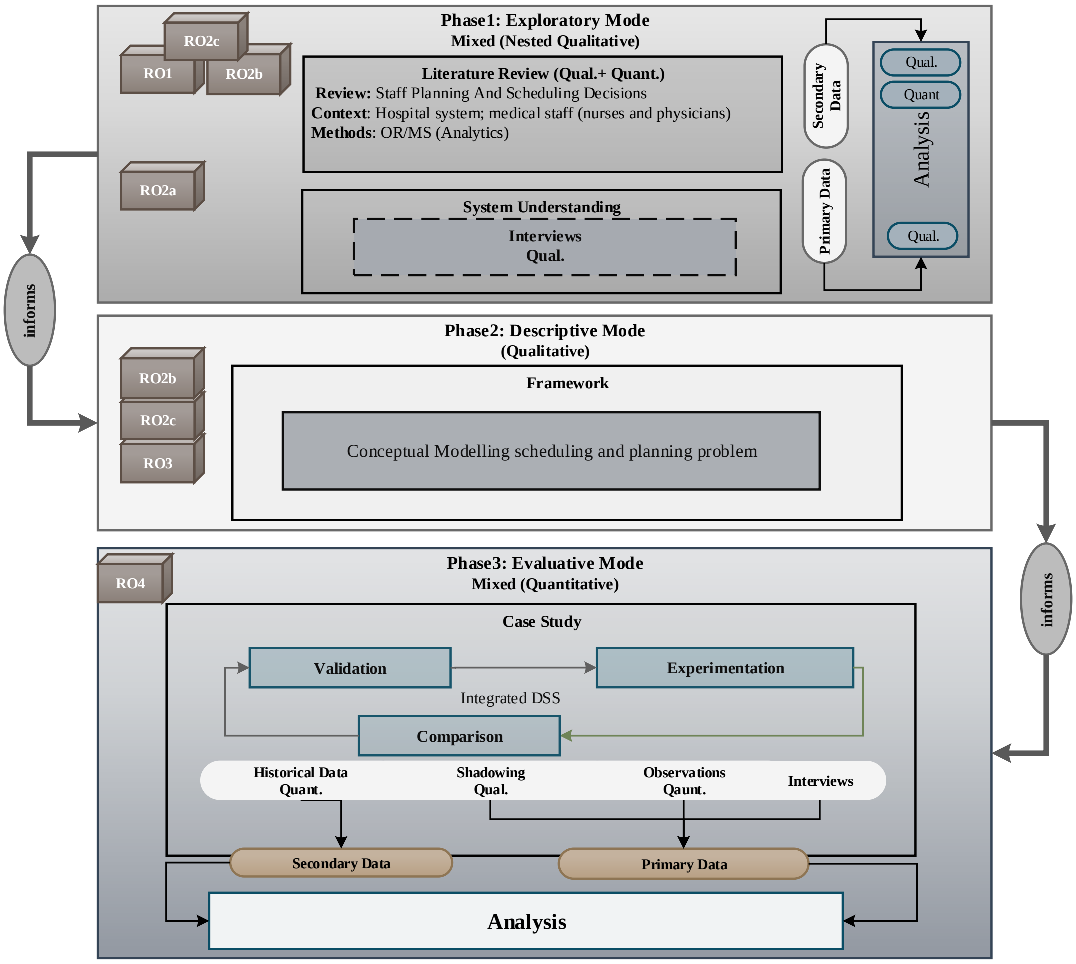


Fig. 3.8 Adopted hybrid research design.

3.5.1 Phase 1: Exploratory Mode

The first phase, exploratory mode, employs qualitative nested mixed methods to investigate the problem which is one of the key components for developing the framework. Hospital systems are complex in terms of the human interactions, process overlap, and criticality of the provided services and limitation of available resources. This stage is armed with an extensive literature review to identify the scientific problem structure and the appropriate solution techniques. The exploratory stage further involved interviewing with various hospital managers including consultants, head nursing staff, and senior physicians to gain a better understanding of the process of staff planning and scheduling, and their challenges.

3.5.1.1 Stage one: Literature Review

A literature review is used to provide the research with an overview of the previous studies (Saunders et al., 2016). Starting research with secondary data is a cost-effective strategy for clarifying the research question and objectives. In this research, first, a primary search was conducted in order to generate and refine the research topic and question.

The preliminary literature review, including articles in academic journals and other material (reports, surveys, media and others), are used to collect the preliminary information about healthcare systems. After the initial or preliminary search, a comprehensive literature review is conducted of the relevant academic literature which aims to gain an in-depth understanding of the state-of-the-art in the hospital staff planning and scheduling decision-making process. The objectives of this review include: exploring prior research, discovering key research gaps, and identifying the main models and solution methods that applied for effective planning and scheduling medical hospital staff through an extensive review of previous works. Since the purpose of the study was mainly exploratory, it adopted an inductive and qualitative approach. In addition, it combined a quantitative dimension for analysing the literature in terms of trends and volumes.

As illustrated in Chapter 2, this review focuses specifically on the staffing and scheduling of medical hospital staff, (in particular nurses and physicians), and applications of solution techniques. The purpose of the literature review is to provide the secondary data that contributes to achieving the first objective (RO1):

> ***RO1: "To identify and gain an in-depth understanding of current models, frameworks, and solution methods that are applied for effective planning and scheduling medical hospital staff."***

In an attempt to achieve this objective, a search for published articles that address hospital medical staff scheduling problems was carried out across academic databases (e.g. ACM Digital Library, EBSCO, JSTOR databases, Elsevier and Springer journals, INFORMS). The literature review process adopted followed a three-step strategy (Figure 3.9). It begins the first step, with scanning the digital libraries noted above to find relevant manuscripts using queries formulated with the main keywords as given in Table 3.3. A combination of word phrases, logical operators (AND, OR and NOT) and wildcard characters (e.g., *, ?) was used.

The second step is refinement. Filters are set to exclude manuscripts deemed irrelevant. Publication inclusion criteria are: (1) Peer-reviewed journal articles that appear in English; (2) the manuscript should address a medical staff planning and scheduling problem in the

Table 3.3 Sample of literature review keywords.

hospital staff; medical staff; personnel; workforce; nurse; physician; doctor resident; schedule; planning;	nurse roster; worklaod; sizing; levelling; budgeting; assignment; reschedule; roster; adjustment; allocation;	nurse to patient; duty; capacity planning, Ward; emergency department; operating rooms, real-time	optimisation; queues; simulation; mathematical; linear; nonlinear integer; mixed integer; stochastic; integer programming; metaheutistc;

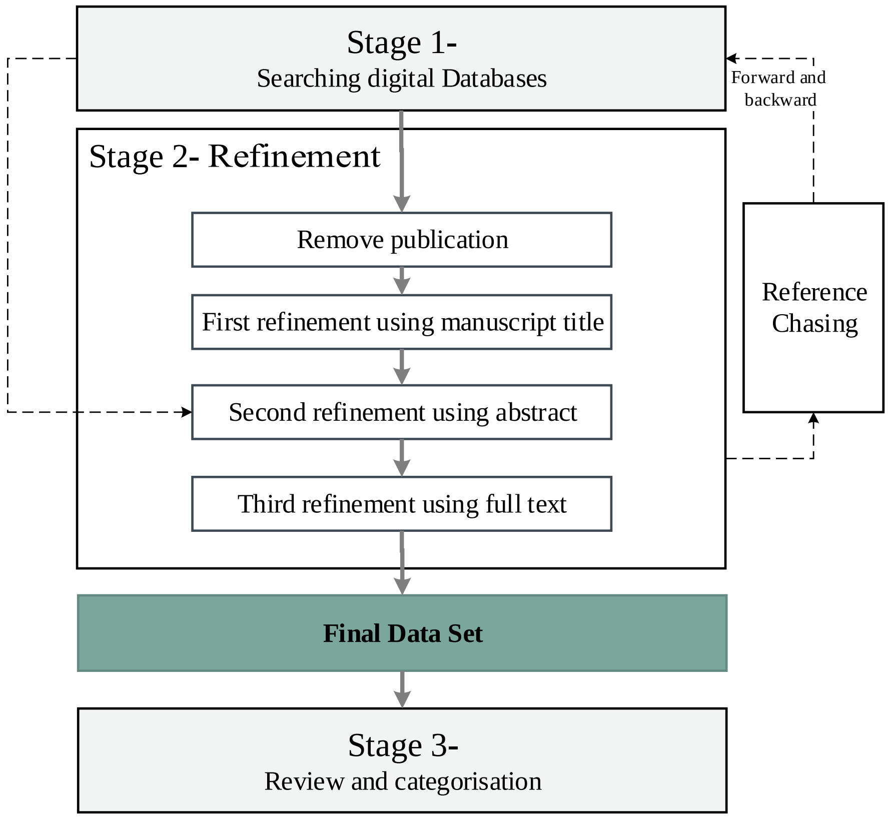


Fig. 3.9 The literature review research methodology.

context of a hospital setting; (3) scientific manuscripts that presented OR/MS method(s) as a solution method(s); (4) practical and management studies of useful insights into the problem. After collecting the initial pool of manuscripts, their reference lists were checked in a backwards cross-referencing process. When the main historical search was completed, researching the databases for relevant articles continued throughout the research to include recently published articles.

In step 3, the articles are classified according to different data attributes (Appendix B.3). For each article in the final dataset pool, detailed information is recorded in an access database. An overview of the data fields collected is presented in Table 3.4. The review does not include home healthcare scheduling or the ambulance scheduling since the focus

Table 3.4 Literature review data collection and recording.

Field	Sample of categories
Publication year	
Country of authors	
Problem Type	Staff planning, scheduling, allocation, assignment.
Staff Resource Type	Nurse, Physician, Resident, SHO, etc.
Other Resources	OR, Beds, Equipment, etc.
Policies	Skill-mix, overtime, part-time, flexibility, floats, agency, staffing policies, scheduling policies, etc.
Scheduling problem Type	Tour, shift, days off, cyclic, acyclic, self-schedule, etc.
Problem attributes	Multiple skills, single skills, experience, seniority, etc.
Application unit	ED, Internal Medicine, OR, etc.
Integration	multi-department, multi-staff, multi-decisions
Type of integration	Hierarchal, recursive, or simultaneous
Evaluation perspective	Effectiveness, efficiency, staff satisfaction, patient experience.
Problem formulation	MIP, GP, stochastic model, simulation, etc.
Solution method/technique	Analytical, exact, heuristic, metaheuristics, simulation, etc.
Software package	CPLEX, GRUBI, etc.
Type of data used	Real, randomised, published dataset, etc.
Planning period	shift, day, week, few weeks, month, few months, year, etc.
Stochastic parameters	demand, arrivals, etc.
Implementation (if any)	Yes or no.

is on staff scheduling decisions inside hospitals. Appointment scheduling was excluded because of its focus on demand-side management rather than supply-side management. The demand forecast is also excluded. Most published articles before 1980 were omitted except seminal papers. The results of this literature review are analysed using both qualitative and quantitative techniques.

3.5.1.2 Stage Two: Exploratory Study

Developing an integrated framework for addressing the hospital medical staff planning and scheduling requires gaining an in-depth understanding of the current practices in the Irish acute system (i.e. hospitals) and how these are aligned with the literature. This stage is paramount to incorporating the hospital managers' view, perceptions, and practices towards the planning and scheduling problem. Although the secondary data gathered from the literature review was extremely useful for getting an extensive overview of the research problem and the state of the art solution methods, more exploration of the research issue is required to enhance the understanding of the staffing and scheduling problem. The purpose of the exploratory study is to support and contribute to achieving the following research objective:

> **RO2a**: ***"Explore the management perceptions of staffing and scheduling practices in Irish hospitals, highlighting the challenges they are facing."***

The exploratory study extends the work of the first phase to complement the literature review. The present research stage is designed to have an exploratory character and to follow a qualitative and inductive approach. The data and valuable insights are collected through semi-structured interviews with experienced individuals and managers who are involved in staff related activities (e.g. creating schedule) in the participating hospitals. Qualitative interviews were deemed to be optimally suited for systematic comprehension of staff planning and scheduling decisions. This study investigates staff management process (i.e. plan, schedule, and control) across several publicly funded hospital departments spread geographically across Ireland. Analysing the collected data aims to identify and describe key themes in participants understanding and to report their practices and challenges they are facing. Hence, an inductive thematic analysis approach is chosen for the scrutiny.

Interviews. Qualitative interview research is among the most common strategies for collecting qualitative data (DiCicco-Bloom & Crabtree, 2006). The interview is a purposeful discussion between two or more people(Saunders et al., 2016). Interviews are popular among both researchers and respondents because they permit face-to-face interaction and provide profound and holistic insights about research topics (Easterby-Smith et al., 2002). Interviews have several forms that provide an organised approach to data collection. A structured interview is a standardised method that employs questionnaire based a predetermined set of questions with a certain order to all interviewees, and it may also be used for collecting quantifiable data (Bryman, 2012). On the contrary, semi-structured and unstructured interviews are a non-standardised method for collecting qualitative data. Semi-structured interviews are divided into themes, and each theme has a set of fundamental questions to be covered. The research can omit some questions during the interview, and the order of items can vary according to the flow of the conversion. In semi-structured interviews, the interviewer has a more active role in adjusting the sequence of the predetermined questions to be asked to the interviewee according to the received answers (Fontana & Frey, 2005). A guideline of predetermined open-ended and closed-ended questions is prepared for the interview. Unstructured interviews act as an informal conversation between the interviewer and the interviewee without predetermined questions (Minichiello, Aroni, Timewell, & Alexander, 1990). In this type of interview, the interviewer prepares and asks questions immediately according to the respondent answers. This study employed semi-structured interviews for collecting the primary data for the exploratory phase. The choice was guided by the nature of the required data and the purpose of the interviews.

Due to time and resources constraints, sampling is widely used for research which can provide affordable and efficient alternative data collection instrument. The sampling design process is usually outlined in the following five steps: (1) define the population, (2) determine the sampling frame, (3) select the sampling technique, (4) determine the sample size, and (5) execute the sampling process (Malhotra, Hall, Shaw, & Oppenheim, 2004). Sampling techniques can be categorised into two main types: probability sampling and non-probability sampling. Probability sampling is widely used in quantitative research where each in the population has an equal chance of being randomly selected to produce a sample that is statistically representative of the population (Bryman, 2012) (Bryman, 2012). By contrast, non-probability sampling techniques are frequently employed in qualitative methods where the selection of individuals from the population is determined by the researcher, not a random (Greener, 2008).

The target population of interviewees for the exploratory study are hospital managers who have management roles in their hospitals regarding staffing and scheduling decisions. Non-probability purposeful sampling is best suited to address the research questions and provide the necessary diversity within the sample. Findings from non-probability samples can be generalised, but not on a statistical basis (Saunders et al., 2016).

Respondent Selection. Twenty-five medical staff managers (fourteen consultants and eleven head nurses) from eleven acute teaching hospitals across Ireland (eight counties) were interviewed within the selected sample. Since addressing the source of information is critical to obtain accurate data (Healey & Rawlinson, 1994), managers seem to be the natural choice due to their expertise in managing staff and the higher likelihood that they would have prior experience in knowledge management and assessment issues. There was no single list to represent the sampling frame, but rather interviewees were selected from among experienced managers to whom the researcher had access and contact details within the relevant population.

3.5.1.3 Exploratory Study Design

The exploratory study is divided into two sequential phases: preliminary exploration and in-depth exploration (Figure 3.10).

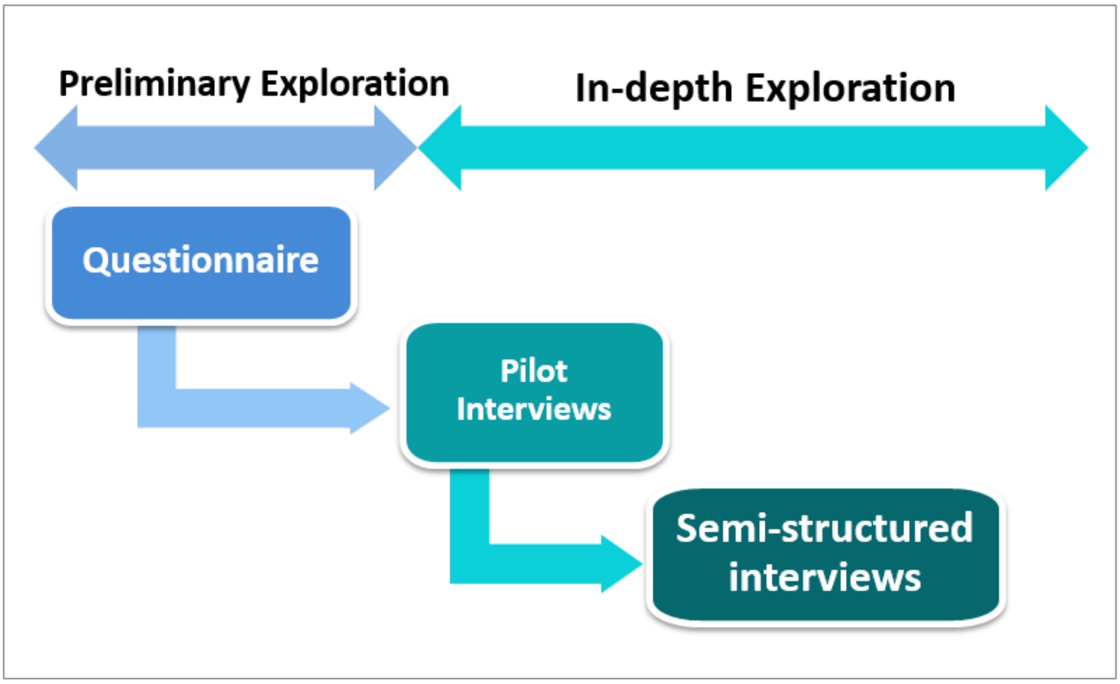


Fig. 3.10 Exploratory Study Design.

Preliminary Exploration Design. The initial investigation attempts to explore how hospital management perceives the importance of the staff scheduling decision through a small questionnaire instrument. When designing this survey, questions were adopted or adapted from other questionnaires or devised by the researcher (Bourque & Fielder, 1995). The questionnaire was constructed and conducted using a paper-based method where the questionnaire was sent and received by post (Appendix B.5).

The questionnaire used rating questions to elicit opinion data about the managers' views on staffing and scheduling related factors. Opinion questions used a five-point Likert scale ranging from 1 (equivalent to "Totally disagree") to 5 (indicating "Totally agree"). Likewise, the important questions used a five-point Likert scale ranging from 1 (equivalent to "Not important at all") to 5 (indicating "very important"). Another type of questions is multi-select from a list to allow respondent to choose all relevant choices.

The researcher took a number of measures to maximise the response rate of the preliminary questionnaire such as: sending cover letter design (Science, 2016), repeated contact (Zikmund, Babin, Carr, & Griffin, 2009), focusing on the importance of research topic (Diamantopoulos & Schlegelmilch, 1996) and offering the option to receive the key findings of the study after its completion as an incentive. After a month from the time of distributing the preliminary questionnaire, the received responses were satisfactory. Out of 100 invitations, 24 were received which is an acceptable rate and sufficient for the preliminary exploration.

In-depth Exploration Design. Before conducting the full study, it was essential to what the practitioners' appetite to the questions and themes. To serve this aim, three pilot interviews with hospital managers at different levels were conducted. This step was crucial in refining the interview questions to reduce the risk of fatal flaws in the full study (Zikmund et al., 2009). Other goals that were achieved from the pilot interviews was the assurance that the literature is aligned with the practice and to get the practitioner's input to introduce or deduct questions or themes.

The interview questions were developed in order obtain accurate and comprehensive results that fulfil research questions. Questions were formulated based on the primary considerations proposed in the literature. Before the pilot study, the interview questions were designed with five main themes: workload analysis, staffing, scheduling, control and IT system. The point exercise was beneficial to refining the questions regarding the bias minimisation through:

- Using straightforward and precise wording,
- Minimising grammatical complexity and long sentences,
- Avoiding leading questions, negatively worded questions, and overlapping questions.
- Reordering the sequence of questions to maintain a logical flow,
- Using practitioners' terms rather the academic terminologies that was used initially, and
- Deleting of some questions.

In addition to the critical improvements in the questions, two new themes were recommended by the practitioners: management responsibility and concern, and work environment. During the pilot interviews, the participants showed a keen interest to discuss and relate the staffing and scheduling challenges to those new themes which led to adapting the design to be included.

The validated questions covered both the literature and the practitioner's view. The refined interview questions of the full exploratory study include seven themes: workload analysis, staffing, scheduling, control, management responsibility and concern, work environment, and IT system (Appendix B.6).

Interview Administration This phase employs multiple data sources (literature review, field observation, etc.), but the core is semi-structured interviews—to obtain both the retrospective and real-time accounts by managers experiencing staffing and scheduling problems. Semi-structured interviews provide the interviewer and the interviewee with the flexibility to explore different issues while ensuring that the objectives of the interview are achieved by having a basic structure of questions (Bryman, 2012). An interview schedule including an introduction about the research and its objectives was compiled and sent by email to interviewees in advance (Appendix B). This helped to familiarise respondents with the research project and to provide them with background information about the topics that would be discussed during the interview. It also gave respondents the opportunity to request modifications to certain questions in order to avoid confidentiality issues. However, since the researcher guaranteed anonymity, no changes to interview questions were requested. Interviews were pre-scheduled and lasted around 20 to 30 minutes. Open-ended questions were asked to encourage respondents to elaborate freely on their answers. Interviewees were probed for further explanation when necessary. To avoid response bias, the interviewer avoided leading questions and did not express a personal opinion on any of the matters discussed (Boyce and Neale, 2006).

Analysis of interviews The researcher has to note that high-quality data analysis depends on high-quality data collection and the strategy that the researcher considers: an inductive approach where the interviews are less structured, or a deductive approach where the interview is structured or semi-structured (Braun & Clarke, 2006; Kondracki, Wellman, & Amundson, 2002). The extant literature discusses the qualitative research methods with an emphasis on the broad and varied ways of using the data gathered from respondents (Taylor & Bogdan, 1984). A summary of qualitative data analysis (Aldarbaq, Ragab & Arisha, 2017) is shown in Table 3.5.

The researcher takes notes during the interviews. Interviews are then transcribed and analysed using content analysis (Hsieh, Shannon, & Shannon, 2005). Computer-aided qualitative analysis software Nvivo was used to facilitate the analysis process. Nvivo allows textual data to be coded under “nodes” which represent themes that emerge from the data. Codes were not pre-assigned and the coding scheme is developed as patterns surfaced from the data. Concepts and constructs that were mentioned by more than one manager were highlighted and coded as potential themes. After a number of iterations, key themes from the

Table 3.5 Qualitative data analysis methods [c].

Descriptions	**Pros**	**Cons**
Thematic Analysis. Systematic theme analysis, suitable for complex phenomena, depends on context analysis of *what* the interviewee said more than *how* the interviewee responded	A foundation method for qualitative analysis. Flexible analysis. Combine the meaning with practical context (manifest or latent text). Suitable for exploratory studies	The researcher spends a long time on data gathering to get high-quality data results
Content Analysis. Used for any type of interview to identify keywords, paragraphs or themes. Suitable for simple reporting.	Researcher spends a short time on the process of analysing the data	Inflexibility, the research should decide before examining the data to use manifest or latent analysis. Describes the phenomenon in a conceptual form, not as physical event s.
Structured Analysis. Dependent on the speakers' characteristics; such as body language, tone and speed, useful for detailed case study and comparison of several narratives.	Suitable for lengthy narrative explanations	Not appropriate for a large number of interviews because it examines the syntactic nature of the interview structure
Discourse Analysis. Committed to specific themes, words, and explanations. **Examining repetitiveness of the interviewee.**	Emphasises the communicative characteristics of individual interactions and how people' interact through common language	Only looks at specific themes, words and explanations which do not provide deeper meaning
Interactional Analysis. Depends on the dialogic process between speaker and listener, speaker and listener collaborate to create meaning and concept.	Useful for studies that highlight relationships between speaker and listener	Unsuitable for exploratory studies
Performative Analysis. Observes what the interviewee is doing rather than telling, based on the narrative performance through language and gesture	Language and gesture aids the listener to understand the phenomenon and to know if the interviewee said the truth or not	Builds analysis based on unspoken words maybe give inaccurate output

[c] (Sources (Alvesson & Karreman, 2011; Braun & Clarke, 2006; Joffe & Yardley, 2004; Kondracki et al., 2002; Nielsen, 2009; Riessman, 2005; Schreiber, Inquiry, & Summer, 1972; Vaismoradi, Turunen, & Bondas, 2013)

analysis data were identified and reported, providing valuable insights. The findings of the exploratory study stage are presented in Chapter 4.

3.5.2 Phase 2: Descriptive Mode (Framework Development)

Results from the first phase are used to "*inform*" second phase, descriptive mode (Figure 3.8). The descriptive mode phase is necessary to extend the exploratory phase to gain a clear picture of the medical staff planning and scheduling problem. It aims to describe and conceptualise the proposed framework. This phase seeks to develop an integrated multi-disciplinary framework for hospital managers to use in medical staffing and scheduling to match patients demand, based on the insights acquired from the literature review and the exploratory study. The development of the integrated framework aims to consider the following research objective and sub-objectives:

RO2b: ***"To identify the key elements for developing an integrated framework for medical staff planning."***
RO2c: ***"To develop an integrated framework for medical staffing and shift scheduling decisions."***
RO3: ***"Assess the implications of incorporating adaptive staff behaviour on the operational performance."***

The aspects of developing this framework to address the staffing and shift scheduling problem literature are discussed in detail in Chapter 5.

3.5.3 Phase 3: Evaluative Mode

The third phase of the research strategy utilised mixed methods to test the proposed framework as informed from the previous phase by its implementation to a real-life hospital. Testing the framework is achieved through a deductive approach which entails combining two purposes in its design: explanatory and evaluative. The evaluative mode seeks to validate the holistic effectiveness of the proposed framework. The applicability of the framework will be evaluated to confirm its validity and present points for improvement. The third phase aims to address the fourth research objective:

RO4: "evaluate and validate the proposed framework."

3.5.3.1 Case Study

Case study as a term is commonly used to describe the implementation of new methods, techniques or frameworks, but it can also be used for interviews based research (McCutcheon & Meredith, 1993). According to (Yin, 2011), a case study is an in-depth and objective investigation of the contemporary phenomenon within a real-life setting where the researcher has little control over events. It often used when the boundaries between the phenomenon being studied and the context within which it is being studied are not always apparent (Yin, 2011), where understanding context is fundamental to case study research. Case study strategy can be categorised into a single case study and multiple case studies (Saunders et al., 2016). A single case study is required when testing a theory is the goal of the research while various case studies are desirable when developing a theory (Yin, 2011). The single case study documents, in detail, the operations of a single hospital/department. This may be used in conjunction with survey research, or some other type of comprehensive data gathering effort, to develop explanations for some of the findings on a more global basis. Case study research strategy is suitable for both qualitative and quantitative research so that data can be collected in qualitative and qualitative manners simultaneously. Case studies were used in several research studies to evaluate decision support and information systems (Cavaye, 1996).

Addressing the fourth research question is achieved through implementing the proposed framework in a real-life hospital department(s) to evaluate its practicability, usability and effectiveness. A case study research strategy is adopted, in this research, because it is the most appropriate research strategy to underpin this research question for several reasons:

1. The ability to study a phenomenon in its real-life (natural) context;

2. The possibility of undertaking an intensive, in-depth and objective examination of case enabling the researcher to gain valuable insights which are difficult to obtain through other strategies, e.g. surveys (Creswell, 2003). This leads to a rich empirical analysis; and

3. The case study strategy does not explicitly manipulate or control variables; rather it studies these variables in their context;

These features are quite suitable for research into identifying an integrated framework where the aim is to perform the study within realistic settings.

3.5.3.2 Tallaght Hospital: Emergency Department Case Study

In this study, the industry partner is Tallaght hospital, which is one of the largest acute university teaching hospitals in Ireland. It serves a catchment community of approximately 450,000 people (most of them in South Dublin and parts of Kildare) and serves approximately 200 General Practitioners (GPs) with a budget of 175 million. Tallaght Hospital is a member of Dublin Midlands Hospital (DMH) Group that includes six hospitals besides Tallaght Hospital (DMHG 2016). The hospital delivers healthcare for adults, children, and older people on one site. With 562 beds, 12 theatres and 14 Critical Care beds in operation, the hospital treats over 410,000 patients per year and employs almost 3,000 employees (whole-time equivalents) from 33 different nationalities.

Tallaght Hospital has the largest Emergency Department nationally. In 2014, Emergency Department (ED) served for 44,640 adult attendances and 31,934 paediatric attendances (Tallaght Hospital Annual Report 2014). It is the nexus of a community of 300 general practitioners (GPs) in surrounding areas and is a major component of the DMH Group which serves a population of over 1.2 million across seven counties. These numbers, while hugely significant, disguise the individual instances of care and compassion provided to patients and their families at some of the most challenging times in a person's life. The ageing population within its catchment area and the resulting rise in chronic conditions mean demand for its services continues to grow. It has been remarkably difficult for management as budgetary restrictions remain in place. Also, the hospital is continuing to expand its services on-site to meet the current and future needs of its patients.

3.6 Reliability and Validity

For this study, triangulation was employed to construct validity by using multiple sources of evidence for data collection: namely documentation, historical records, interviews, direct observations, and participant observation. Seeking confirmation from multiple data sources leads to more reliable results. Internal validity is the extent to which a causal relationship can be built, whereby certain stipulations are designated to result in other stipulations, as distinguished from artificial relationships, while for external validity, discovering the domain to which a study's findings can be generalised (Yin, 2011). Therefore, in this study, some validation and verification techniques were performed during the case study to validate the collected data from interviews and observations with staff and senior managers. The analysis of these data has also been validated. Moreover, the results of the framework have been validated statistically as well as qualitatively with decision makers. This is to ensure the internal validity of the framework.

In the context of this study, many factors strengthen its external validity. Due to the standard features and challenges between healthcare facilities, the emergency department has been chosen for this research as a case study. The characteristics and features of the ED are similar to those of other hospital departments (e.g., intensive care unit, operating rooms, and radiology department), such as a high level of complexity, demand uncertainty, limited resources, and a high level of human interactions. The issues of staffing, scheduling (staff, operations, and patients), demand assessment, and resource allocation are all common between these departments. Also, addressing these issues usually involves multiple, often conflicting, objectives such as reducing waiting time for patients, increasing the efficiency, and achieving high levels of service quality. Therefore, the framework was used for resolving many of these problems through optimal staffing and staff scheduling, workload assessment, and scenario analysis, which are common problems that occur in other healthcare facilities as well as other service sectors service operations. Therefore, it is believed that the empirical evaluation of the framework through all these phases of the case study contributes towards increased confidence in the transferability of findings to a broad range of healthcare setting.

3.7 Dissemination Plan and Impact

The findings of the research are disseminated in both academic and industry formats. The outcomes of each stage were published in peer-reviewed academic conferences and journals as research articles. Research findings/outputs are also shared with industry partners, HSE and Tallaght hospital, and healthcare professionals that have contributed to the development of this investigation. This includes director-level managers in the HSE who have the decision-making authority to influence the take-up of the research and senior healthcare professionals in each of the main Dublin hospitals. Working papers from this project were distributed to this group as the project developed. The implementation of the project at the Tallaght Hospital will also require the development of briefing reports for the hospital executives and healthcare professionals. This periodic briefing is essential to maintain the confidence of the collaborators in the research project.

Chapter 4

Exploratory Study

> Blindly following ancient customs and traditions does not mean that the dead are alive, but that the living are dead.
>
> *Ibn Khaldoun(1332–1406)*

4.1 Introduction

The exploratory phase of the research was designed to identify the underlying elements of staffing and scheduling of medical staff before further steps towards the integrated framework took place. The literature review contributed to pitching the theoretical grounds reported; however, given the applied nature of the study, it was crucial to incorporate the practitioners' perspective in the early phases of framework design. This can help in bridging the gap between theoretical studies and practice by exploring management's understanding of staffing and scheduling in the context of Irish hospitals. An exploratory study was conducted during the second research stage with the aim of gathering primary data about staffing problem. The specific objectives of the study were to:

1. Explore how hospital management perceives the importance of the staff scheduling problem,

2. Explore the interest of practitioners in this research study and check the need for a staffing assessment tool to support their decisions,

3. Discuss the challenges that managers face and their impact on operational performance, and

4. Find out the main factors that managers incorporate when they assess staffing workload.

To achieve these objectives, two phases of the exploratory study were designed. In phase 1, preliminary exploration, attempted to address the first specific objective (mentioned above) through a questionnaire instrument. The questionnaire aimed to capture the hospital manager's perspective regarding the importance of staffing and scheduling decisions about the relevant variables from the theoretical literature. Twenty-four managers participated in the questionnaire from the different hospital across Ireland. The second phase (in-depth exploration) used one-to-one, face-to-face in-depth semi-structured interviews that conducted to achieve the objectives 2, 3 and 4 (mentioned above).

4.2 Phase 1: Preliminary Exploration

The preliminary exploratory phase provides an overview of the management perspectives regarding the staffing and scheduling decisions without going in-depth. In the initial phase, a questionnaire (Appendix B.5) is designed to explore the perception of hospital managers in the following:

1. The importance of organisational related factors on staffing and scheduling decisions,

2. Mangers' perspectives on the factors that may cause staff dissatisfaction and burnout,

3. The criteria of a high-quality schedule,
4. Frequency of schedule disruption, and
5. The importance of considering staff preferences.

This preliminary questionnaire has distributed to sample of a 100 hospital potential managers from which 24 responses were received resulting in 24% response rate.

The results of the analysis are shown in Figure 4.1. The first part attempts to explore the importance of the hospital organisation characteristics on their staffing and scheduling decisions. The results (Figure 4.1a) shows that 68% of the respondent believes the structural layout of the unit is very important or somewhat important, 80% of managers agreed on the importance of patient pathways and process of care when they are staffing their departments. The administrative work and personal time are also one of the important factors with 76% agreement. Surprisingly, 44% of the manager's view is that downstream resources such as inpatient care are not a major factor for staffing or scheduling decisions. Similarly, 48% of the managers cannot decide the importance of overcrowding (number of boarded patients).

The second part is concerned with the practices that may affect staff dissatisfaction or burnout. The analysis (Figure 4.1b) reveals that the majority of managers agree on understaffing (78%), overtime (72%), cancellation of breaks or change in annual leaves (68%) working undesirable shifts (64%), schedule disruption (60%) and inappropriate skill mix (56%) are practices that cause staff dissatisfaction.

The third part attempts to explore the criteria of a high-quality schedule. The results (Figure 4.1c) showed that the most important criteria are meeting the demand requirements (80%), and staff fairness (80%). 54% of the managers do not consider the patient experience one of the measures of high-quality schedule. This may be partially explained as the patients perspective is reflected by meeting the demand requirements criterion. Cost is not an essential criterion (72%) and this because most of the unit managers do not involve in budget challenges and issues which occur in higher level decisions.

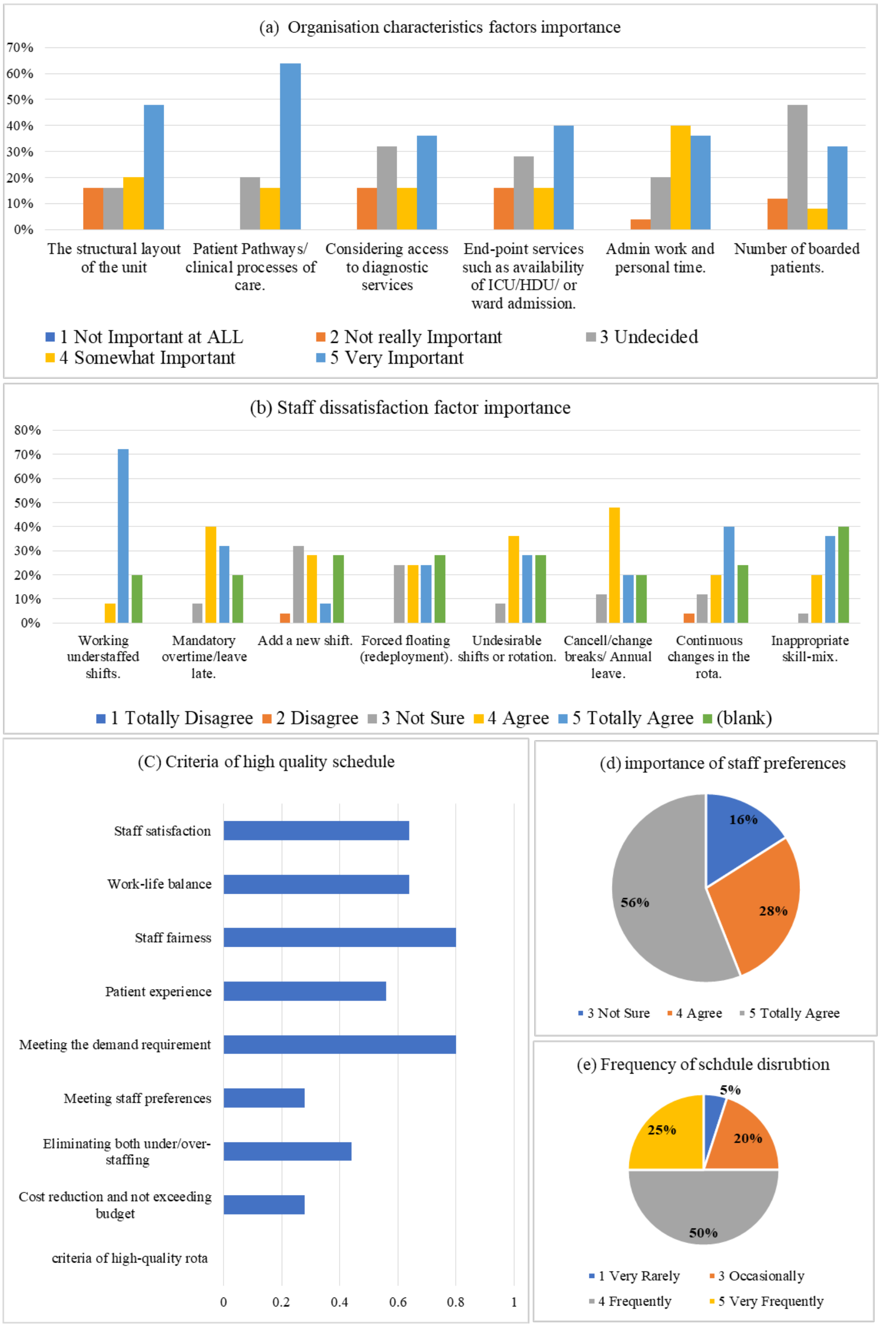


Fig. 4.1 Results of preliminary exploration phase.

One of the contradictions in the answers is 78% of the participants do not consider staff preference as an important criterion for scheduling while in part d (Figure 4.1d) 82% of the managers agreed or totally agreed on the importance of considering staff preferences. Finally, Figure 4.1e showed that a majority of the participants (75%) reported that roster is frequently or very frequently disrupted. This initial result leads to the second phase which is an in-depth exploration using interviews to deepen the discussion.

4.3 Phase 2: In-depth Exploration

Incorporating the practitioners' perspective regarding the medical staff scheduling decisions entails collecting qualitative data and using an inductive approach for reasoning. Semi-structured in-depth interviews are adopted as the most suitable data collection instrument to allow informants to express their beliefs in an unobstructed manner while maintaining a general framework of inquiry that provides a degree of comparability between responses (Irish hospitals).

To gain insights into the subject under investigation, data was collected by interviewing managers who are involved in the staffing and set up the schedule. Interviews were conducted with a purposefully selected sample of twenty-five managers from eleven different hospitals spread geographically across Ireland and covering a diverse range of specialities such as emergency medicine, surgery, orthopaedics and gynaecology. Most of the participating hospitals are publicly funded university hospitals, and collectively participant hospitals make up the primary healthcare providers in Ireland (Table 4.1).

For analysing the data, a latent content analysis is employed to interpret interview data and amalgamate the main findings by discovering general patterns and exploring how different interviewees responded to the same questions. Using the qualitative interpretation software NVivo, interview transcripts are coded to identify themes within the data and glean practical insights. Emergent concepts were identified through degrees of similarities and differences within responses. Proposed themes were reviewed and clarified in the subsequent rounds of coding to establish the study's findings. The administrative methodology of the interviews is described in the former chapter, and the results are presented in the subsequent sections of this chapter.

Table 4.1 Participants Hospital Profiles.

Hospital	Inpatient Discharge	Day Case Discharge	Emergency Inpatient Discharges	Elective Inpatient Discharges	New ED attendances	Total no. outpatient attendances
Hospital A	24,654	86,183				
Hospital B	18,689	46,185	14,759	1,416	43,792	125,162
Hospital C	19,872	8,722	3,836	731		121,489
Hospital D	44697	76,789	27,031	6,546	64,333	186,606
Hospital E	28,549	34,787	24,338	4,042	60,523	159,643
Hospital F	12,649	9,489	8,391	586	24,315	41,955
Hospital G	37,056	88,231	22,609	8,807	59,447	250,024
Hospital H	24,857	32,294	18,606	2,065	38,084	63,810
Hospital I	18,495	34,141	13,928	2,380	33,430	92,078
Hospital J	17,537	11,128	14,193	541	38,167	33,410
Hospital K	20,168	37,978	16,056	4,066	58,487	242,201
Total	**267,223**	**465,927**	**192,072**	**38,992**	**525,843**	**1,339,919**
National	**544,533**	**903,009**	**365,391**	**80,399**	**993,070**	**2,839,834**
%	**49%**	**52%**	**53%**	**48%**	**53%**	**47%**

A confidentiality protocol was applied as part of the research ethics. That means neither participants' profiles nor would their hospitals be declared without their consent. The data provided was fed directly into the development of this analytical tool without prejudice. Also, this qualitative study does not involve any form of invasion of the respondents' integrity. All the participants were given a detailed letter describing the content and the aim of the study. Their participation was voluntary, and the data was analysed anonymously such that the results are non-traceable to an individual participant.

4.4 Results/Findings

The sample includes 25 hospital managers (14 physicians and 11 head nurses). The number of female and male participants are 12 and 13 respectively. Their years of experience in healthcare generally and as managers are summarised in Table 4.2. Five themes have been emerged from the analysis: patient aspect, staff aspect, organisational aspect, lack of management support, and technology-enabled.

Table 4.2 Managers' profiles.

Level	Range (value)	Number of Participants
	5 – 9	10
Year of Experience as manager (years)	10 – 14	5
	15 – 19	5
	20+	5
	Less than ten beds	6
Unit Capacity (Beds)	11 – 19 beds	7
	20 – 30 beds	6
	30+ beds	6
Staff Type	Consultant	14
	Head Nurse	11

4.4.1 Patient Aspect (Demand for Care)

Understanding the patient's demands and their care needs is a fundamental component to staffing the required number of medical staff and their skill mix to meet the demand. Positioning the patient at the centre of the healthcare system suggests that one of the pillars of efficient staffing and scheduling decisions lies in the right understanding of the demand for care. The assessment of patients requiring care entails a multifaceted view regarding volume, profiles, and patterns of patient presentations (Figure 4.2). This assessment will support the managers in gaining valuable information which aids them in deciding the optimal allocation of staff resources and staffing skills to match patient's needs.

Participants have expressed their concerns regarding understanding the demand for care. They considered demand assessment as an essential element in the staffing and scheduling of their staff. They mentioned various characteristics of demand including volume, predictability, inappropriateness, control, intensity and severity mix.

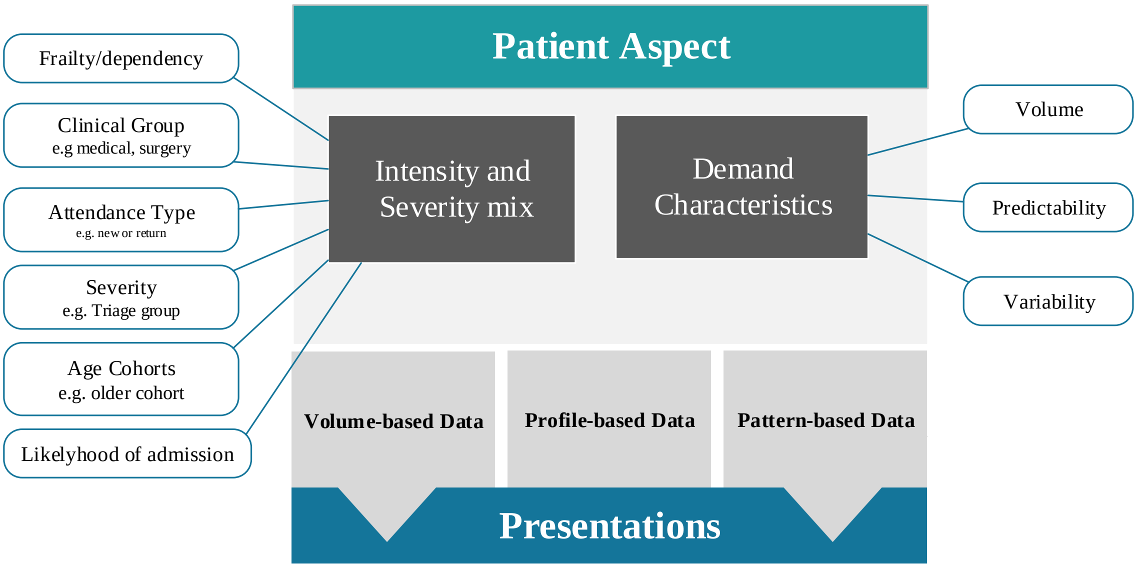


Fig. 4.2 Demand for care (Patient Aspect)

Patient Aspect-Volume. Participants stated that the most important factor for demand is the volume, number of the attendances or cases. Obtaining vital information on the demand volume is the primary factor in staffing decisions.

> *Our planning is mainly relied on the number of patients arriving. For instance, Mondays are the busiest. Therefore we put more staff on Mondays. Saturdays and Sundays the quietest days, so we have less staff on these days.*

Patient Aspect - Predictability. Understanding patient's arrival patterns provide valuable insights into the demand shape. Participants emphasised the importance of arrival patterns of patients during the day, week, and months to identify peaks which will inform staffing decisions. However, many responses agreed that the demand is to a great extent predictable regarding volume patterns, while others, contradicted this view implying that acute care demand is unpredictable. For example, one of the managers has emphasised the demand predictability:

> *Every week we have a predictable number of people to deal with. There are maybe few days where we might put extra staff because we predict it is going to be busy such as a Tuesday after bank holiday weekend.*

On the other hand, another participant has stressed that demand is hard to predict:

> *For trauma theatre, you cannot predict the demand, because it is unscheduled. The demand depends on the day of admission, and the day before. So you may have a very busy trauma theatre with a cancellation for the next day because it is a half day only, but the elective is the full day, or you may have just one case or none. There is no feeding prediction for this; you have to realise it.*

Patient Aspect - Variability. Fluctuation in demand is a crucial feature in services, and in particular labour-intense processes. Poor performance (e.g., reduced productivity, throughput, and efficiency) is a symptom of these fluctuations, and its implications should not be underestimated. Such variability is the fundamental challenge of balancing capacity with demand. For instance, if a given process takes longer than its planned average processing time, the system often does not adapt, and thereby the system inevitably slows down. This builds up over time and ultimately deteriorates system performance.

Patient Aspect - Intensity and severity mix. Relying on demand volumes is not sufficient for efficient staffing and scheduling of medical staff as it does not reflect the workload. Not all patients are the same, and they can be distinguished according to their severity/acuity, age, frailty and medical conditions. The intensity of demand and severity mix includes several variables that reflect the patient clinical group (co-morbid medical conditions), severity (acuity), and the predicted disposition category (e.g. admitted or discharged patient). These four factors enable managers to assess the volume, profile, and pattern of patient's demand which is a fundamental element for making temporal informed-decisions regarding medical staffing.

> *Patient frailty is an increasing factor, and I suppose it's a national trend, but it is a growing factor here in Donegal. We see more elderly than before; nearly 70 percent of our patients are over the age of 65 years old. At the moment we have 27 older patients delayed discharge because they are waiting to go to community hospitals. That has an enormous impact on nursing staff in particular.*

Although participants have expressed the importance of patient profiles and its influence on the staffing intensity, most of them did not take it into account while others consider it as a secondary factor.

Patient Aspect - Inappropriateness. One of the exciting topics of the discussion with the interviewees is that the majority of unscheduled patients do not need hospital-level acute care. However the inability to access community health care force patients to take the unscheduled care route which in turn creates an immense pressure. For example, in ED, Christmas time and New Year are hectic because the General Practitioners (GPs) and outpatient clinics are off.

> *Regarding patients' acuity, what we try to do is we look at our triage category. Triage Category one, two and three is about 20 percent of the total. But we invented a minor injury clinic off site. So the vast majority of our patients are not seen in here at all. They are seen somewhere else. So, what comes through our doors are category one, two, category or three. It is so hard to see any category four and or five in this building. What used to happen is that patients used to come here and we say no, no, no why don't you go to Smithfield (minor injury clinic). Now the GPs know, and patients know they don't come here at all. And that's only Monday to Friday. We run our minor injuries here on Saturday and Sunday.*

Benefits of assessing the demand for care include:

1. The temporal assessment of the demand for care helps to identify the demand peaks and patterns across the spectrum of the day, week, or year (from month to another).

2. Informed-decisions to allocate and deploy staffing resources. Practical assessment and understanding of the demand for care facilitate better allocation and deployment decisions to meet the temporal demand. It also supports managers to manage the increase in demand and allow to meet the service level.

4.4.2 Staff Aspect

Staff are the second pillar of healthcare delivery that represents the supply side. The analysis of the interviews revealed several topics and issues that are grouped under staff aspect theme.

Staff-Aspect - Lack of scientific staffing method. As participants stated, there are several methods for staffing that mainly depend on the nature of the department or unit. However, most of the methods for staffing shifts lacks a scientific base. Participants rely more on their experience and heuristics for the estimates to align staff to the predicted demand. These methods are professional judgement. The majority are based on average methods considering patient volume as the primary factor.

> *We have not looked at it scientifically. We try to have high staffing levels at the times when we are at the busiest times and the minimum number of staff at midnight.*

Staff Aspect - Staffing Issues. Participants have articulated on several staffing issues includes inappropriate skill mix, situational understaffing, staff shortage. These issues are common in urban and rural hospitals, but it is more pronounced in hospitals outside Dublin. However, the impact of these issues is more significant for the Great of Dublin area hospitals than other hospitals due to the large population and catchment areas of Dublin hospitals.

Staff Aspect - Inappropriate skill mix. Participants emphasised the importance of the competency of the medical team to meet the various patient's needs. There is a concern about the improper mix of more inexperienced junior staff.

> *We opened the short stay ward last year here in January, and we have no staffing for it at all. Then we began AMU (Acute Medical Unit) here in March so we could move from one location to another so we needed I think about 13 or 14 nurses but we could not find them from the pool of experienced nurses from the rest of the hospital. So we had to take in some newly qualified nurses.*

Staff Aspect - Situational understaffing . All participants reported that they are often running their units understaffed due to staff absenteeism (e.g. study, sickness or maternity leaves). They considered this as a fundamental constant frustration factor that impacts on their ability to deliver the healthcare service.

> *For instance, understaffing happened when we had three absent recently. And mostly what we had to do was just have to balance the staff alongside the acuity of the patients on the floor. And then I step into whatever role that's needed. So, I usually would move somebody from the AMU down to the short stay ward to plug that gap if that's necessary. And then I would step into the coordinating role in the AMU and then if we are still inadequately staffed, then we will merely manage the stream of patients coming into the AMU until such a time that we believe it is unsafe to carry on or if it under too much trouble*

> *One of the frustrations is when we find a sudden drop of staff, and we cannot find a solution to put or allocate our team, and we have to start looking for anyone who can fill the shortage. Indeed, it is a challenging to communicate with the administration and to give them the reasons that we cannot continue understaffed, and this is critical to the patient care. Apparently, it is a challenge*

because every month someone is away, and then you end up in a situation where there are only one or two persons are around who have to cover the shortage for few days in a row!

Situational understaffing is a symptom of the most prominent problem in healthcare nationally and internationally which is the shortage of medical staff. Participants, physicians and nurses, stated that they found problems trying to find people to do the work and it takes a long time to fill vacancies. Participants mentioned that a large number of Irish nurses and physicians have emigrated to Australia, Canada, and the USA seeking a better working environment, lifestyle, work-life balance and payment.

Currently, here we have seven consultants, and we have to fund for expanding that to twelve over the next two years. It's fine to say we have increased staff. And we need to be able to fill the post that we have, but we are having difficulty filling the current positions because it is not an attractive speciality (emergency medicine), given the negative press associated with the overcrowding in EDs nationally. That's an issue. So, before we even move to expansion, we need to be able to fill our current post.

We found real challenges trying to get people to work here, and we cannot fill our posts. It means a massive pressure on the current doctors that would spiral to make everything even worse!

Policies and rules of individual organisations dictate the strategies for these institutions to deal with the understaffing problem. Among the tactics used by participants are to find a replacement staff member from a local team, other teams, float or bank, or use locum/agency.

The vast majority of the time if somebody gets sick or ill we have to go and get a locum. And occasionally we may not get a shift filled for a month if someone has resigned and gone off to America or whatever.

At the odd times, we need locums, but we have to cut them down as possible. So, the occasions that we need locums are when people are doing exams; there are many people are off-duty, if there is a course that everyone is going to or at the end of each rotation. When doctors leave early sometimes, we have to get a locum, but we try to stick to our rules.

Another strategy is the workaround plan which includes: increasing work intensity, speeding up, working overtime and reorganising the work.

All of the nurses here are probably working slightly above and beyond what they should be doing. Moreover, so it makes it very difficult if I am not able to give them their requests or if I am maybe making them work excessive hours which sometimes they know they have to.

The problem is that we do not have anyone to compensate this, so if anyone has any sick leave or is absent for any reason, we do not have anyone to cover his or her place, so we have to work around it.

Other strategies are stated by participants to overcome the staffing shortage such as recruiting scheme that attracts overseas medical professionals.

We spend a lot of time recruiting, trying to get doctors from around the world, giving them what they want. I would say at least a day a week, one of the consultants is on the phone to Egypt, to Australia to wherever encouraging people coming in. At the moment of our twelve registrars, we have three who have come from Saudi who trained initially in Egypt. We got one from Eastern Europe, they are from all over the place, and we are continually encouraging people to come.

4.4.3 Organisational Aspect

The organisational environment represents the location and the climate where patients receive healthcare services and staff provide these services. The organisational aspect focuses on the hospital characteristics and operational processes variables that identify the working environment, which influence the ability of medical staff team to be efficient and effective (Figure 4.3). The participants mentioned few critical elements related to the organisational and operational characteristics.

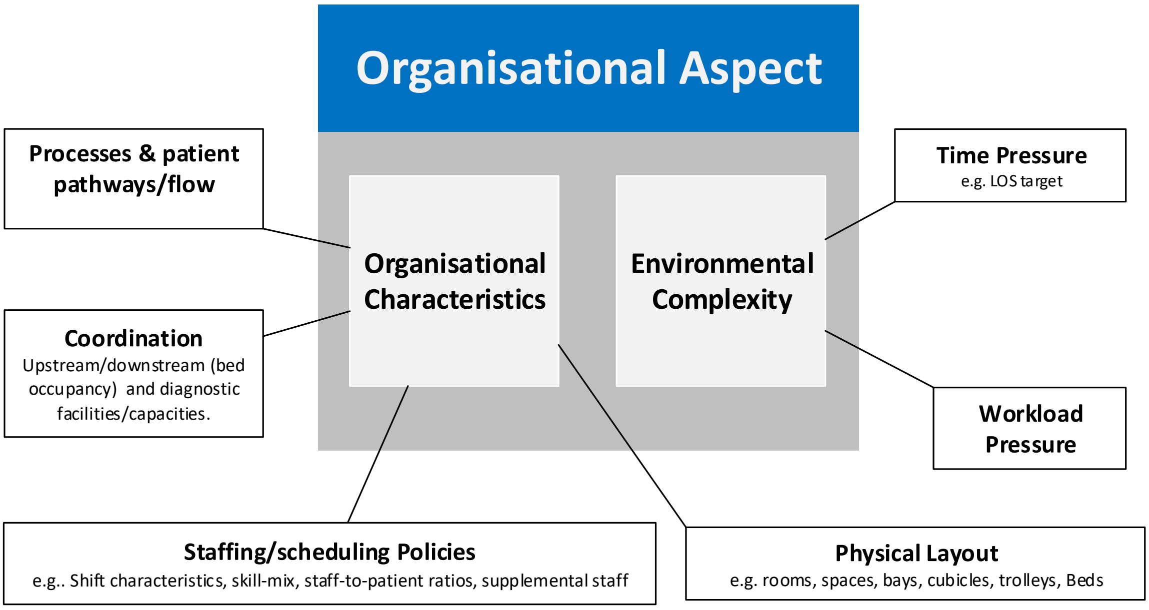


Fig. 4.3 Organisational Aspect.

Coordination. The horizontal coordination between managerial areas in the healthcare system provides the required information, resources and materials to enable both effective and efficient health care delivery. Enlarging the scope by considering the upstream facilities/unit, which represent the demand generators, and downstream facilities/unit which constrains the patient flow. As stated by the participants, there is an apparent lack of coordination between the different upstream and downstream resources. They provided evidence for this such as increasing number of boarded patients, overcrowding and the cancellation of cases are due to the lack of coordination between different interrelated resources.

> *Our biggest challenge is boarded patients who completed their ED care and are waiting for an inpatient bed. Those patients are boarded in the ED for up to 72 hours. I believe that our ability to do the emergency work is compromised by the fact that all our resources are going to looking after these boarded patients. Patients coming do not get to be seen their care is not prioritised. So, you know the actual numbers coming through the door is not the problem, I think we can manage it if we do not have to provide care to admitted patients as well. So, if the hospital could take responsibility for them and look after them, we would actually be able to do our work!*

Layout & Physical Resources. Participants stated that the physical infrastructure and design of the unit which has a direct impact on care delivery including spaces, treatment bays, diagnostic areas, and waiting areas. The layout has a significant impact on staff efficiency as poor design results in long travelling distances.

> *We also look at some trolleys within each department, and you also need to consider layout within the department.*

> *The layout of the ward is not suitable for day surgery because they are too spread out. It would make it easier if we had one open plan area. The other problem is theatre is down on the ground floor. So, we are up and down all the time. 10000 steps, I put it on my phone; just to tell my daughter how many steps I was walking.*

Also, fragmented layout leads to using more staff than required as stated by one of the participants for instance:

> *Where we are here means we have to run our recovery. Whereas if we are with the other theatres, we could all combine, so there are many more recovery nurses in this hospital than what is needed because of the structure because we are in three different places.*

Processes & Patient Pathways/ Flow . Participants have expressed that delivering care is a complex task. Understanding the complexity of the adopted care processes, model of care, and patient pathways are essential for making better staffing decisions.

Environment Complexity. Participants described their workplace as a stressful environment. There are growing pressures due to high perceived workload which has a significant impact on increasing the pressure on the staff. They described stressful, chaotic situations as heavy workload influence their ability to do their jobs. Most of the participants emphasised that their employees are under continuous pressure and they have to work hard (**Work Intensity**) to meet the demand which in turn reduces the lack of time spent with patients.

> *We had an indeed awful working environment, and massive overcrowding, where our doctors were gone off sick frequently. It was too painful; they hated coming in to work.*

Different reasons such as understaffing, overcrowding, lack of capacity, and lack of resource coordination have been mentioned are among the leading causes of the abnormal workload. The stressful and work overload environment were associated with low morale, burnout and staff dissatisfaction.

Even just morale of staff like everything just goes downwards. We cannot stop patients' arrival, clean the place, see patients, or do anything. So, we are paralysed.

According to the participants, everything is compromised when you are overloaded and understaffed. Patients are going to wait longer and longer, and they became vulnerable to high risk.

There is a huge risk, an unacceptable level of risk, people are dying to the extreme because it is not a proper place for them and everything is compromised. We cannot stand over the level of care that is provided when we are asked to look after 30 or 40 extra people that are not our responsibility, so that is our biggest fear.

According to the participants, various coping strategies are employed to deal with the stressed and burned-out staff including for instance:

1. Work organisation,
2. Providing mentorship,
3. Providing support,
4. Giving breaks and time out,
5. Using feedback and listen to them,
6. Encouraging social activities such as day outs, and
7. Rotation of the different unit.

4.4.4 Lack of Management Support

Most of the participants expressed their opinions about the management concerns and helped to address their problems regarding staffing and scheduling issues. The participants articulated four issues regarding the management that affect their ability to provide patient care: (1) lack of proactivity & responsiveness, (2) lack of vision, and (3) lack autonomy & flexibility for improvement.

Lack of Proactivity & Responsiveness . Participants have described the response to staffing and scheduling related issue as slow, and reactive rather than proactive. They only respond when things become chaotic.

It is only when something happens to someone somewhere that there is a response. Moreover, that is a shame because we think that our senior nursing management should be defending our establishments above and beyond everything else because everything else suffers. We do not have the adequate nursing resources. Moreover, there's no evidence to support that is being done.

Lack of vision . Participants described the solution for staffing and scheduling issues as short-term fixes rather than the long-term plan with clear objectives and directions.

Probably not on the chronic national understaffing of doctors, we know there is a national issue. So, we do not know if management is doing anything about that; we cannot see any improvements.

In the last couple of weeks, HSE announced the ten-year plan. The chairman claimed free GP care for everybody and no private care in public hospitals loads. In fact, they set their heads up high in the sky; we are so far from that if a patient wants an ENT (Ear, Nose & Throat) appointment s/he has to wait five years! So, I do not know where we are going with healthcare in Ireland.

Lack of Autonomy & flexibility for improvement. Professional autonomy refers to the authority given to a unit/department to make decisions and the freedom given to act in accordance with the professional knowledge. Some of the participants highlighted that the Irish hospital system is less flexible for change where the management model adopted is more centralised.

I think medical assessment has been established a lot longer in the UK and the benefit has been demonstrated for many more years. In the UK, there's a bit more flexibility, autonomy and opportunity to evolve and develop the service. Further, if we can demonstrate a successful change, then we get the resources to *continue that change. Here, we do not have such autonomy, which has not been devolved yet. I presume it might be changing to be fair, but it is still very much a top-down model to get additional resources. We have to go throughout the chain of command, which takes a long time.*

4.4.5 Technology

Over reliance on memory . Almost all the participants depend on their experience and memory in setting up staff schedule for both nurses and doctors. However, they described the difficulties of staff scheduling, particularly in nurses as most of the participant doctors are using a rolling roster.

Lack of decision support. According to the participants, they acknowledge the need for a data analytical tool that helps them to understand the implications of their decisions. Across all the hospitals such tools do not exist. All the participating hospitals have an IT system for patient tracking that provides the ability to produce some reports. Managers use these reports for further analysis using MS Excel for doing some statistical analysis and charting.

Not all the participants have acknowledged their need for a decision support. Most of them agreed that using predictive analytics can help them in managing their unit efficiently.

Oh god yeah. If the CEO had a simulation, she could test scenarios like what if I cancelled ENT surgery today what difference does that make. Alternatively, if she said ok I need two more consultants down in the radiology department so we can get through more imaging because of the backlog. Now that is the same stuff that was doing in the clinical process except you are doing it now in the managerial process. So, it has to make sense.

Currently, physician and nurse scheduling is generated manually using pen and paper or using MS Word or MS Excel for organisation purposes. Scheduling process requires a lot of time and effort from the unit manager to prepare the schedule.

> *I do it manually. I know the people that are on study leave, or on annual leave. I take that into account. We have a rolling roster when it comes to weekends; I do it according to the activities during the week.*

Lack of tracking . According to participants, it seems very difficult to track their staff regarding the shift and schedule patterns in the case of manual schedule. Besides, it is a time-consuming process to look for a piece of information a diary book.

> *I suppose the main thing is that I could not see patterns on it because I spent much time going back through books and asking who has mandatory training was done? Who has worked on many weekends? Who has worked the late shift on a Friday? Did she do it six times? So I could do a good Roster if a system would allow me to see these patterns.*

4.5 Discussion

Understaffing is a widespread problem in all eleven hospitals across different departments. Most of the managers interviewed highlighted that the most substantial issues they are facing are the situational understaffing. This is a result of absence, long-term leaves and demand fluctuations where managers have to find the additional staff at short notice (if any) or to continue understaffed. These make the staffing and scheduling responsibilities a daunting task. At the same time, the management's ability to fill the vacant jobs in order to maintain trained and experienced staff is one of the critical issues in the Irish healthcare system. This mainly because of the shortage in some specialities and skill sets required along with the unattractive work environment and financial packages. The consequences of understaffing not only jeopardise the quality of care and patient safety but also has a significant adverse impact on staff dissatisfaction and morale.

Burn-out issues were associated with the stressful work environment and inadequate resources, (particularly in Emergency Department), as doctors and nurses have demonstrated that their staff are under constant workload stress and they utilise various coping strategies to deal with burned-out staff. The inability of staff to meet the highest level of care due to short staffing and feeling the patients may be at risk put an enormous mental pressure on medical staff. Another stressor on the hospital managers is their involvement in doing daily administrative work to fix the scheduling aspects to maintain adequate staffing levels.

Staffing decisions across the eleven hospitals tend to be based primarily on historical averages rather than using benchmark or standard staffing method. The primary factor that is considered in staffing is the demand volume rather than the severity mix or patient acuity. This reality reflects the inadequacy of staffing methods and explains the increasing pressures on the hospital staff. Also, manual staff scheduling is predominant, and only one out of eleven hospitals use scheduling software. Head nurse or consultant use their experience to design the schedule, and they deal with all scheduled administrative issues, which is a time-consuming task taking attention of managers away from patients.

In Irish hospitals, the exploratory study revealed that there is a lack of using decision support tools for staffing and workload analysis. Despite the fact that there are information systems deployed, their analytical functionality is limited to just reporting. This may also be demonstrated by the lack of the awareness of hospital managers regarding the potential impact and usefulness of using analytics to understand the demand for care which potentially leads to better staffing decisions.

In summary, this chapter presents the second stage of the research that includes an interview-based exploratory study. The study is conducted to understand the problem of staffing and scheduling in the Irish healthcare system and to identify key elements from the managers' perspective. Practitioner insights and discussion are fascinating and, in many cases, confirmed the findings of academic research literature.

Four aspects of staffing and scheduling were identified by the study (Figure 4.4):

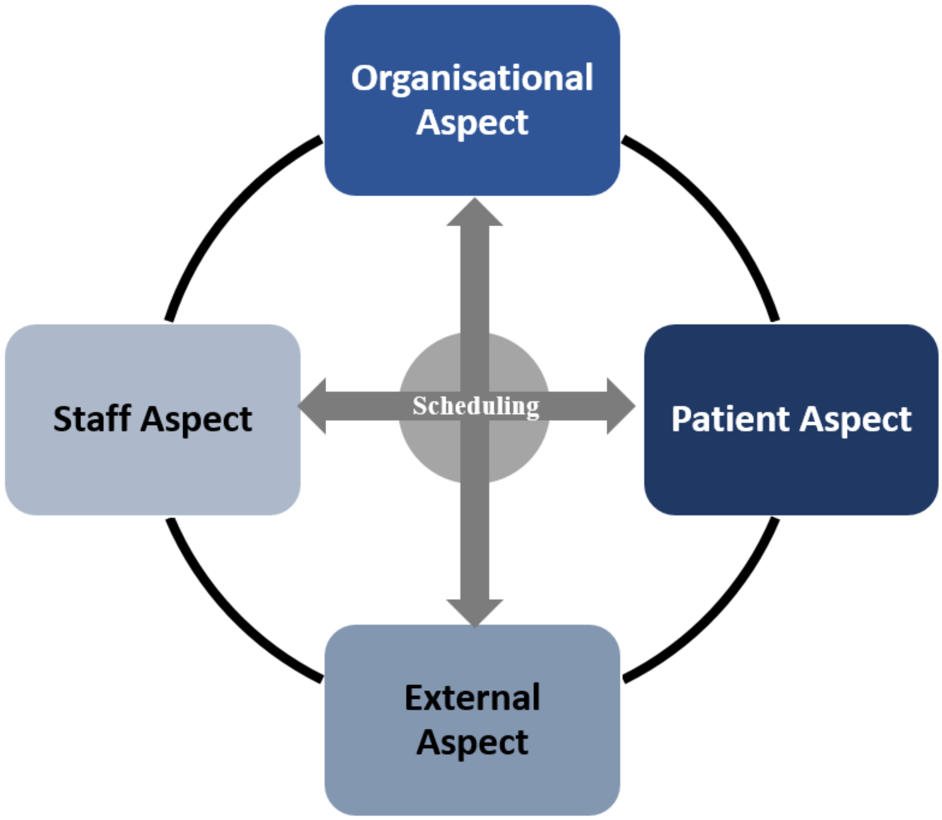


Fig. 4.4 Theoretical model components.

1. **Patient aspect.** This represents the demand side, and it is the primary focus of the hospital services. It determines workload volume, acuity, and the need for care that may introduce uncertainty into the system.

2. **Staff aspect** – it reflects the supply side regarding the number of available hours, staff size and skill-mix.

3. **Organisational aspect** - focuses on the organisation characteristics, managerial factors and operational processes variables that identify the working environment and affect the ability of medical staff team to be efficient and effective.

4. **External aspect.** It includes the factors and variables that are outside the organisational environment and may have direct or indirect impacts on determining the hospital staff planning and scheduling. Examples of these factors that may impose extra constraints are state legislation, labour union regulations, staff shortage/supply, economic factor and restructure and reform of the health services.

4.6 Limitations of this study

This study conducted 25 in-depth semi-structured interviews across eleven different hospitals across Ireland. Although, for an in-depth insight and understanding of the managers' perspectives of staffing and scheduling of medical staff, it would be interesting to include the staff perceptions in addition to their managers' views. Also, this study is limited to physicians and nurses.

4.7 Conclusion

The exploratory study has conducted 25 semi-structured face-to-face interviews in eleven different hospitals in the Irish healthcare acute system to capture and analyse managers' perspectives in practice. This qualitative inquiry provided a sharp lens into the perception of hospital managers in staffing and scheduling medical staff. Participants discussed a broad range of factors some of them applicable to daily practice and others just suggestions. Five themes have been identified and extracted from the analysis of the transcripts: demand for care, staffing and scheduling issues, organisational aspects, management concern, and technology-enabled.

This research revealed that several factors prevent or inhibit the management from improving the staffing decisions such as lack of coordination with other departments and lack of support from the management. Therefore, the findings of this chapter and the literature review in Chapter two have informed the development of the framework (Chapter 5).

Chapter 5

Integrated Scheduling Framework

> Imagination is more important than knowledge. For knowledge is limited, whereas imagination embraces the entire world, stimulating progress, giving birth to evolution.
>
> *Albert Einstein (1879-1955)*

5.1 Introduction

As identified from the exploratory study (chapter 4), the hospital managers rely on simple average-based methods such as average treatment time, average demand volume, and average acuity to manage and plan staffing decisions. Variability, uncertainty, processes, constraints, patient flow rules, physical capacities, coordination with other hospital facilities are among the factors that influence the staffing and scheduling decisions. The current practices, therefore, are inadequate to comprehend the dynamics and complexity associated with the hospital system. Therefore, this chapter discusses the conceptual development of the proposed integrated framework for medical staff scheduling in the hospital context. The framework utilises a hybrid multi-method modelling and simulation (hybrid M&S) approach which has the potential to comprehend and understand complex systems. The components of the solution framework are introduced and explained in detail. The development of this framework is the product of this research that attempts to provide an integrated solution that can help hospital managers make better staff scheduling decisions.

5.2 Overview

Given the dynamic and detailed complexity of medical staffing and scheduling in the hospital context, multi-disciplinary approach can be effective to develop an integrated decision support framework for staffing and scheduling. Components required for developing this framework (i.e. resulted out of literature and exploratory study) are shown in Figure 5.1.

The framework development phases are: demand for care, understanding dynamics, and optimisation (Figure 5.2). Phase one utilises data analytics, statistical analysis and machine learning to address and understand the patient's demand (patient aspect). Machine learning (ML) classification models are proposed to model the crucial patient-related decisions made by the staff members such as determining the severity of patients. This component learns from data to predict the critical decisions. The ML component aims to improve the predictability of staff workload. This component is embedded into the simulation model. The outputs of the statistical analysis and machine learning in phase 1 feed into the developed simulation models in the second phase.

Phase two combines process modelling, conceptualisation and hybrid simulation to capture the dynamics and complexity of the hospital system. In the second phase, discrete-event simulation is used to model the detailed system complexity and capture the main factors that impact staff workloads such as severity mix, frailty and coordination with the hospital facilities. These factors are obtained from the exploratory study and the literature. The simulation component aims to predict performance due to changes in the incorporated factors

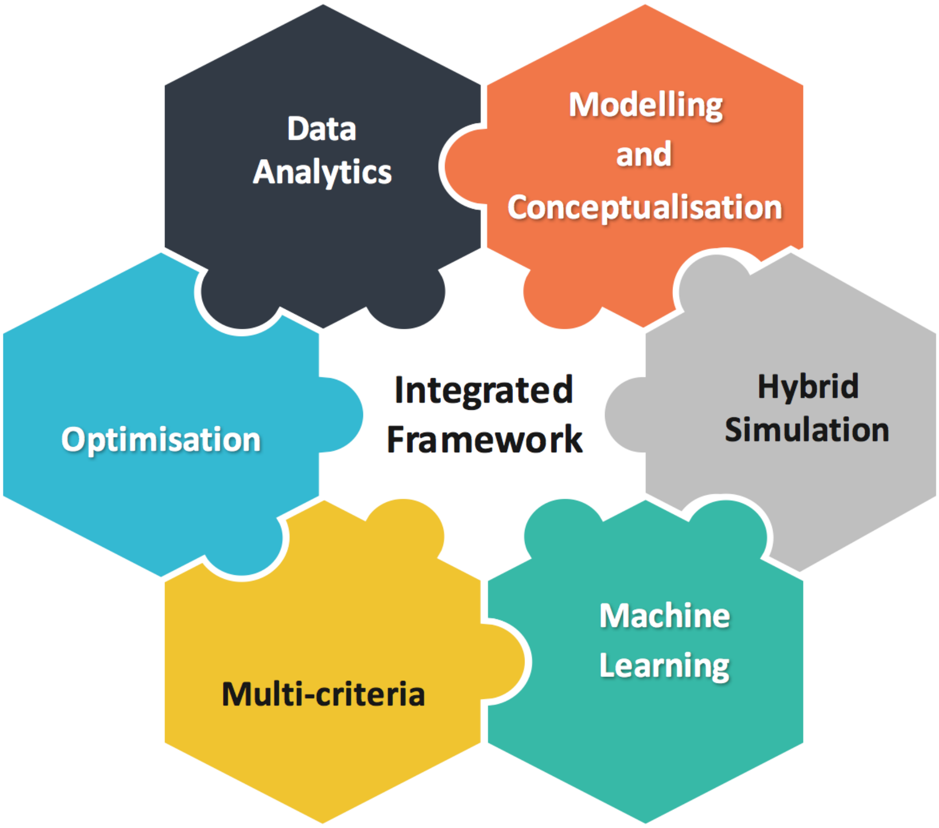


Fig. 5.1 Simplified Framework components.

and also provides a mechanism for scenario analysis. The System dynamics (SD) component models the adaptive staff behaviour as a result of burn-out effect. This component aims to provide a threshold for the level of staff utilisation to reduce the impact of burnout which can be used a constraint when generating the temporal staffing patterns.

Phase 3 is the optimisation phase which has two stages: staffing optimiser and shift scheduling. Stage one determines the staffing patterns that match patient's demand and consider all the main factors that have been incorporated into the simulation model. Stage one, staffing optimiser solves a simulation optimisation problem to obtain a (near-) optimal temporal staffing profile for each staff type. Stage one problem is formulated as a multi-criteria stochastic optimisation problem.

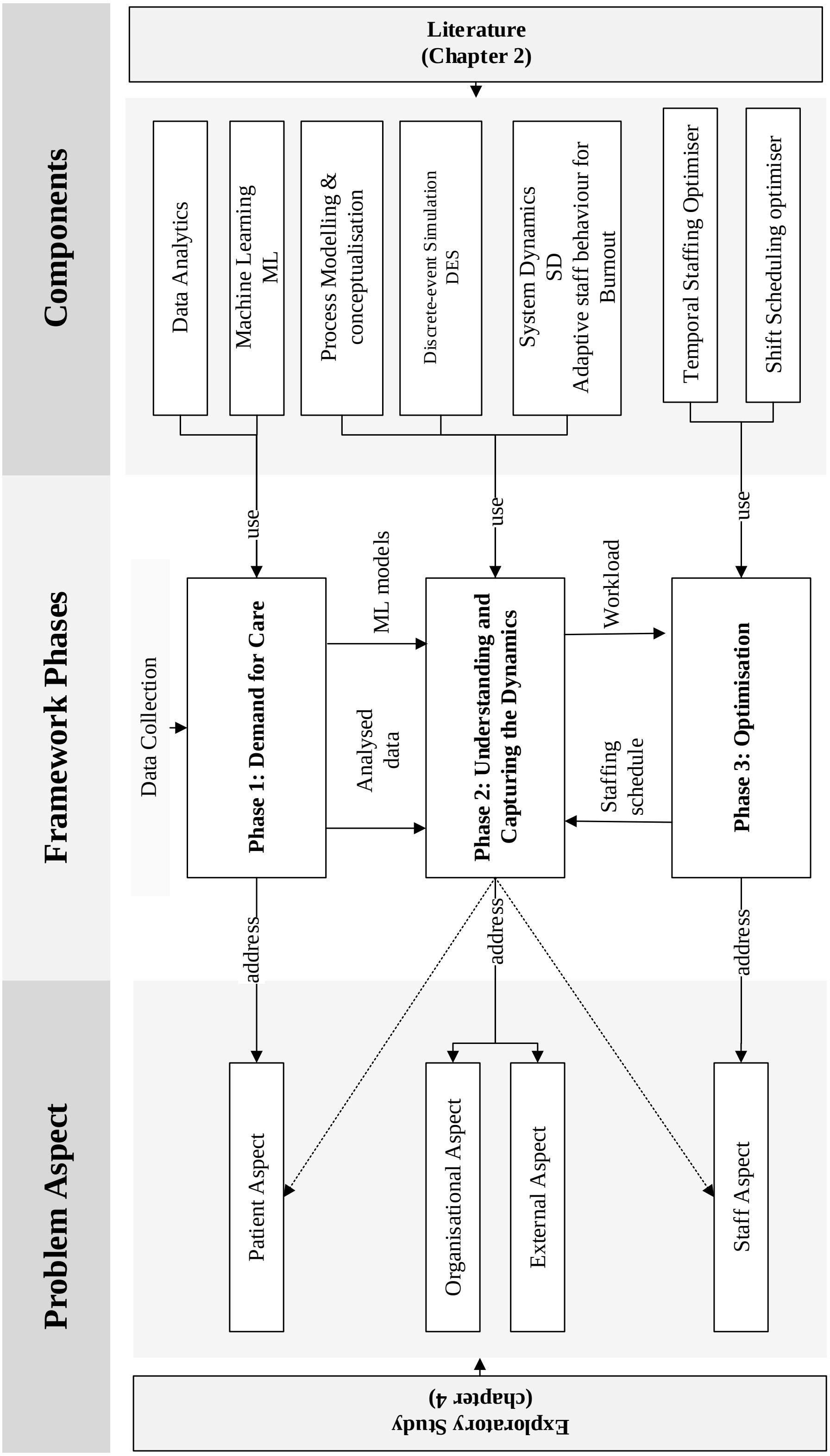


Fig. 5.2 Framework phases.

The desirability approach is proposed to overcome the difficulties of combining several objectives with the information given by the decision maker (Rashwan et al. 2016). The output of the staffing optimiser is the staffing requirements per time block (i.e. hourly). In the second stage, the shift schedule optimiser determines the shifts that satisfy the staffing needs obtained from stage one aiming to minimise under/overstaffing. The simulation model is the performance evaluator for the schedule solutions obtained.

A detailed representation of the integrated framework components is depicted in Figure 5.3. Further, the coordination between these components is illustrated in detail along with highlighting their points of integration across this chapter.

5.3 Phase 1: Demand for Care

5.3.1 Data Collection

Data collection is required across the four aspects of medical staffing and scheduling as pointed out in chapter 4: patient, staff, organisation and external. The framework utilises various methods of data collection to incorporate multiple perspectives (i.e. qualitative and quantitative). Interviews and observations have a qualitative nature, which is of a great benefit in understanding and modelling of the workflow (processes) in the healthcare facility (Figure 5.4).

This type of data enables one to incorporate the practitioners' view (judgemental-based) to enrich the understanding. Quantitative data (evidence-based) has factual nature and depends on verifiable information (to a great extent). This type of data is collected from different sources including Hospital Information System (HIS) and local databases. As the operational data mainly encompasses information-technology system (ITS), the data can be extracted or retrieved by different technologies such as Structured Query Language (SQL) and the retrieved data can be stored in various formats including XML, JSON, MS Excel, or even text files.

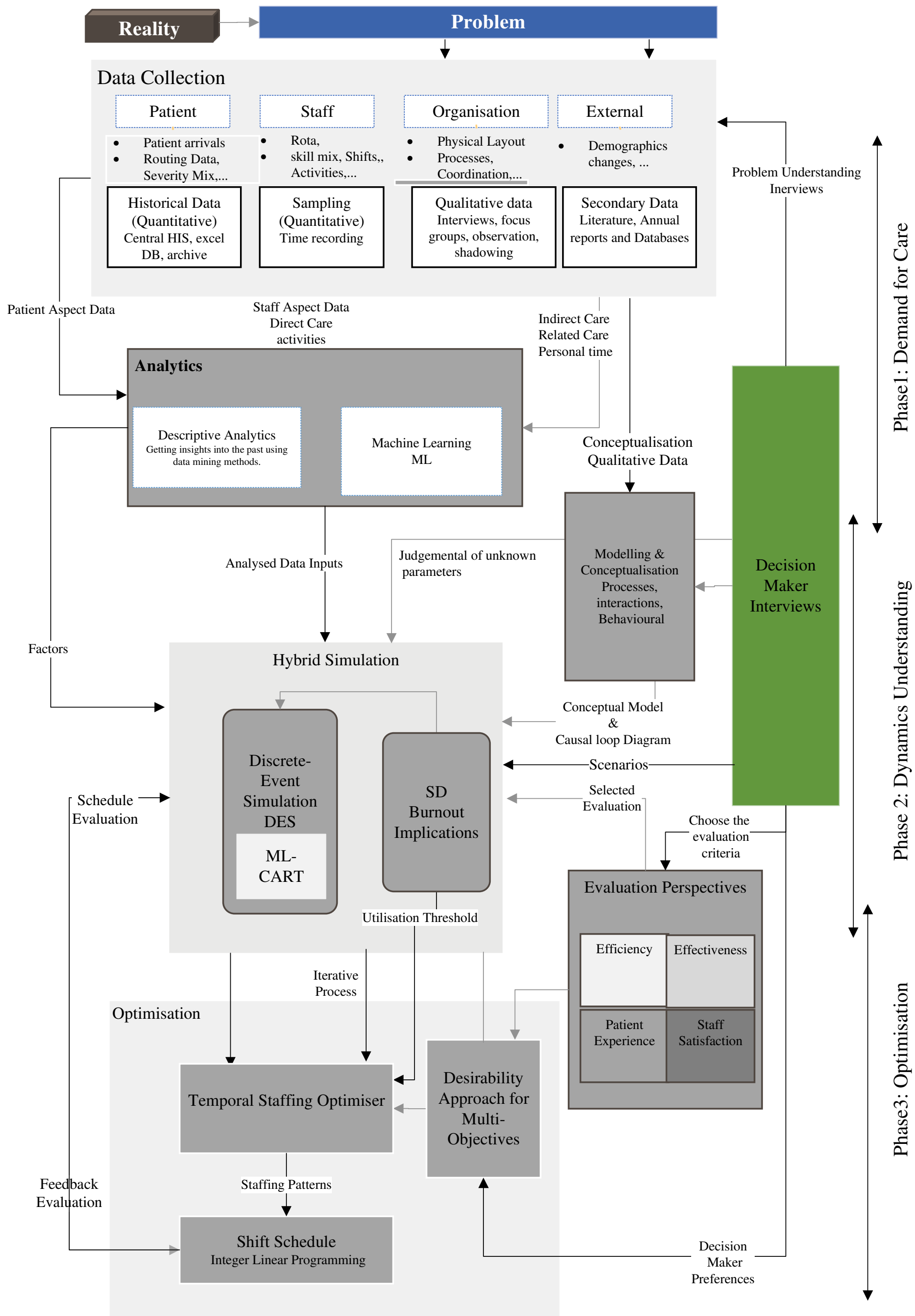


Fig. 5.3 Detailed Framework Components.

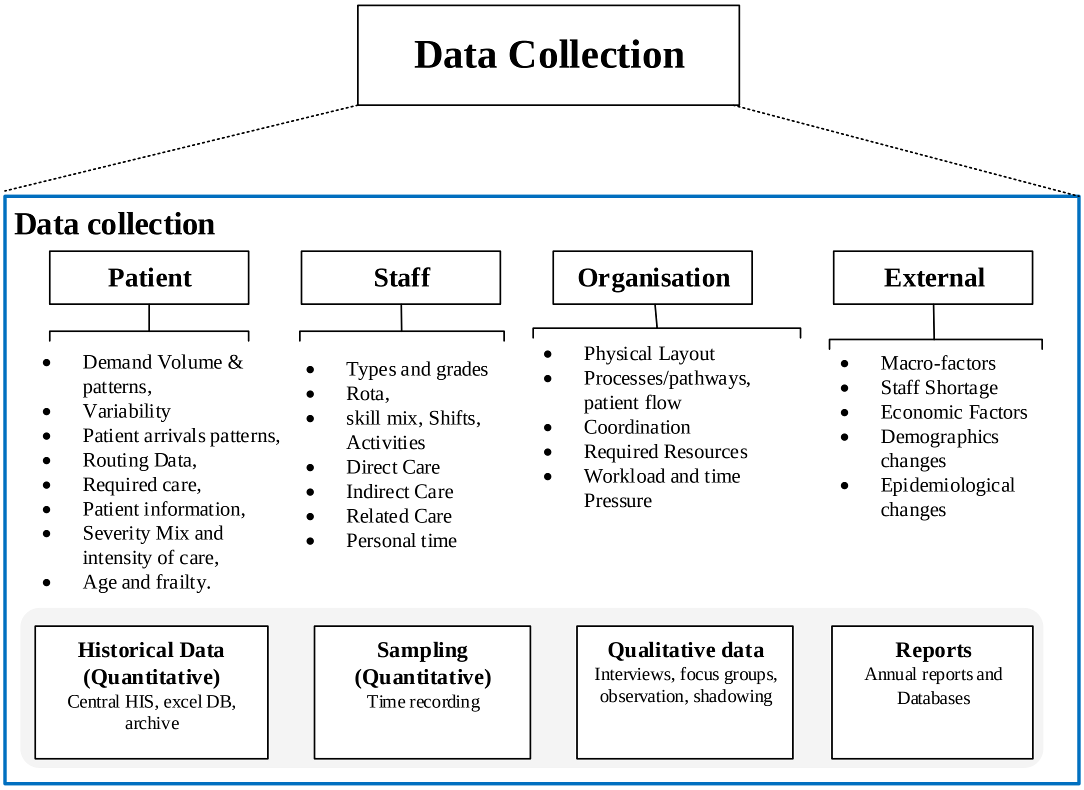


Fig. 5.4 Data Collection.

One of the integral factors in ensuring an efficient model is the quality of the data phase. The modelling outcome is dependent on the data at various levels, particularly when the simulation constitutes the ultimate environment for experiments.

However, to incorporate the time factor, patients' records are collected from the (HIS), including valuable information regarding patients and their care steps such as arrival time, mode of arrival, referral type, and time of discharge or admission. The patient's data are recorded by several types of staff such as administrators, nurses, and doctors through the stages of patients' care. Due to the elevated levels of pressures within healthcare processes, hospital records sometimes lack accuracy and consistency.

5.3.2 Analytics Component

As previously stated in chapter 4, understanding the patient's demand and their care needs is an essential component to staffing the required number of medical staff and their composition or mix to meet the demand. Within the proposed framework, incorporating demand patterns, patient profiles and the related statistical models that acquire patient aspect's factors require sophisticated techniques. Therefore, the data analytics component (Figure 5.5) helps to assess the multifaceted nature of patients demand considering patient volume, severity mix, and patterns of patient presentations. Data analytic algorithms allow extraction of the trustworthy information and insights from the data. The analytics components utilise descriptive and predictive data analytics methods. Descriptive analytics is a key for analysing the historical input data to capture the insightful information from the data. Different procedures and approaches from the statistical analysis and data mining are useful for this purpose. The output for descriptive analytics are the probability distributions and parameters that are required for simulation. The other element is the machine learning component which is described in detail in the next section.

5.3.3 ML Component for Learning Decision Rules

Staff members make important sequential decisions during the patients stay such as patient escalation, speciality referral, assigning patient acuity/severity level, or making a disposition decision (admit or discharge). Such decisions have implications on the staff workload and patient care plan. From the machine learning (ML) perspective, these decisions can be described as a classification problem that aims to predict the patient class (e.g. admit or discharge) based on the actual patient's records. Incorporating machine learning into the simulation model improves the predictability of the model. Many ML algorithms can address this classification problem. Selection of the ML classification algorithm requires a trade-off between accuracy, interpretability, computational complexity and ease of implementation.

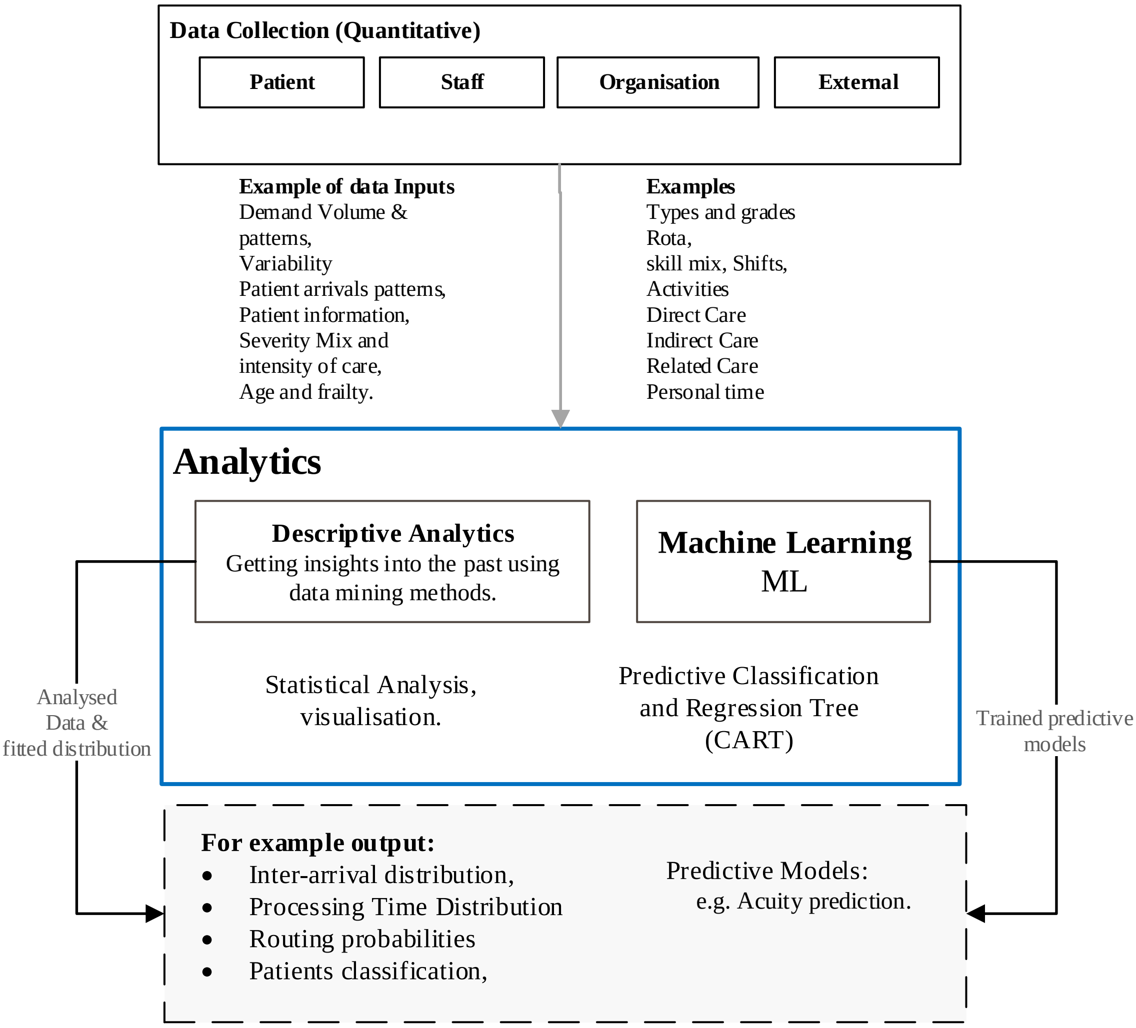


Fig. 5.5 Data Analytic Component.

This framework adopts the Classification and Regression. Tree (CART) algorithm to predict the patient-related decisions within the simulation model. The CART algorithm is supervised learning where at each node it uses a binary partitioning of patients based on their most informative feature (independent variable) to predict the dependent variable. CART can be easily explained and interpreted by the medical staff, easy to be implemented and incorporated into the simulation model. Also, during the exploration of various algorithms, CART has a good accuracy compared to more sophisticated models (e.g. random forest and support vector machine) with less computational complexity.

An example of the prediction of the patient disposition (i.e. admit or discharge) is given in Figure 5.6. The splitting of the tree continues to minimise the variation in the dependent variable. The prediction is obtained from the leaf nodes using the majority rule. In the framework, instead of using the class majority (most likely class at the leaf nodes) the class probabilities at the leaf nodes are used to sample the patient class.

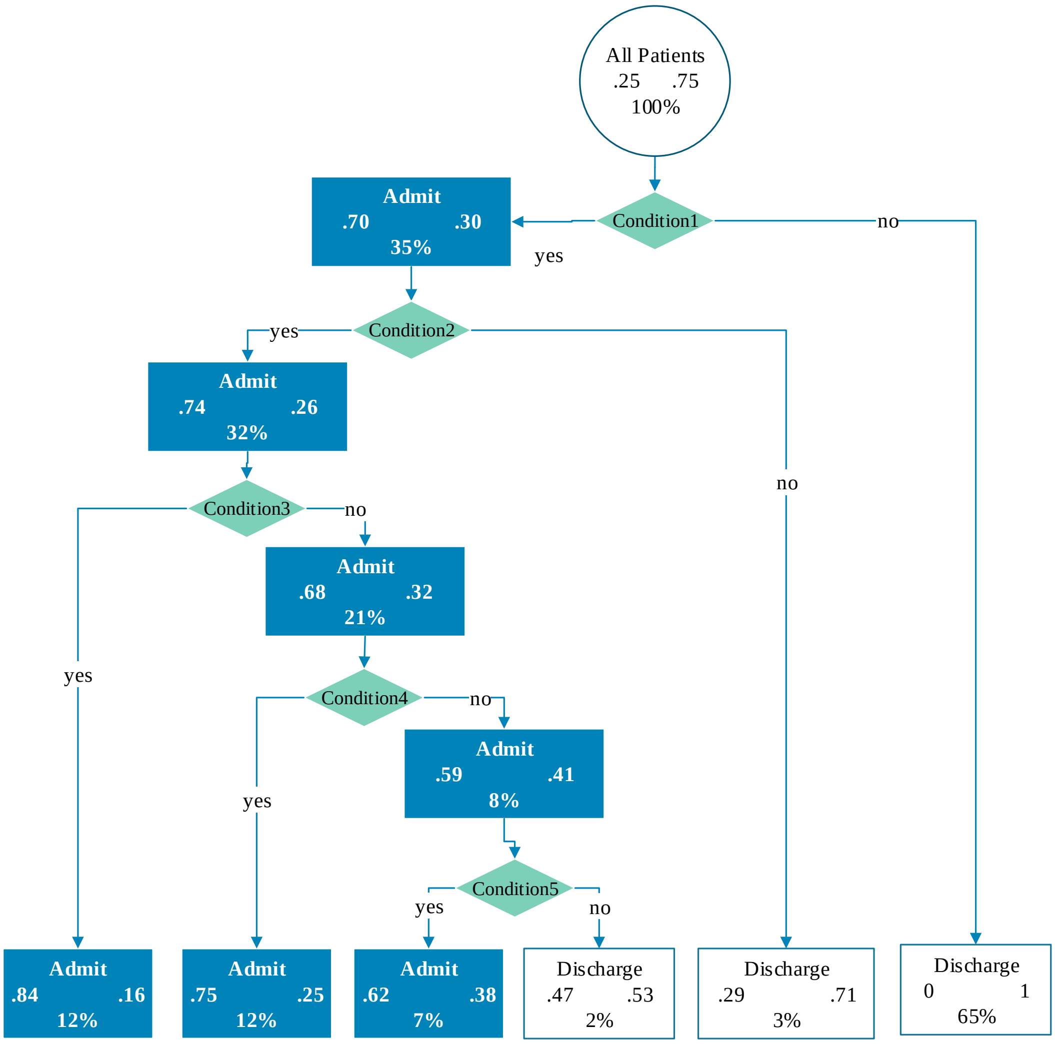


Fig. 5.6 Example of a binary class CART to determine a patient disposition.

5.3.4 Medical Staff Activity

To accurately assess the utilisation of medical staff, the method of direct observation/activity analysis is employed to record the medical care activities. The medical staff time can be distributed into four categories of activities by identifying and classifying clinical and managerial activities occurring during the various stages of patient care. These categories include direct care, indirect care, unit-related care, and staff activities (Figure 5.7).

Direct care is the activities that require face-to-face interaction between a medical staff member and the patient, which are usually delivered at the bedside such as clinical assessment, medication management, moving & handling, procedures, assistance, and communication. Indirect care activities do not require direct interaction with patients but are still essential for their care episodes such as consulting other medical professionals, documentation, handover and providing clinical instruction. The unrelated care includes all activities that are not related to a particular patient but connected to the wider system such as team meetings, administrative work, clerical and training. Finally, staff activities contain all individual staff activity such as breaks, personal time, and unoccupied time.

The framework captures the direct care provided to patients. To incorporate the indirect, related care, and personal staff activities, a workload (utilisation) threshold is set within a specified range. This threshold ensures that the average staff workload (i.e. utilisation) does not exceed this target. A recommendation of the workload threshold is informed from the SD component.

5.4 Phase 2: Understanding Dynamics

As previously pointed out, staffing and scheduling of hospital staff is a multifaceted problem. Given the systems' path dependencies, time-varying factors (e.g. demand) and the stochastic nature of the systems, system equilibrium is not attainable. Therefore, in the absence of

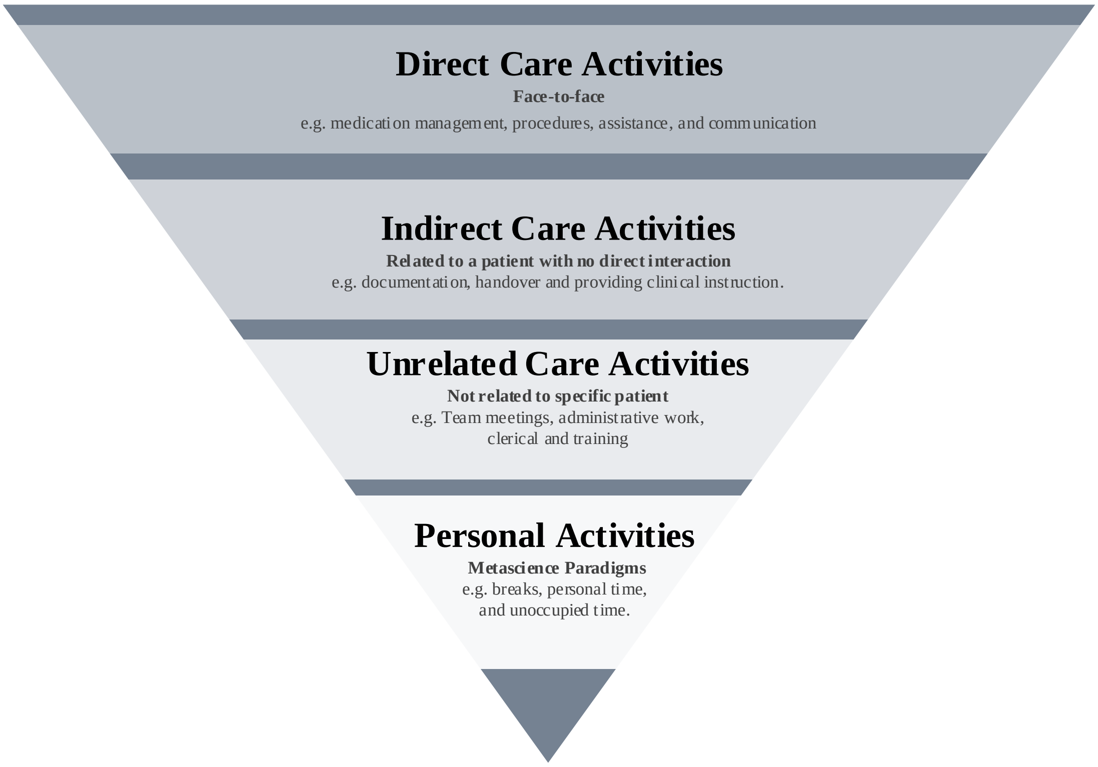


Fig. 5.7 Categories of medical staff activities.

specific equilibrium conditions, a future state of the hospital system can only be estimated by explicitly tracing the evolutionary path of the system over time, beginning with current knowledge conditions. As a result, modelling the system using steady-state closed-form equations such as queuing networks to account for all underlying factors as previously discussed is not achievable. Alternatively, the underlying system is modelled as a detailed microscopic simulation model that accounts for all problem elements and factors.

5.4.1 Process Modelling Component

Conceptual modelling is a major step of model building, and it is potentially the most significant stage in a simulation study. Modelling the underlined business processes requires knowledge from the individuals directly involved in the service delivery. The data collection phase combined interviews, focus group, and observation from literature (Figure 5.8). Modeller uses these various methods to get as much information as possible without influencing or manipulating the problem definition. Since model conceptualisation is an iterative process, it requires close interaction with experts and practitioners to obtain holistic insights the system aspects.

There are two outputs of this component: business process conceptual model for DES and feedback conceptual model for SD. Business processes are mapped into a conceptual model using one of the well-developed modelling languages (i.e. flow chart and state chart diagram) where sub-processes and activities are identified. The control flow definition is created through the identification of the entities that flow through the system.

Finally, the resources are identified and allocated to the activities as required. The process model should be verified to ensure that the model does not contain errors and is logically valid. Feedback conceptualisation is an important activity for modelling and captures the adaptive behaviour of staff as a result of burnout. Key variables and factors can be identified through a series of interviews, focus groups and secondary data from the literature. Feedback conceptualisation is captured by the commonly used conceptualisation tools causal loop diagrams and subsystem diagrams. A fundamental principle is modelling, and conceptualisation should be focused on a problem instead of a system and guided by a clear purpose and objectives.

Due to the complexities embedded within healthcare processes, it is challenging to get a precise view of the business process and dynamic feedback with enough details. Therefore, the majority of simulation studies manually develop the process model using documentation, direct system observations and interviews with stakeholders and experts (e.g. consultants, nurses. . . , etc.). This manual process is time-consuming, and arguably the longest stage in any modelling and simulation (M&S) study. This lengthy process affects the validity and effectiveness of the M&S study, and it varies significantly due to the ever-changing nature of

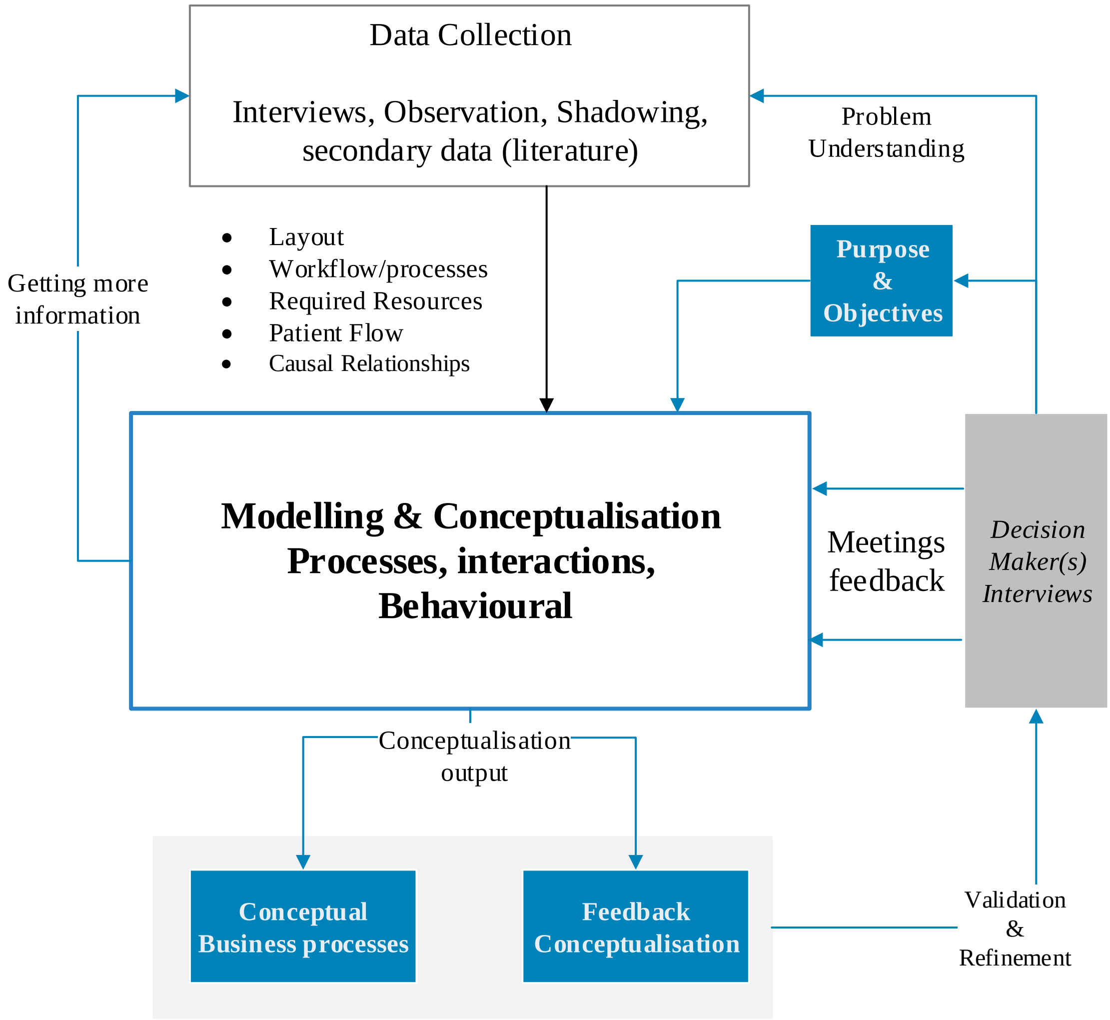


Fig. 5.8 Process modelling component.

healthcare operations. Moreover, the perception of the actual process is influenced by the experience of the individual who is studying it which results in biased models. In addition, this approach is not easily reproducible as the model with a partial view of the processes. Therefore, it is essential for any successful M&S healthcare study to develop conceptual models that are a close reflection of reality promptly. This requires continuous refinement and validation from the stakeholders to enhance the credibility of the conceptual model.

Once the conceptual model is validated, the model translation begins, which combines the validated conceptual model and the results of the data analysis from phase one. Within this framework, simulation models either DES or SD can be developed by any suitable simulation commercial package or with a programming language.

5.4.2 Simulation Components

In healthcare applications, simulation paradigms such as discrete-event simulation (DES) and system dynamics (SD) are widely used to capture and understand the dynamics of the system (Arisha & Rashwan, 2016). DES offers a better representation of detail complexity and can capture the processes and factors dynamics. While, SD enables for an easier representation of dynamic feedback, which can capture a holistic vision to describe the interaction of various factors. Developing useful hospital models entails different forms of thinking to consolidate various stakeholders, policies, distinct groups of patients and other complex elements. The dynamic nature of contemporary healthcare settings requires the use of modelling approaches to understand the complex systems that, in turn, necessitates the acquisition of a proper level of data and knowledge. The framework utilises a combined DES and SD simulation.

5.4.2.1 DES component

The DES model simulates the patient flow in the hospital to capture the resource consumption, particularly staff, over time. It investigates the relationships and interactions among the main factors as identified in the exploratory study and the literature. The factors incorporated are grouped into four categories (Figure 5.9): patient aspect (e.g. severity mix, patterns), organisation characteristics (e.g. processes, pathways, resources), staff aspect (e.g. staff types, staff availability, and schedule), and external aspect (e.g. frailty and ageing). The physical infrastructure and layout sub model represent the organisational aspects and model the organisation structure under investigation, which can be arranged into a set of working

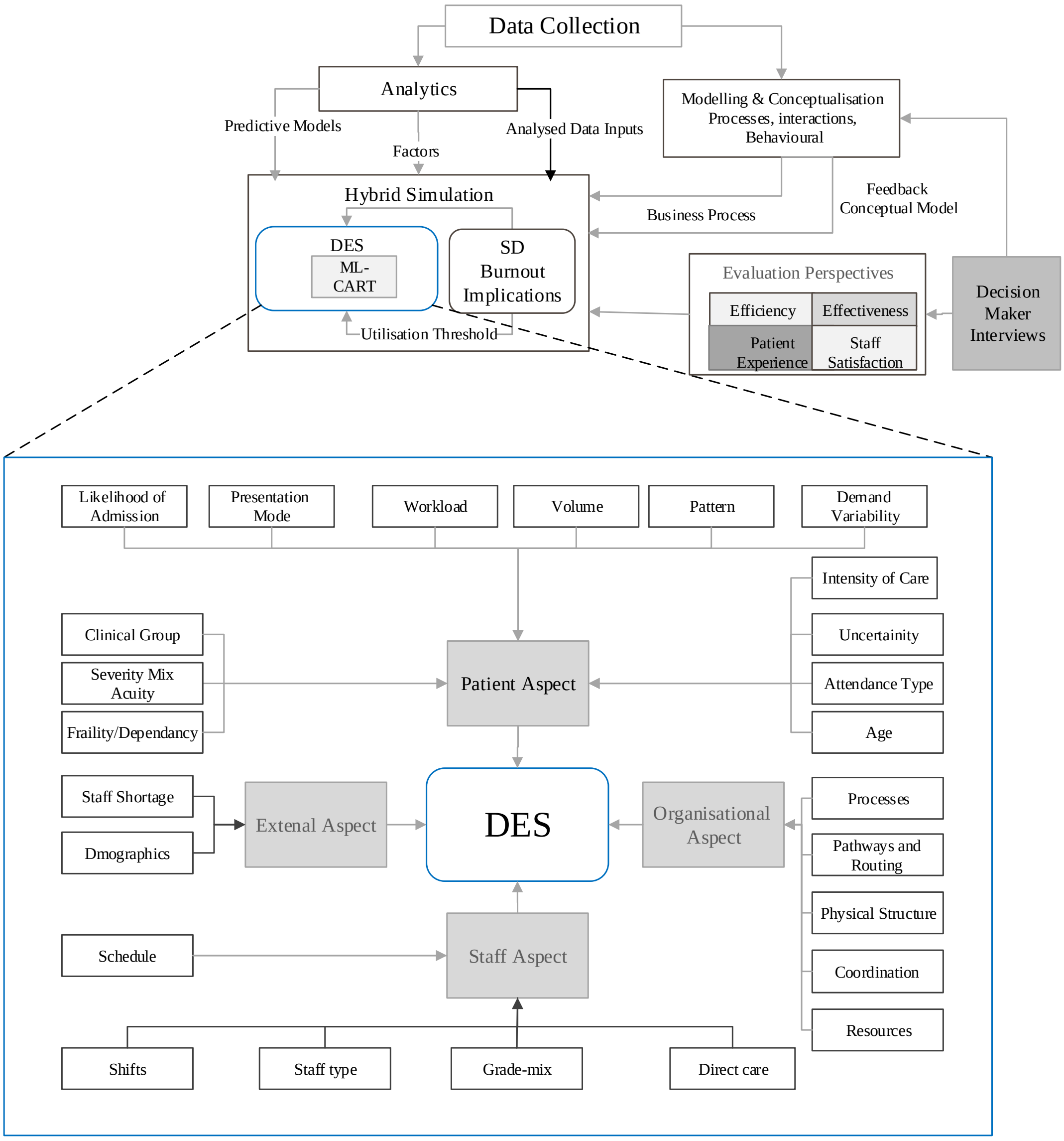


Fig. 5.9 DES component that incorporates the main factors.

stations. Each workstation contains an operation (service) area which is equipped with medical staff and physical resources (e.g. beds). The primary function of the workstation is to provide healthcare services to certain patient groups, which can be decomposed into a set of care activities or procedures that are typically performed sequentially by one or more medical staff. Patients and staff are represented as agents with different attributes. This structure is described perfectly with DES. Performance appraisal is an integral part of any planning processes. The evaluation perspectives for evaluation metrics (discussed in chapter 2, section 2.6) is employed. The evaluation perspectives include efficiency, effectiveness, staff satisfaction, and patient experience metrics.

Verification and validation is an influential part of simulation modelling as these provide the techniques which the credibility of the model can be guaranteed. Verification of the simulation model is applied by comparing the outcome data of the simulation model with the data obtained during the data collection phase.

Once the simulation model is verified and validated, the decision makers can use the replicated model to investigate some decisions and alternatives (i.e., what-if scenarios) to foresee the consequences of these decisions. For example, a design of experiments (DOE) can be used to test a number of scenarios to obtain answers to these what-if? statements. Depending on the set up of the model and the number of the parameters, the number of potential scenarios and experiments increases significantly due to the multiple possible parameter combinations. Following the experimental design, production runs are necessary to provide the data, which is used to analyse the simulation output, where performance measures) can be retrieved and compared with the system under investigation.

5.4.2.2 SD component (Burnout)

Workload balance of medical staff has always been an issue for hospital management. Hospital staff shortages are linked to unrealistic workloads. Medical staff often suffer 'burnout' due to the complexity of the inadequate staffing. The burnout of staff can lead to mistakes in diagnosis, operational difficulties, failure in achieving hospital performance targets and most importantly deterioration in patients' outcomes.

The SD component is an aggregate model that identifies the key factors affecting staff behaviour using system dynamics (Rashwan & Arisha, 2015). The adaptive staff behaviour as a result of burn-out component examines the staff reaction in a consistently demanding working environment. The Burnout component seeks to reflect the implications of constant workload pressures on medical staff performance during their shifts. Theoretical foundations of literature and evidence from field studies are used during the modelling stages. This component has focused on the response of medical staff to demand capacity imbalance and aims to recommend workload (utilisation) threshold to work pressures, and the integration with other framework components (Figure 5.10).

Four elements are used in the SD model to integrate the patient flow in a clinical medical unit and incorporate staff behaviour in response to workload stresses and burnout. The model seeks to explain the implications of constant workload pressures on staff performance during their shifts and to provide a utilisation threshold to feed into phase 3 (i.e. utilisation constraints in staffing). Theoretical foundations of literature and evidence from field studies are used during the modelling stages. There are four elements that the model considers:

- Patient flow element tracks the physical movement of patients.
- Medical Unit capacity component-models the management policies regarding staff size, bed capacity, staff scheduling, and personnel skill-mix. This part considers different types of human resources with different experience levels such as senior nurses, assistant nurses, senior physicians (registrars), junior physicians (Senior House Officers, SHOs) and consultant physicians.
- Staff Behaviour component that models how the staff deals with workload stresses. This study has focused on the response of nurses to demand capacity imbalance and work pressures.
- Performance measures.

Medical teams tend to perceive the workload pressures when they notice a deviation between the planned work to be completed within a period and the actual work done in the same span of time. Under constant work stresses, the medical staff struggle to cope with the

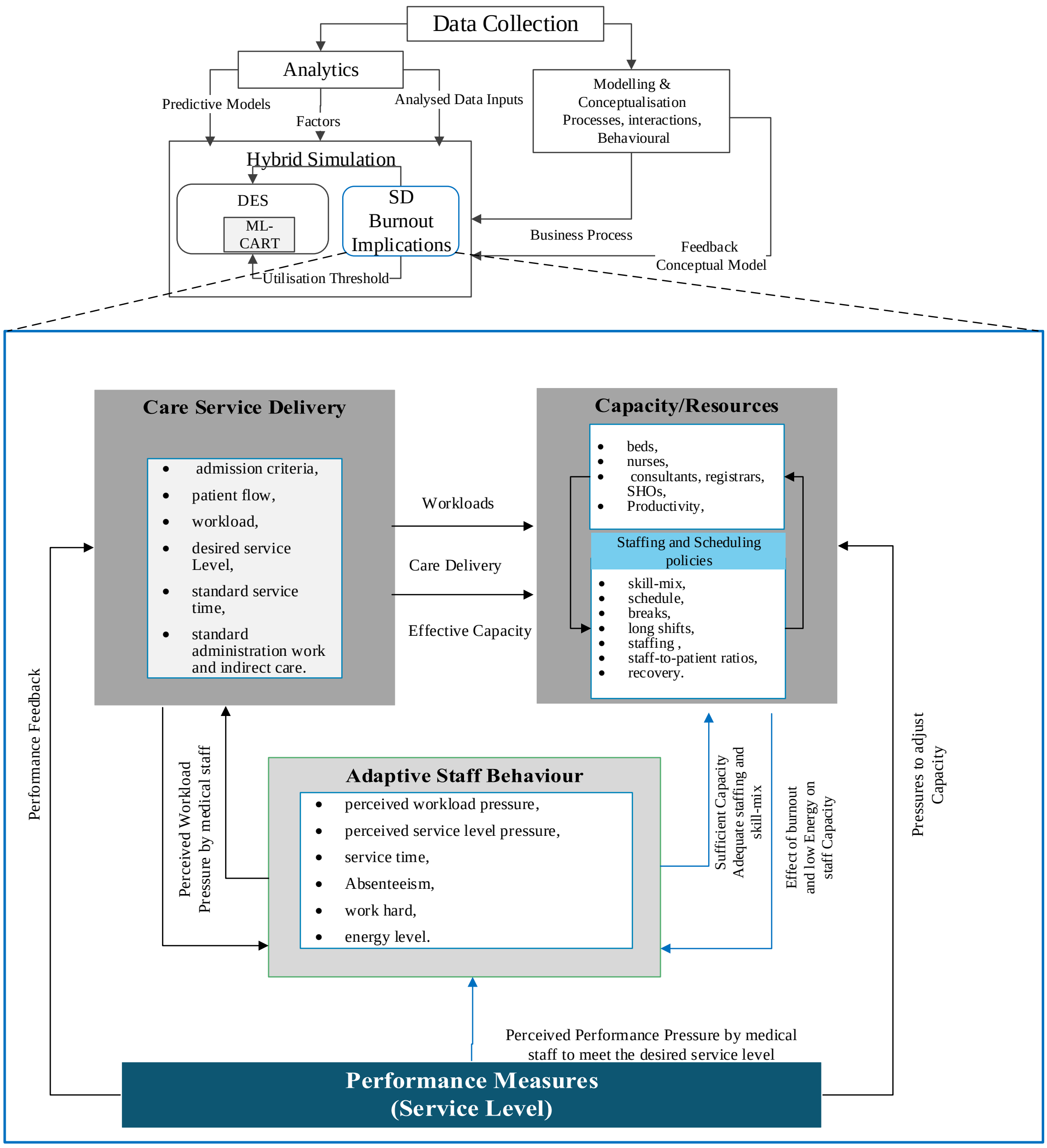


Fig. 5.10 Adaptive behaviour component.

increasing demand during their working hours while sustaining the anticipated quality of care. Staff satisfaction and quality of care are determined by how the staff adapted to respond to work pressures. Since workload stresses have direct consequences on quality of care and staff satisfaction, it becomes essential to understand the behaviour of staff when they work under these pressures that can easily lead to burnout. On one side, the imbalance in service capacity and demand eventually translate into difficulties.

Workload Pressures

In the literature of both behavioural and operations, the workload is often represented the number of tasks of a specific class (amount of work) over a certain period or the number of regular work hours assigned to a work group (Bendoly & Hur, 2007). Accordingly, staff performance is linked to an interval of time-work indicators such as average completion rates, daily output, or utilisation. In this study, the workload on nurses (W) at any particular moment of time is composed of the number of tasks for patients who are undergoing their treatment and also the patients who are currently waiting to be seen. The admitted patients stay in the unit until they are treated and discharged from the unit. Because hospitals often cite bed capacity as the key constraint that prevents the admission of new patients, so the bed capacity utilisations are strong drivers of admission and discharge decisions, and in turn, determine the length of stay. Therefore, the rate of admission (A) is mainly determined by the minimum between the available unit bed capacity-the difference between unit bed capacity (B) and occupied beds (W)-and patients waiting to be admitted to the unit (P),

$$A = \min\left(P, B - W\right) \tag{5.1}$$

Workload (W) is increased by the admission rate (A) and reduced by the discharge rate (D),

$$\frac{d}{dt}W = A - D \tag{5.2}$$

Mathematically, the discharge rate (D) is determined by the effective staff capacity (C_{eff}) divided by the treatment time per patient (T). In the care of overstaffing, it is constrained with the number of patients that can be treated from the workload divided by the treatment time per patient (T).

$$D = \min\left(\frac{C_{eff}}{T}, \frac{W}{T}\right) \tag{5.3}$$

Excessive workload is defined as the overwork beyond an expected amount of workload (e.g. the standard nurse-to-patient ratio)over a given period (Kc & Terwiesch, 2009). Quantitatively, the workload pressure proxy (W_p) can be represented as the ratio of the actual staff-to-patient ratio (N_A)-the ratio between the workload (W) and and the effective staff capacity (C_{eff})-and the standard nurse-to-patient ratio(N_S).

$$W_p = \frac{N_A}{N_S} = \left(\frac{W}{N_S \cdot C_{eff}}\right) \tag{5.4}$$

Workload pressure (W_p)value is less than one implies overstaffing while if it is greater than 1, this indicates that the unit is stretched, and stresses on nurses will take place. Since nurses have different psychological attributes, perceptions, and expectations, the workload pressure effect will strike after a delay in time subject to their agility. Extremely high workload pressure can prevent the unit from effective treatment of patients within a reasonable time given the unit nurse/doctors capacity, work hours, time allocated for patient treatment, and support received from other units such as laboratories and radiology. The perceived workload pressure (W_p^p) was modelled using first-order exponential smoothing over a time to perceive workload pressure (T_w),

$$W_p^p(t) = \frac{1}{T_w} \sum_{k=0}^{T_w-1} W_p(t-k) \tag{5.5}$$

An important component of this work is modelling the staff behavioural reactions to the recognition of an over extended workload and its impact on the patient experience. The model assumes that the length of stay can be used as a quantitative proxy for patient experience, which is consistent with related prior studies and the empirical findings. From now, this study will refer to patient experience time as the average length of stay in the unit. Following Little's Law (Little, 2011), the average patient's experience time (L) is the ratio between workload (W) and discharge rate (D).

$$L = \frac{W}{D} \tag{5.6}$$

On the other hand, the hospital managers are under pressure to maintain the target PET (L) by healthcare executives. This type of pressure is referred to as the desired service level pressure (L_p) that can be mathematically defined (Equation 7) by the ratio between the actual PET (L) and the desired PET (L^*). Similar to perceived workload pressure, the service level pressure (L_p^p) is formulated using unweighted first order moving average over a smoothing parameter (T_s)-time to perceive the desired service level pressure.

$$L_p = \frac{L}{L^*} \tag{5.7}$$

$$L_p^p = \frac{1}{T_s} \sum_{k=0}^{T_s-1} L_p(t-k) \tag{5.8}$$

The model assumes that all staff are homogeneous in their perception of both the workload and service level pressures.

Adaptive Behaviour of Staff

Nurses can respond to high perceived workload pressure by working hard and increasing work intensity(I). This response entails that they increase their efforts, concentration, engagement, and cutting short their number and duration of breaks. They can also work overtime to fill the demand. The mathematical formulation of the work intensity (I) is the normal (reference) work intensity (I)multiplied by the effect of the perceived work pressure on the intensity$(f_i(W_p^p))$.

$$I = I \cdot f_i(W_p^p); f_i(1) = 1, f_i^{'} \geq 0 \tag{5.9}$$

The work intensity is modelled as the normal work intensity I adjusted by a nonlinear function of the perceived work pressure. The reference policy $f_i(W_p^p) = 1$ means that work intensity never changes-no more effort than the normal is performed regardless the amount of work. The function $(f_i(W_p^p))$ is monotonic increasing with upward sloping that passes through the point $(1,1)$ and approach to equilibrium at a maximum work intensity $(I^{\max})$ when perceived work is high (Figure 5.11). The 45° line reference policy (i.e. the red line) policy reference is obtained by assuming the $f_i(W_p^p) = W_p^p$.

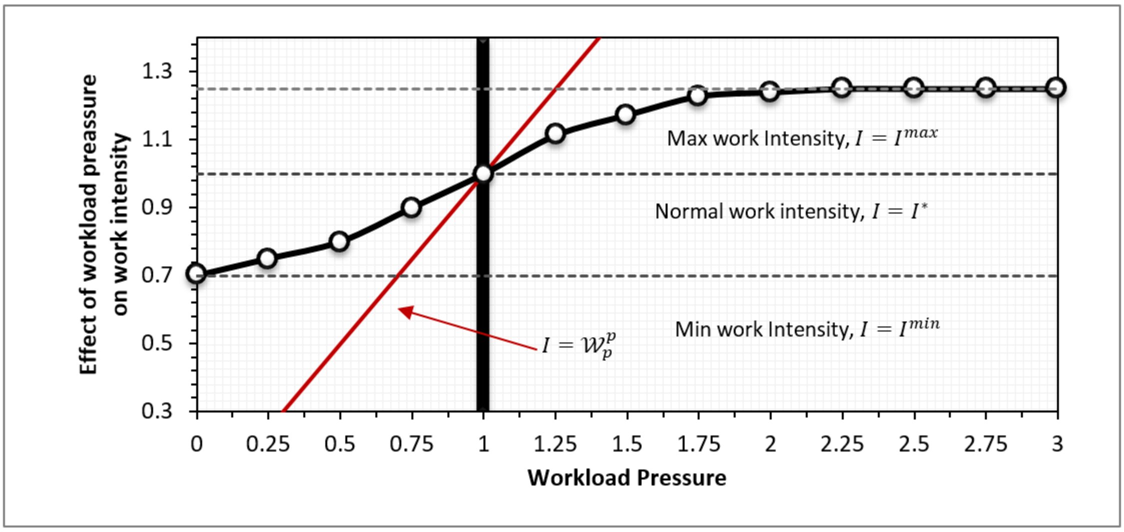


Fig. 5.11 The effect of perceived work pressure on the work intensity.

Also, adaptive staff behaviour can be extended to reduce the non-direct care (e.g. administration work) associated with the patients such as documentation work, data entry and writing reports that are an essential element in the process. Non-direct care the tasks performed away from the bedside (Myny et al., 2011). Nurses may have to cut off the time dedicated to doing administration work to free up some time as a reactive action to high workload pressure. This adaptive behaviour will impact the percentage of staff time that are allocated to perform administration and training tasks (i.e. proportion of admin work). Formally, the percentage of administration work (W_A) is a standard percentage of administration work (W_A) adjusted by the effect of the perceived workload pressure on the administration work $(f_A(W_p^p))$.

$$W_A = W_A \cdot f_A(W_p^p); f_A(1) = 1, f_A^{'} \leq 0 \tag{5.10}$$

The function $f_A(\cdot)$ is a monotonic decreasing function with downward sloping as given in Figure 5.12.The extreme reference policy (red curve) reveals that when the perceived workload pressure is less than one; the staff spend too long time in administration work and indirect care while it assumes too the staff take short time when the perceived workload is greater than one.

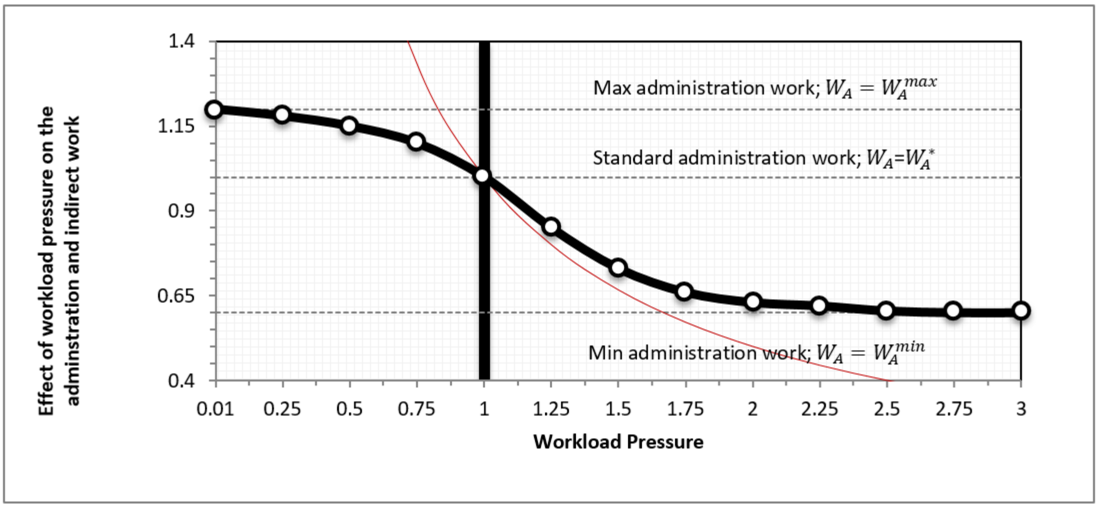


Fig. 5.12 The effect of the perceived work pressure on the percentage of administration work.

Increasing work intensity creates a balancing loop by adjusting the effective nurse capacity and, in turn, alleviates the workload pressures (balanced feedback loop B3 and B4). Working hard increases the discharge rate (productivity) of the patient's due to the rise in the effective nurse capacity, and this will contribute to the reduction of the workload pressures (balanced feedback loop B4). During the interview with the nurses in the hospital, they indicated that they often implement this practice, but flagged that they feel worn out quickly due to this.

The assumption of service time-time taken by a resource to care for a patient- is independent of the system status such fixing employee productivity over a period becomes invalid (Kc & Terwiesch, 2009). The adaptive behaviour of the staff, in particular at the peaks, towards the system state (e.g. current workload) has to be taken into account. Although there is a relative lack of empirical research that reports such behavioural aspects to the change in the work environment, there are some observations about the tendency of medical staff to adjust the service time due to high workload and medical errors created from staff due to some behaviour aspects.

Research reported that nurses sometimes tend to reduce time allocated to some activities to cope with the high demand imposed on them (Kalisch et al., 2009). Nurses can also react to high perceived workload pressures and desired PET by adjusting the time allocated per patient and reducing the care attention thereof (Kuntz & Solz, 2013). The allocated time per patient(T) is the standard time per activity per patient (T) adjusted by the effect of the perceived workload pressure in the allocated time $f_{tw}(W_p^p)$ and the effect of the perceived desired service level pressure$f_{tl}(L_p^p)$.

$$T = T \cdot f_{tw}(W_p^p) \cdot f_{tl}(L_p^p);\ f_{tw}(1) = 1, f_{tw}^{'} \leq 0, f_{tl}(1) = 1, f_{tl}^{'} \leq 0 \tag{5.11}$$

If it is assumed that the service time is independent of the system status-staff are insensitive to workload and desired time service pressures-the allocated service time is constant. In this case, $T = T$ where $f_{tw}(W_p^p)$ and $f_{tl}(L_p^p)$ are always unity. Figure 5.13 depicts the effect of perceived workload pressure on the service time $f_{tw}(W_p^p)$.

These adaptive staff behaviours have a direct impact on the nursing staff service capacity. The effective service capacity C_{eff} is determined by adjusting the number of on-duty nursing staff (C) by work intensity(I), percentage of the administration work(W_A) and effective productivity (U),

$$C^{eff} = C \cdot I \cdot U \cdot (1 - W_A) \tag{5.12}$$

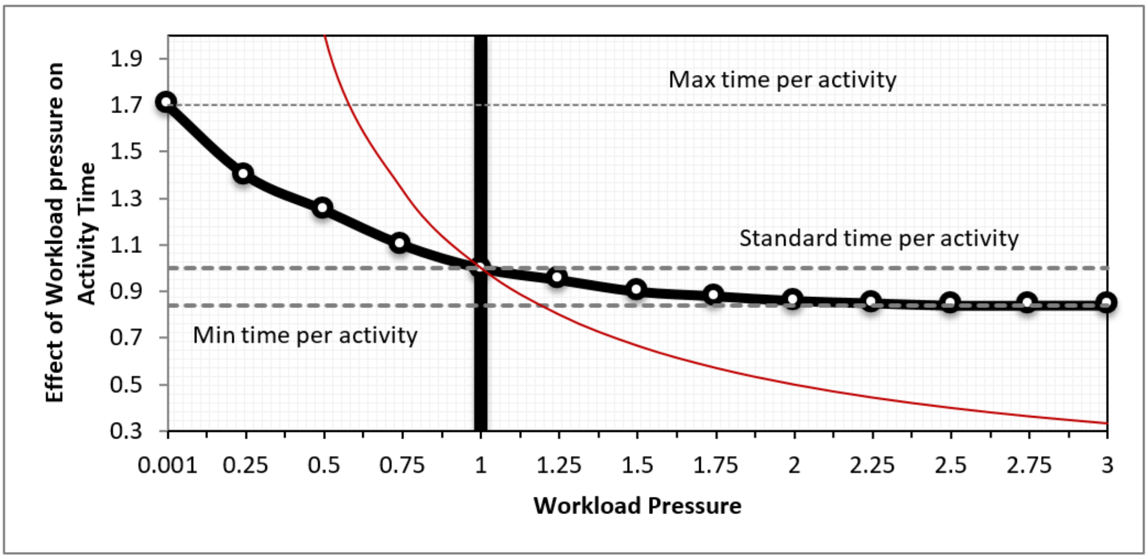


Fig. 5.13 the effect of workload pressure on service time.

Assuming the staff nursing (N) can be categorised into two classes: experienced (N_e) and junior (N_j) nursing staff such that $N = N_e + N_j$ and $N_e = N \cdot S$; where S is the skill-mix ratio (SMR). SMR (S) can take a value in$[0,1]$, where zero means that all staff nurses in a shift are not experienced, and one means that they are all the senior experienced team. Effective number of nursing staff planned to work (C^p) is the sum of the experienced nurses (N_e) and junior nurses (N_j) adjusted by the junior nurse productivity fraction(u),

$$C^p = N_e + N_j \cdot u; N_e = N \cdot S \tag{5.13}$$

Considering the standard productivity of the experienced staff is 1, the junior nurse productivity fraction (u) is a value in $]0,1[$ that reflect the relative productivity of the inexperienced staff compared to experience one.

The number of on-duty nursing staff is determined the effective number of nursing staff who are planned to work (C^p) adjusted by absenteeism likelihood P_a and number of recovered from absenteeismR_a.

$$C = C^p \cdot (1 - P_a) + R_a C = C^p \cdot (1 - P_a) + \frac{C^p \cdot P_a}{d_a} \tag{5.14}$$

The impact of unplanned staff absenteeism continues for a while (time delay; d_a) until the nurse manager can find a replacement. The effective productivity (U) is adjusting the standard nurse productivity (U) by the effect of energy level on the productivity $f_{ep}(e)$-the relationship is depicted in Figure 5.14.

The energy level is given by equation .

$$U = U \cdot f_{ep}(e); f_{ep}(0) = 0, f_{ep}(1) = 1, f_{ep}^{'} \geq 0 \tag{5.15}$$

This clearly has undesired consequences on managing the caring capacity and quality of caring. The adaptive behaviour of staff to the high workload by working faster may be unnecessary to increase the capacity at the peak time where the management will depend on the ability of staff to accelerate the work rate temporarily. Reducing the treatment time per patient effectively speeds up the discharge rate which decreases workload and eventually reduces the workload pressures (loop B2 and B5). Similarly, reducing the administration work increases the effective nurse capacity, thus ultimately mitigates the pressure (loop B6). This reaction creates two balancing feedback mechanisms that limit both workload pressure and desired PET pressure.

Implications

Despite reducing the time that highly skilled and expensive staff spend doing secondary activities is desirable decreasing the time devoted to ancillary activities might have unanticipated yet significant clinical and financial consequences (Powell, Savin, & Savva, 2012). In the short run, such adaptive behaviour may appear desirable, but it has substantial staff's adverse

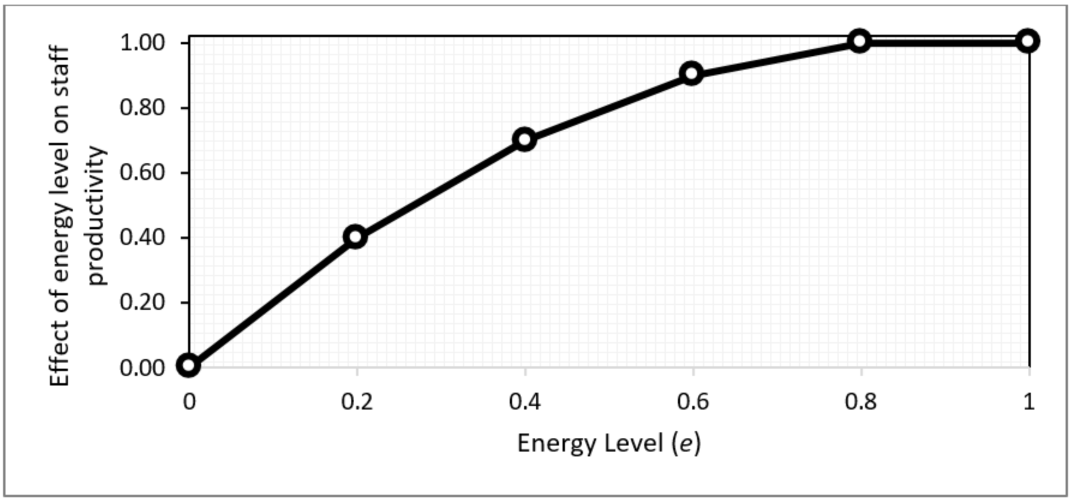


Fig. 5.14 the effect of energy level on the staff productivity.

outcomes (e.g. stress, burnout and job dissatisfaction) and adverse patients' outcomes (e.g. quality of care and patient's safety). This could lead to a total net decline in performance. Decision makers should thus take into consideration the full set of possible implications of a temporary increase in service rates (Kc & Terwiesch, 2009).

In the occupational health literature, job strain stems from the imbalance between the demands on workers and the resources they have (e.g. human resources). For instance, the demand-control model assumes that job strain is a result of high demand (over workload and time pressure) and when resources are lacking (job control) (Karasek, Jr, Karasek, & Jr, 1979; Karasek, 1998). Accordingly, Healthcare staff who are under constant stream of severe occupational stressors such as time pressure, high workload, and uncertain patients acuity are vulnerable to experiencing severe burnout, both mental and concentration, and little motivation is among the consequences of fatigue (Blachowicz & Letizia, 2006; Stimpfel, Sloane, & Aiken, 2012). Burnout results from a combination of factors including prolonged job pressure on workers, stress due to demand fluctuations, shortage of experienced staff, and work environment. Needless to say, that staff burnout is one of the main factors that deteriorate the organisational morale and equally the productivity rate (Homer, 1985). It can be argued that fatigue and burnout deteriorate the PET because the decision maker could take a longer time to take a decision and/or fatigued employee is more likely to make medical errors that entail more time to be fixed.

The long run of increasing the productivity is not sustainable. Sustained working close to full utilisation to fulfil the excess workload with minimal cost leads to substantial implications and ultimately reduces the productivity and may increase the operating costs. In addition to the quality considerations that result from these adaptive behaviours.

Formally, the energy level (e) of the staff is represented by stock variables that accumulate the difference between the recovered (e_r) and drained energy(e_d),

$$\frac{d}{dt}e = e_r - e_d. \tag{5.16}$$

The nurses' burnout process begins when the staff attempts to fulfil the high workload by working intensively and for long hours which increases the stress exposure, in turn, draining their energy. Therefore, draining the nurses' energy level reduces the nurses' productivity, thus reducing the effective nurse capacity and increasing the pressure. In turn, it depletes their energy further and increasing the opportunity of nurses' burnout to happen. The unintended consequences create a reinforcement feedback loop (R1). Growing the staff fatigue (depleted energy) increases the exposure to constant work stress, and the energy drained more rapidly creating a reinforcement loop R2 (frustration-exhaustion). Unlike with high energy levels, which enhance individual morale and satisfaction. This in turn assists in recovery much sooner from temporary fatigue (loop R3) resulting from burnout. The failure to fulfil the desired goal (desired PET) is an additional stressor that creates pressure from the management that pushes staff to works hard to achieve the service level and, in turn, undermines the energy.

Recovery from burnout can be achieved by reducing workload and fewer management expectations, which supports staff. Also, shift breaks and days off helps to recover the energy decay during the day and the week. Without adequate breaks to recuperate, the energy will deplete faster. However, when the unit is under work stress, the nurses may not take appropriate breaks during their duty hours, or they cannot find the staff coverage at the break time. Thus, the inadequacy of shifts breaks delay the fatigue recovery and increases the exhaustion. This behaviour creates a reinforcement mechanism loop (R4). Another implication of burnout is the likelihood of random absenteeism is associated with low energy level. High workloads due to irregularities in scheduling, unpredictable demand and adverse working conditions have a direct impact on the absenteeism behaviour (Linda V Green et al., 2013). Increasing the absenteeism reduces the number of staff nurses available to work, thus reducing the effective productivity, which in turn raises the workload pressure and eventually the fatigue. Reinforcement loop R5 depicts this unintended implication. The impact of unplanned staff absenteeism continues temporarily (time delay) until the nurse manager can find a replacement.

5.5 Phase 3: Optimisation

5.5.1 Stage 1: Temporal Staffing Optimiser

Simulation components in phase two allow one to test a variety of scenarios and explore the implications of influential factors either controllable or uncontrollable. As described in phase 2, the simulation model incorporates the main factors that impact the staffing decisions and should be reflected in the optimisation stage. Therefore, the simulation (DES) acts as the system performance evaluator for the decisions.

The aim of the staffing optimiser is to find the (near) optimal staffing patterns (b_{st}) . This requires solving a simulation optimisation problem that considers multiple objectives including minimising the expected waiting time and patient length of stay (LOS) and balancing staff utilisation. The list of notations used is show in Table 5.1. The general mathematical formulation of this problem is:

Table 5.1 Notations for staffing problem.

Symbol:	**Description**
S	The set of staff types, $S = Nurse, ANP, SHO, \dots$.
T	A set of time blocks$T = 1, 2, \dots$, where the day is divided into equal sized time intervals (e.g. 4-hours or 1-hour each).
R^+	Set of integer values.
I	A set of stochastic objectives, $I = 1, 2, \dots |I|$.
J	A set of stochastic constraints, $J = 1, 2, \dots |J|$.
K	A set of deterministic constraints, $K = 1, 2, \dots |K|$.
t	Time block; $t \in T$.
s	Staff type, $s \in S$.
n_{1j}	The lower bound of stochastic constrain t_j .
n_{2j}	The upper bound of stochastic constraint j .
m_{1k}	The lower bound of deterministic constraint k .
m_{2k}	The upper bound of stochastic constraint k .
l_{st}	The minimum number of staff of type s at time block t.
u_{st}	The maximum number of staff of type s at time block t.
b_{st}	The required number of staff type s at time block t .

$$\min_{b_{st} \in R^+} f_i(b_{st})$$

(P.1)

$$\text{s.t.} \quad g_j(b_{st}) \geq n_{1j} \qquad \forall j \in J \tag{5.17}$$

$$g_j(b_{st}) \leq n_{2j} \qquad \forall j \in J \tag{5.18}$$

$$h_k(b_{st}) \geq m_{1k} \qquad \forall k \in K \tag{5.19}$$

$$h_k(b_{st}) \leq n_{2k} \qquad \forall k \in K \tag{5.20}$$

$$b_{st} \geq l_{st} \qquad \forall s \in S, t \in T, b_{st} \in V \tag{5.21}$$

$$b_{st} \leq u_{st} \qquad \forall s \in S, t \in T, b_{st} \in R^+ \tag{5.22}$$

Where, b_{st} is the number of staff type s required at time block t , $f_i(b_{st})$ is a stochastic performance function i , and $g_j(b_{st})$ is a stochastic constraint j with lower bound n_{1j} and upper bound n_{2j} . Both f and g are evaluated using the simulation. l_{st} and u_{st} are lower and upper bounds for the b_{st}.

Other criteria or constraints can be added. This problem is a nonlinear discrete simulation optimisation problem which makes the most appropriate optimisation method to be metaheuristics (as discussed in chapter 2) or by a state of the art simulation optimisation solver. The problem can be reformulated into a single objective problem using the desirability multi-criteria approach.

5.5.2 Multiple-criteria based Desirability Approach

The desirability function approach was introduced by Harrington (1980) to optimise multiple simultaneous objectives by transforming the estimated objective $y_i(x)$ into a unified scale ($[0,1]$) called a desirability index which denoted by d_i , i.e. $d_i(y_i)$. The alternative solution is ultimately desirable (i.e. ideal objective value) when $d_i(y_i) = 1$, where $d_i(y_i) = 0$ for an undesirable solution. Desirability function overcomes the difficulties of combining several objectives and balances the optimisation of multiple criteria by enabling flexible weighting for each objective (Costa et al. 2011). This approach allocates an overall desirability index to a set of objectives and selects the decision variables settings such that the overall desirability function is maximised.

Suppose that there are p criteria to be optimised simultaneously denoted by a vector of objective functions $y = (y_1, y_2, \ldots, y_p)$, which depend on n decision variables $x = (x_1, x_2, \ldots, x_n)$. The decision maker selects these criteria. Due to the complexity of real-world healthcare applications, the analytic representations that relate y and x in a closed form do not exist. In this case, simulation models or surrogate models (possibly p different models) are used to obtain p predicted responses (mean) $y = (y_1, y_2, \ldots, y_p)$. The individual desirability d_i

for each of the p equations is calculated, which is high when the levels of response y_i are desirable and low when the level of y_i is undesirable. The desirability approach requires three steps (Figure 5.15):

1. predicting the response vector y for input vector x ,
2. transform the predicted responses into individual desirability vector d, and
3. combine them into an overall desirability D .

The global desirability (D) of a solution that combines all the individual desirability values $y_i(x)$ can be obtained using a weighted geometric mean (Derringer, 1994) who proposed a weighted geometric mean which is given by $D = \prod_i^p d_1(y_1)$.

(Overall Desirability)

$$\begin{aligned} D(d_1(y_1), d_2(y_2), \ldots, d_p(y_p)) &= (\prod_{i=1}^{p} (d_i(y_i))^{w_i})^{\frac{1}{\sum w_i}} \\ &= \exp(\frac{1}{\sum w_i}(\sum_{i=1}^{p} w_i \ln(d_i(y_i)))) \end{aligned} \quad (5.23)$$

Where w_i is the relative weight of objective y_i among the other objectives such that $0 < w_i < 1$. The weights reflect the decision maker preferences that can be obtained using the Analytical Hierarchical Process (AHP) technique. Clearly, D satisfies $0 \leq D \leq 1$. The larger value of D, the more desirable solution.

The desirability function has three forms depending on the optimisation criteria selected and their acceptable limits given by $(U_i - L_i\ )$, where L_i and U_i are the lower and upper acceptable limit of objective $y_i$respectively. The choices of L_i and $U_i$are depends on the nature of the criterion. Three forms of the desirability transformation depending on the nature of the criterion: the smaller-the-best (STB), larger-the-best (LTB), and nominal-the-best (NTB) for minimisation, maximisation, and attained target value, respectively. STB seeks to have

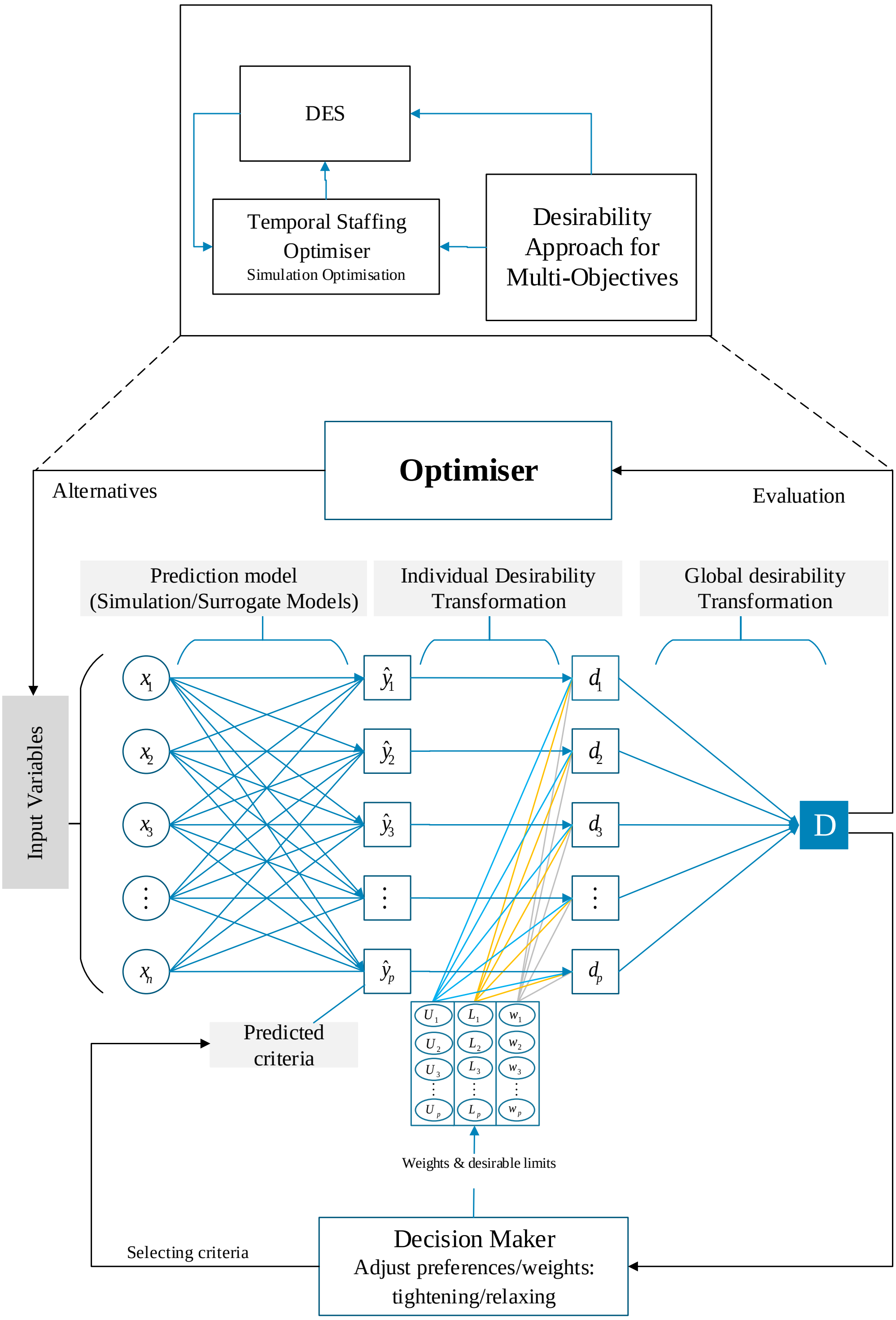


Fig. 5.15 Desirability approach for multi-objectives optimisation.

smaller objective value as possible, which can be described by the following equation:

$$d_i^{\min}(y_i(x)) = \begin{cases} 0 & if y_i(x) > U_i \\ \left(\frac{y_i(x)-L_i}{U_i-L_i}\right)^a & if L_i \leq y_i(x) \leq U_i \\ 1 & if y_i(x) < L_i \end{cases} \quad (5.24)$$

where a is the shape parameter $(a > 0)$of the desirability function $d_i(y_i)$. The function shape is linear if $a = 1$, convex if $a > 1$, and concave when $a < 1$ (Figure 5.16a). Similarly for maximisation criterion, LBT type can be defined by the following equation:

$$d_i^{\min}(y_i(x)) = \begin{cases} 1 & if y_i(x) > U_i \\ \left(\frac{U_i(x)-y_i(x)}{U_i-L_i}\right)^a & if L_i \leq y_i(x) \leq U_i \\ 0 & if y_i(x) < L_i \end{cases} \quad (5.25)$$

where b is a shape parameter (Figure 5.16b). Finally, when there is a target value T_i that is the most desirable, NTB type transformation can be represented by:

$$d_i^{target}(y_i(x)) = \begin{cases} 0 & if y_i(x) < L_i \\ \left(\frac{y_i(x)-L_i}{U_i-L_i}\right)^a & if L_i \leq y_i(x) < T_i \\ 1 & if y_i(x) = T_i \\ \left(\frac{U_i-y_i(x)}{U_i-L_i}\right)^b & if T_i < y_i(x) \leq U_i \\ 0 & if y_i(x) > U_i \end{cases} \quad (5.26)$$

A graphical representation of desirability transformation from the different optimisation criteria under various shape parameters a and b is given in Figure 5.16. The shape parameters are chosen such that the desirability function is easier or difficult to achieve. Smaller values for the parameters make easy to reach a satisfactory desirability levels, while choices larger values of and b cause the desirability curve slow and difficulty to obtain satisfactory levels. Shape parameters, lower and upper bounds, and target value are chosen by the modeller with

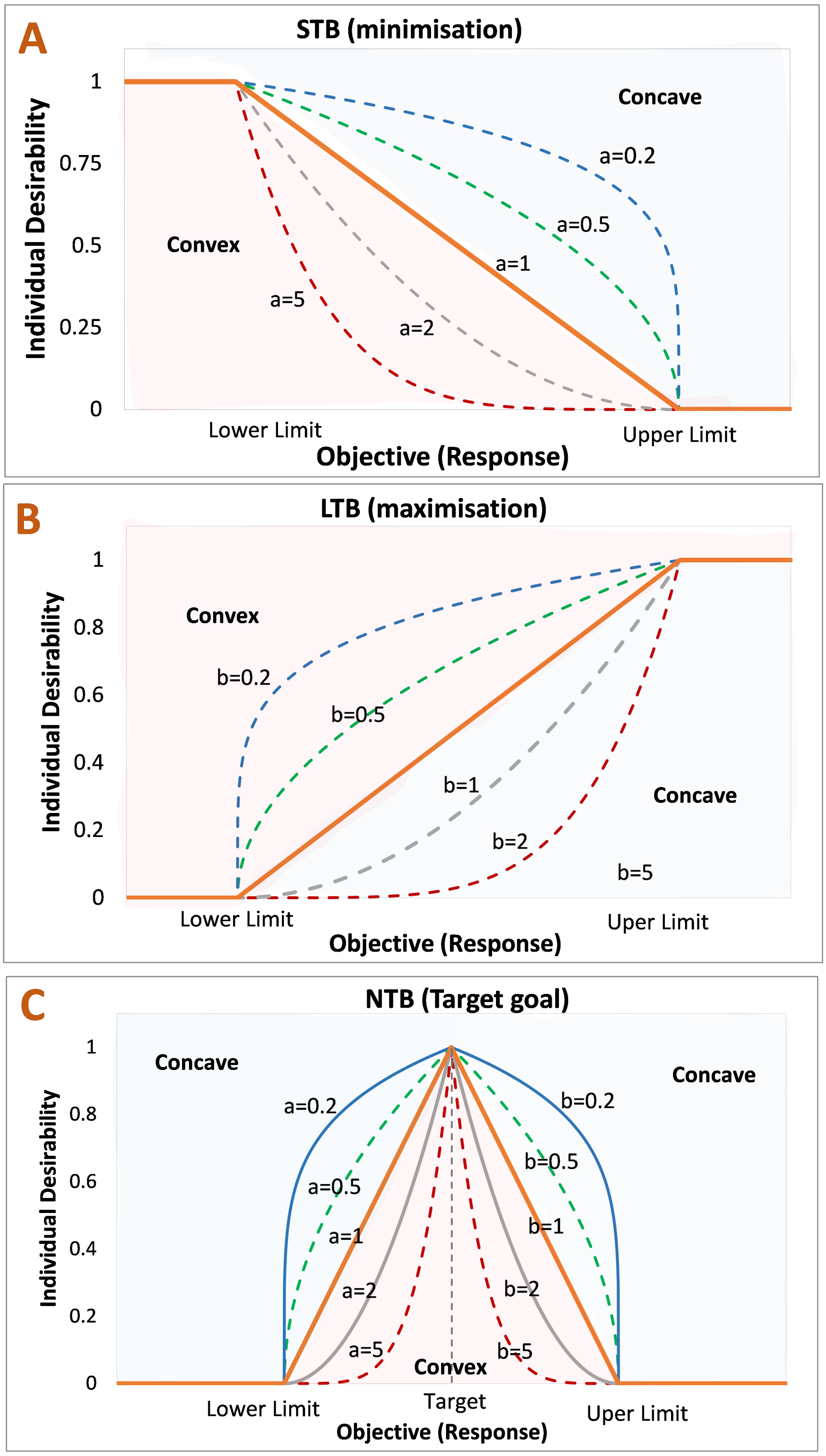


Fig. 5.16 Forms of Individual desirability function.

coordination with the decision maker based on the problem context. The adjustment of a preference parameter is conducted by tightening or relaxation in iterative/interactive mode.

5.5.3 Stage 2: Shift Schedule Optimiser

The staffing Optimiser feeds optimal temporal staffing requirements, as well as shift patterns into the shift schedule optimiser to determine the shift schedule scheme for each resource type. The decision variables in this model are to determine the number of staff resources that start at a specific shift subject to the staffing requirements obtained from the staffing optimiser (Figure 5.17). This problem is a bi-criteria optimisation problem that aims to minimise the understaffing and overstaffing. This formulation is similar to the shift staggered formulation presented by (Sinreich et al. 2012).

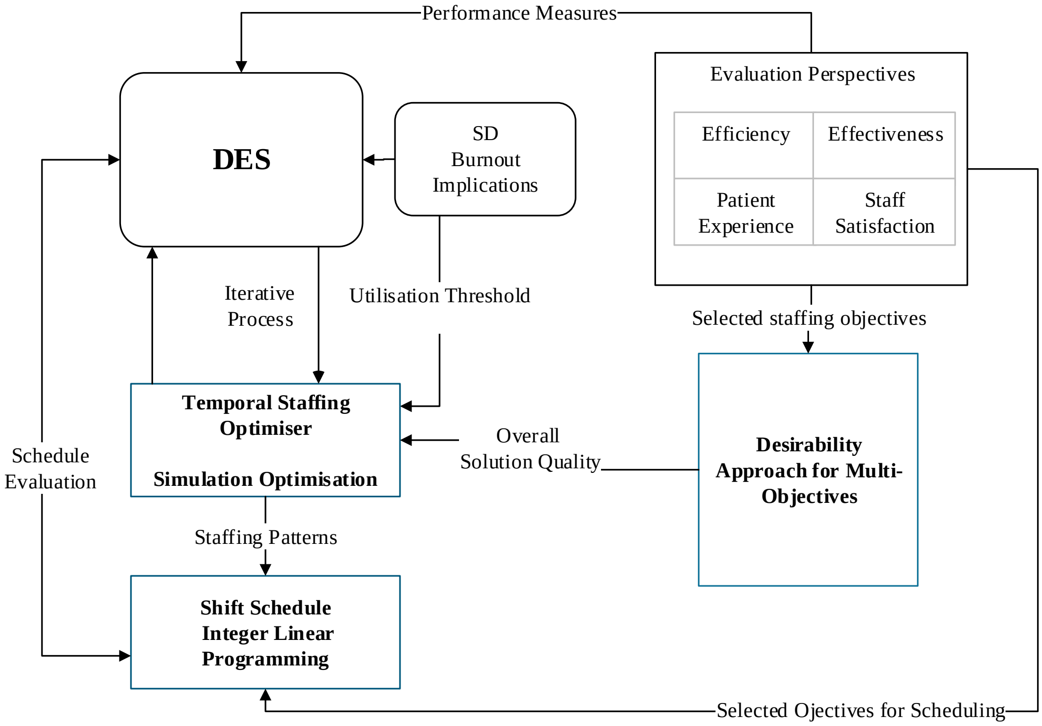


Fig. 5.17 Optimisation phase and the interaction with phase 2.

Table 5.2 Notations for shift scheduling formulation.

Symbols	**Description**
S	The set of staff types, $S = Nurse, ANP, SHO, \ldots$
T	A set of time blocks $T = 1, 2, \ldots$, where the day is divided into equal sized time intervals (e.g. 4-hours or 1-hour each).
R^+	set of positive integer numbers.
M	A set of fixed available shifts
t	Time block; $t \in T$.
s	Staff type, $s \in S$.
m	Shift m, m $\in M$.
b_{st}	The required number of staff type s at time block t .
l_{st}	The minimum number of staff of type s at time block t.
u_{st}	The maximum number of staff of type s at time block t.
x_{sm}	Number of staff of type s that work at shift m.
y_{st}	Number of staff of type s allocated to time block t.
O_{st}	The overstaffing of staff type s at time block t.
U_{st}	The understaffing of staff type s at time block t.
β	Penalty coefficient for being understaffed.
α	Penalty coefficient for being overstaffed.
a_{tm}	$= \begin{cases} 1 & \text{if the time block } t \text{ is covered in shift m.} \\ 0 & \text{Otherwise.} \end{cases}$

Formulation1: shift schedule model (fixed start)

The first formulation uses fixed shifts regarding start time and length to meet the staffing requirements. The list of notation used for formulating the shift schedule model is given in Table 5.2. Accordingly, the problem can be formulated as:

$$\min_{x_{sm} \in R^{+}} \sum_{t} \beta \cdot U_{st} + \sum_{t} \alpha \cdot O_{st}$$

(P.2)

$$\text{s.t.} \quad y_{st} = \sum_{m \in M} a_{tm} \cdot x_{sm} \qquad \forall s \in S, t \in T \tag{5.27}$$

$$y_{st} \geq l_{st} \qquad \forall s \in S, t \in T \tag{5.28}$$

$$y_{st} \leq u_{st} \qquad \forall s \in S, t \in T \tag{5.29}$$

$$U_{st} = \max\{(b_{st} - y_{st}), 0\} \qquad \forall s \in S, t \in T \tag{5.30}$$

$$O_{st} = \max\{(y_{st} - b_{st}), 0\} \qquad \forall s \in S, t \in T \tag{5.31}$$

$$x_{sm} \geq 0 \qquad \forall s \in S, t \in T, x_{sm} \in R^{+} \tag{5.32}$$

The objective function minimises the total penalised understaffing and overstaffing across all time blocks t . Constraint 5-8 describes the number of staff of type s that work at time block t. Constraint 5-9 and 5-10 preserves the minimum and a maximum number of staff of type s that work at time block t. Constraints 5-11 and 5-12 calculate the amount of understaffing and overstaffing, respectively. Finally, 5-13 is the non-negativity constraint and integrity constraint.

However, this model is a nonlinear model due to constraints 5-5 and 5-6. Understaffing and overstaffing are mutually exclusive. Therefore, the model can be linearised by combining constraints 5-5 and 5-6 in one constraint and make U_{st} and O_{st} decision variables instead of auxiliary variables. The resulting linear model is:

To allow shift flexibility, the definition of the matrices (a_{tmk}) is modified where each shift of a length m has (a_{tm}) matrix. A sample of this matrix for 12-hour shift is given in 5.18.

$$
\mathbf{A} = \begin{array}{r c}
 & \begin{array}{cccccccccccccccccccccccc} \mathbf{1} & \mathbf{2} & \mathbf{3} & \mathbf{4} & \mathbf{5} & \mathbf{6} & \mathbf{7} & \mathbf{8} & \mathbf{9} & \mathbf{10} & \mathbf{11} & \mathbf{12} & \mathbf{13} & \mathbf{14} & \mathbf{15} & \mathbf{16} & \mathbf{17} & \mathbf{18} & \mathbf{19} & \mathbf{20} & \mathbf{21} & \mathbf{22} & \mathbf{23} & \mathbf{24} \end{array} \\
\begin{array}{r} \mathbf{1} \\ \mathbf{2} \\ \mathbf{3} \\ \mathbf{4} \\ \mathbf{5} \\ \mathbf{6} \\ \mathbf{7} \\ \mathbf{8} \\ \mathbf{9} \\ \mathbf{10} \\ \mathbf{11} \\ \mathbf{12} \\ \mathbf{13} \\ \mathbf{14} \\ \mathbf{15} \\ \mathbf{16} \\ \mathbf{17} \\ \mathbf{18} \\ \mathbf{19} \\ \mathbf{20} \\ \mathbf{21} \\ \mathbf{22} \\ \mathbf{23} \\ \mathbf{24} \end{array} &
\begin{bmatrix}
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1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \\
1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1
\end{bmatrix}
\end{array}
$$

Fig. 5.18 12-hour shift coverage matrix for time block equals 1-hour.

Formulation2: shift schedule model (fixed start)

The linear version of the formulation one is given as:

$$\min_{x_{sm} \in R^+} \sum_t \beta \cdot U_{st} + \sum_t \alpha \cdot O_{st}$$

$$
\text{(P.3)} \quad \begin{array}{lrll}
\text{s.t.} & y_{st} = \sum_{m \in M} a_{tm} \cdot x_{sm} & \forall s \in S, t \in T & (5.33) \\
& y_{st} \geq l_{st} & \forall s \in S, t \in T & (5.34) \\
& y_{st} \leq u_{st} & \forall s \in S, t \in T & (5.35) \\
& O_{st} - U_{st} = y_{st} - b_{st} & \forall s \in S, t \in T & (5.36) \\
& x_{sm}, O_{st}, U_{st} \geq 0 & \forall s \in S, t \in T, x_{sm} \in R^+ & (5.37)
\end{array}
$$

This model uses an mixed linear programming model MIP. A Branch and Bound (B&B) algorithm is a candidate to solve the linear relaxation of this problem. Also, the model can be solved for each staff type separately. Formulation 1 and 2 assume that a set of shifts is given as an input with fixed start times. Previous formulations can be modified to allow the model to select the shifts start times and the number of staff assigned to each to match the fluctuated demand. This adds more flexibility for addressing the shifted demand using different shift lengths and flexible start times.

Formulation 3: shift schedule (flexible start)

This formulation requires some modifications in some of the model notations used in the first formulation which can be described in Table 5.3.The flexible shift scheduling problem can be formulated as following:

Table 5.3 Modified notations.

Symbols	
M	A set of different shift lengths. e.g. 12-hour, 11-hour, 8-hour
m	Shift Shift of length m , $m \in M$
P_{ms}	A set of prohibited start times for a shift of length m assigned to staff types, $P_{ms} \in T$.
x_{smk}	Number of staff of type s that starts their working shift of length m at time block k.
a_{tmk}	$= \begin{cases} 1 & \text{if the time block } t \text{ is covered in shift of length m that starts at } k \\ 0 & \text{Otherwise.} \end{cases}$

$$\min_{x_{smk},O_{st},U_{st}\in R^{+}} \sum_{t} \beta \cdot U_{st} + \sum_{t} \alpha \cdot O_{st}$$

$$\text{s.t.} \quad y_{st} = \sum_{k\in P_{ms}} a_{tmk} \cdot x_{smk} \quad \forall s\in S, t\in T \tag{5.38}$$

$$y_{st} \geq l_{st} \quad \forall s\in S, t\in T \tag{5.39}$$

$$\text{(P.4)} \quad y_{st} \leq u_{st} \quad \forall s\in S, t\in T \tag{5.40}$$

$$O_{st} - U_{st} = y_{st} - b_{st} \quad \forall s\in S, t\in T \tag{5.41}$$

$$x_{smk}, O_{st}, U_{st} \geq 0 \quad \forall s\in S, t\in T, k\in K, and x_{smk}\in R^{+} \tag{5.42}$$

5.5.4 Conclusion

This chapter presents a framework for addressing operational modelling of hospital medical staff. The framework incorporates three integrated phases. Demand for care phase attempts to understand the patients demand using analytics and machine learning. Phase two is a detailed DES simulation model to capture the uncertainty, complexity of hospital system to understand the dynamics of patient flow that creates staff workload. SD model aims to evaluate the implications of staff burnout and the adapted staff adaptive behaviour. The optimisation phase attempts to find the optimal staffing requirement and solve shift schedule problem.

Chapter 6

Framework Validation: case study

> The true method of knowledge is experiment.
>
> *William Blake (1757–1827)*

6.1 Introduction

The objective of this chapter is to evaluate the usefulness of the proposed framework to be used as a foundation for addressing the staffing and shift scheduling in a hospital context. Chapter 5 has discussed the conceptual framework and its phases. Validating and evaluating the potential managerial benefits of the proposed framework is undertaken through a case study in a real-life hospital. A typical case study in a hospital partner is selected to implement the proposed framework in the Emergency Department and Acute Medical Assessment Unit (AMAU).

6.2 Study Setting

6.2.1 The Emergency Department (ED)

The rapidly increasing costs along with the growing demands on emergency departments (EDs) have put the health care decision makers under constant pressure to manage and control their system more efficiently. Overcrowding in EDs tends to be a significant international crisis that negatively affects patient safety, quality of care, and patient satisfaction.

ED overcrowding has been declared a "National Emergency" in Ireland since 2006. In 2015, emergency presentations were up by 15,170 patients, and the proportion of those who were admitted is 35% (HSE, 2015b)Additionally, prolonged waiting times have been reported with more than 100 patients on trolleys for hospital admission every day; with 23% of patients waiting more than 24 hours (HSE, 2015b). Although Ireland is not alone in experiencing this kind of figures (Bond et al., 2007; Forero et al., 2010; Schafermeyer & Asplin, 2003), it is important not to underestimate the probable catastrophic consequences this situation has on patients, staff, and healthcare sector across the state.

Tallaght Hospital has the largest Emergency Department nationally that operates 24 hours a day, seven days a week throughout the year (continuous healthcare service). In 2012, Emergency Department (ED) served for 41,781 adult unscheduled patients (Tallaght Hospital Annual Report 2015). This number has increased by 9% in 2015 and still growing (Figure 6.1) with a sustained growth has been seen in the over 65 years age group which is +41% over the last six years. This age group has an associated higher acuity, the likelihood of admission, longer length of stay and a higher incidence of both Influenza and Noro-virus, resulting in a considerable number of bed days lost due to isolation requirements.

The department has officially, 31 monitored trolley spaces; 5 of these trolley spaces (resuscitation area) are reserved for major trauma and critical care patients. The remaining areas are divided into two zones: Majors Zone with a capacity of 18 trolley spaces, and

Minors Zone with eight trolley spaces. The ED also provides two triage rooms. Five distinct areas can be identified: a waiting room for walk-in patients waiting for triage, a diagnostics area (e.g. X-Ray), an ED resuscitation area, an ED major assessment area, and an ED minor assessment area.

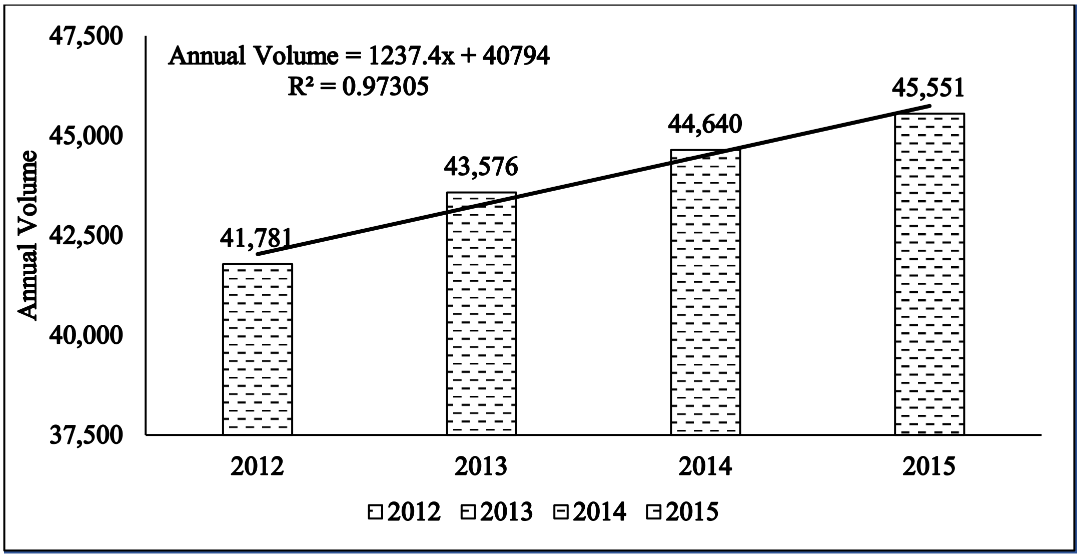


Fig. 6.1 The growth of patient attendances.

In Tallaght hospital, the staff faces several challenges to maintain a safe, dignified, and high-quality of healthcare service considering the pressures of delivering a range of demand-led services to its catchment area. Management struggles to set the adequate staffing to meet the sustained increasing demand to maintain the waiting time in acceptable margins. These pressures are significant in the nursing and medical discipline, where both national and international competitive factors produced inadequate resource levels. Tallaght Hospital is not immune to the national shortage of nursing and clinical staff, and they are suffering from a significant shortage of nursing staff. They are seeking to take a proactive approach to nursing recruitment (including overseas) and equally important to focus on retaining their highly skilled staff.

6.2.2 The Acute Medical Assessment Unit (AMAU)

The National Acute Medicine Programme (AMP) is an initiative to alleviate the pressure from EDs to minimise the length of stay, improve efficiency, and reduce overcrowding (HSE, 2010). AMP aims to provide medical patients presenting to the ED with a fast track to hospital services. The AMP recommends that in the Irish context, acute medical presentations to hospitals are best managed in dedicated medical units, staffed by physicians and a dedicated multidisciplinary team, these units are called acute medical units (AMUs).

The benefits of AMUs are derived from the efficient streaming of medical patients to a location where they can be seen without delay by a senior medical doctor. If admission is required, this will occur within a defined period, and the patient will be admitted to the most appropriate clinical area in the hospital. Patients will have access to these units based on their acuity level and other criteria that should be set by each hospital. AMUs are usually divided into two sub-units: acute medical assessment unit (AMAU) and short stay unit (SSU). AMAU acts as the first gateway for acute medical patients referred from the ED, while the SSU is used by patients who need to be admitted to the hospital but their estimated length of stay is below a certain threshold. Patients can also be admitted directly to hospital clinical wards from AMAU (Figure 6.2).

Recently, Tallaght hospital opened both AMAU and SSU. The AMAU as a discontinuous healthcare service that works as a 12 hours unit; it opens from 9:00 - 21:00, but only accepts patients till 18:00 to allow beds to be released for the next day. The SSU works as a short stay ward, on a 24/7 basis, for acute medical patients who need to be admitted to the hospital, and whose length of stay is estimated to be less than five days. In Tallaght hospital, the only access to the AMAU is through the ED after patients are being triaged and assigned a triage category, the triage nurse contacts the AMAU consultant or registrar so that they can accept or reject the case. Patients routed to the AMAU are those medical patients triaged as category 2 or 3, and wouldn't need any resuscitation or isolation facilities, they are only moved to the

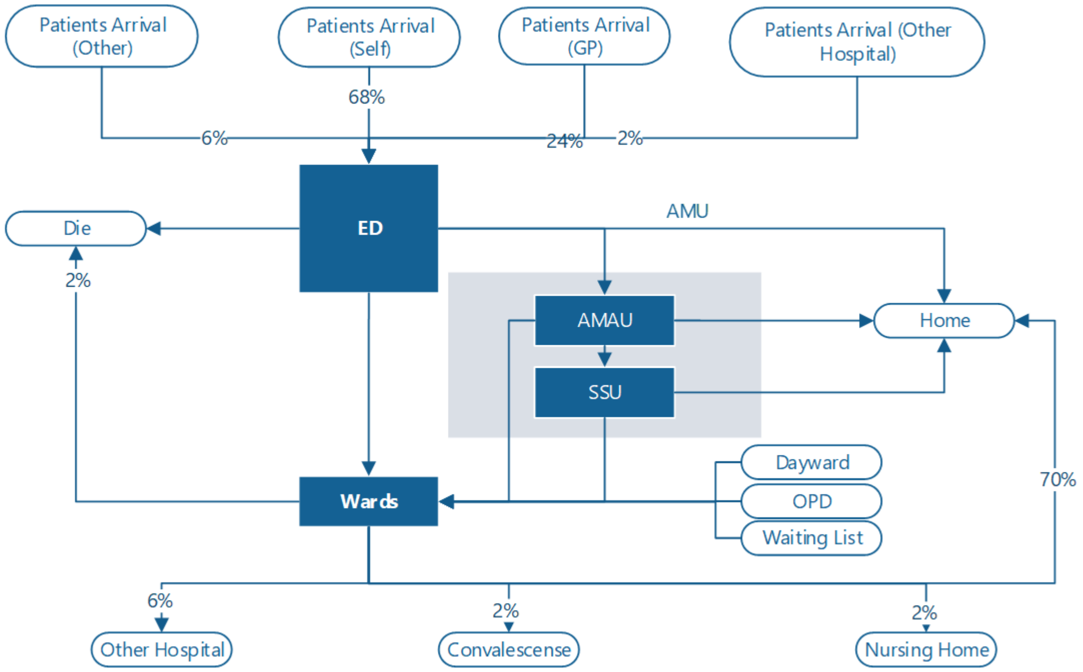


Fig. 6.2 A generic patient pathways with the AMAU/SSU.

AMAU if a trolley is available for them. The two units along with the emergency department share resources among them, and some resources with the hospital.

The capacities of the SSU and AMAU are 24 beds and 11 trolley spaces respectively. While the SSU has 24 beds, only 12 of them are under the governance of an acute medical consultant and the remaining 12 beds are under the management of standard medical consultants in the hospital.

6.2.3 Data Sources

The data collected for this project utilised both quantitative and qualitative data types. The quantitative element was collected from the historical data of ED logs, electronic patient records (EPRs) from the ED IT system, and direct observation. The direct and indirect time per activity and staff rota are not stored in the IT system. This was collected from interviews and observations. The qualitative data such as pathways, routing, and conceptual modelling have been gathered through observation, interviews, and focus groups. The sources of each data element are summarised in Table 6.1. All data and information collected are completely confidential and cannot be linked back, individual patients.

Table 6.1 Sources of data elements.

Data Elements	Data Source
Patient's Arrival times, patient's acuity, diagnosis,LOS, and demographic data.	Historical Data from EPR, ED and AMAU logs.
Starting time of direct activities: Registration, Triage, seeing a doctor, treatment, etc.	Historical Data from EPR.
Duration of direct activities per patient	Observations, shadowing, and interviews and group discussion.
Duration of indirect activities (e.g. admin work and report writing, prepare drug prescription, find a bed in ward)	Interviews and reports.
Patient flow: pathways, routing probabilities, conceptual modelling.	Historical Data from EPR, Interviews, and observations.
Human resource and non-human resource capacities: nurses, consultants, doctor etc.	Interviews and group discussion.
Number of AMAU and ED boarders and review patients	ED/AMAU logs
Inpatient admission, capacity, and LOS	Historical Data from EPR and Tallaght hospital annual report.
Organisational characteristics: physical capacity (beds, rooms, etc.), layout, processes	Interviews and observations.
Staffing and scheduling policies.	Interviews and daily rota

6.3 Phase 1: Demand for Care

Demand understanding by assessing patients' volumes and their profiles is a critical phase for making informed decisions regarding staffing and scheduling in the emergency department. This requires collecting operational data about patients presented to the ED.

6.3.1 Data Collection

The sample data collected from all anonymous acute patients are gathered retrospectively for one year for patients that are presented to ED and AMAU between April $1^{st,}$ 2016 and March $30^{th,}$ 2017. A total of 47,433 anonymous patient records from ED and 2980 anonymous patient records from AMAU have been collected through the hospital's information system, which is used by the staff (e.g., administrators, doctors, and nurses) to record data about each patient through the stages of their care. Description of the collected historical data fields is summarised in Table 6.2. This information is critical for informing and strengthening the understanding of the demand for care in the ED.

6.3.2 Data Analytics

There are several potential challenges for gathering the relevant information for assessing the demand for care data, typically as in other healthcare modelling projects. First, the quality of patients' records is subject to the level of pressures within healthcare processes, which can significantly affect the accuracy and consistency levels of the data. Second, there was a dearth of data about certain parameters, for example, time providers spend on patients and direct/indirect activities that were not captured by the HIS. This kind of information is estimated by observation, judgement through shadowing, group discussions, and interviews. For each activity (e.g. triage or treatment) three times are collected through the observations which are then validated through the interviewing the staff. The three processing time parameters collected were the minimum, most likely and maximum time taken by a staff type to perform a certain activity to a patient. The triangular distribution was used to model the uncertainty associated with each activity given the three parameters. The collected data of the providers processing time are given in Table C.3 in Appendix C.

The third challenge with data, in this case, was inconsistencies between different staff, such as variations in values between consultant's estimates and nurses' estimates. After numerous extended meetings with stakeholders, assumptions based on the stakeholders' knowledge in the field were used to overcome the absence of precise data and lack of information.

Table 6.2 Description of data fields.

Variable	Data Type	Description
Data for the Emergency Department (ED)		
Unique ID	numeric	Unique patient ID.
Date Registered	Timestamp	Arrival time.
Attendance Type	Categorical nominal	e.g. New or unscheduled Return
Arrival Mode	Categorical nominal	e.g. Ambulance or Walk-in
Source of Referral	Categorical nominal	e.g. Self, GP, or another hospital
Patient Sex	categorical nominal	e.g. male or female
Patient Age on Arrival	Numeric	number of years min 15, max=116
Presenting Complaint	Categorical nominal	e.g. Chest pain
Clinical Group	Categorical nominal	e.g. Medical, Surgical, RTA, or Orthopaedics
Triage Date	Timestamp	Starting time of triage process
Triage Category	Categorical ordinal	e.g. very urgent, urgent, immediate, standard, or not-urgent
Care Group	Categorical Ordinal	e.g. resuscitation, major, or Ambulatory
Time into Department	Timestamp	Time a patient has been assigned to a bed in a particular a care group.
ED Clinician Time	Timestamp	Time was seen by a clinician.
Speciality Referral Time	Timestamp	Time a patient has been referred to a speciality team.
Bed Request	Timestamp	Time an inpatient bed has been required (from admitted patients).
Diagnosis	Categorical nominal	e.g. Abdominal Pain, chest pain or back pain.
Discharge Outcome	Categorical nominal	e.g. admitted discharge home, to another hospital, or to OPD clinic.
Discharge Destination	Categorical nominal	e.g. Home, Ward, GP, another hospital.
Date Discharged	Timestamp	Time a decision has been taken either admit or discharge.
Left Dept. Date	Timestamp	Time a patient has left the ED.
Data for Acute Medical Assessment Unit (AMAU)		
AMAU Reg. Time	Timestamp	Patient registration time in the AMAU.
AMAU Doctor Time	Timestamp	Time was seen by a clinician.
AMAU Diagnosis	Categorical nominal	e.g. Abdominal Pain, chest pain or back pain
AMAU DTA Time	Timestamp	Time a decision has been taken either to admit or discharge.
AMAU Date Discharged	Timestamp	The decision to be admitted time.
AMAU Discharge Outcome	Categorical nominal	Time a decision has been taken either to admit or discharge.
AMAU Left Dept. Time	Timestamp	Time a patient has left the ED.
Data for the Ward		
Ward Admission date	Timestamp	Time of admission to the inpatient ward.
Ward Discharge Date	Timestamp	Time of discharge from inpatient ward
LOS	Numeric in days	Length of stay in inpatient ward (days)
Speciality Group	Categorical nominal	e.g. medicine, surgical, paediatrics, or orthopaedics.
Admission Source	Categorical nominal	e.g. elective or emergency.
Ward Discharge destination	Categorical nominal	e.g. Home, long term care, rehabilitation or mortuary.

Therefore, before extracting knowledge dataset and data analysis procedures, data pre-processing is an important step to prepare data for modelling and analysis by applying statistical techniques for removing, adding, cleaning or transforming of the original data set. This step attempts to obtain a clean and consistent data set. Several techniques from data mining are applied to manipulate the data including:

- K-Nearest Neighbour (KNN) and row clustering (k-means) techniques are used for imputing the missing data
- Outlier detection, e.g. Figure 6.3,
- Near-to-Zero variance technique is implemented to remove the informative variables (predictors), and
- Subsampling using synthetic minority over-sampling technique (SMOTE) algorithm is adopted to deal with class imbalances in the training data in the classification.

Variable re-engineering is also employed to generate more informative independent predictors (Table 6.3).

The transformation of some variables is required. The most common and straightforward transformation is to centre and scale the predictors. Centring the data can be achieved by subtracting the sample mean from the all the values, and scaling the data requires each value of a variable to be divided by its sample standard deviation. In addition to centring and scaling is an important step to improve the numerical stability of the calculations. The skewness of the variables is fixed using Yeo-Johnson Power Transformations (2000).

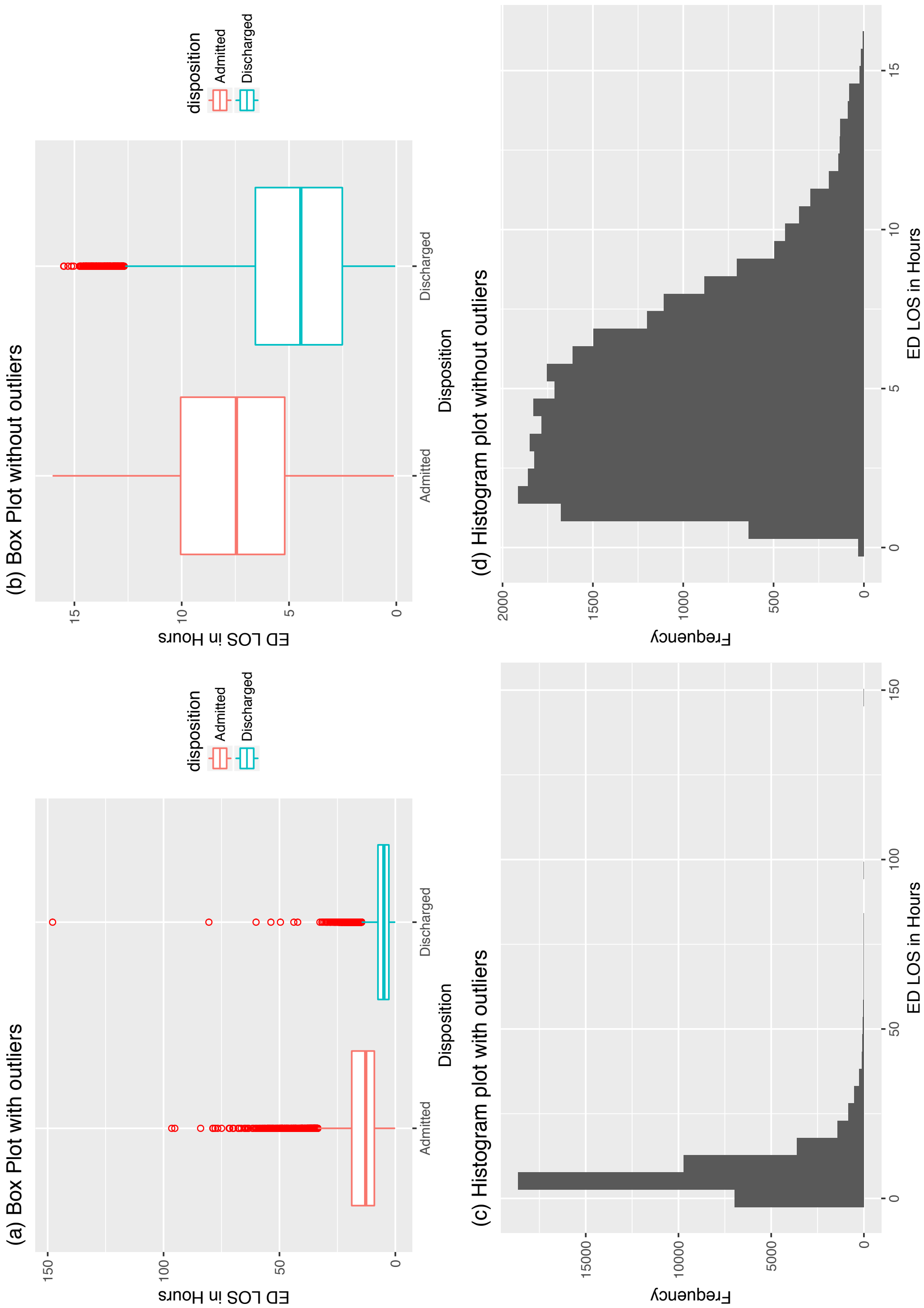


Fig. 6.3 Outlier detection using for ED LOS.

Table 6.3 Re-engineered variables.

Re-engineered variables	**Added Variables**	**description**	**Reasons**
Single Variables			
Arrival date	Isolation into separate predictors: month, week, day, the hour.Inter-arrival time.Counting number of patients who arrived Counting number of arrivals within interval of h hours		- Patterns of arrivals across months, days, weeks, and hours. - Looking for more informative variables for demand prediction. - Demand intensity per time t (e.g. moth, day, hour)
ED Clinician time	Left without being seen (LWBS)	This is a binary variable that takes one if a doctor has seen a patient and zero otherwise.	Service level and performance indicator
Speciality Referral Time	Need Speciality	This is a binary variable that takes one if a patient has been referred to a speciality team by a doctor and zero otherwise.	Informative predictor for prediction
Discharge out come	Disposition	Re-coding all categories into two main disposition decisions: admitted or discharged	For patient's segmentation.As a predictor to the PET
Combined Variables			
Arrival Date and discharge date	Patient Experience time in hours	(discharge date - arrival date) in hours	Patient Time tracking Service level
Arrival date and Left Dept. Date	Time to left the department	(Left Dept. Date-Arrival date) in hours	Performance tracking
Discharge date and Left Dept. Date	Boarding time	(Left Dept. Date-discharge date)	Performance Blocking Informative predictor
ED Clinician time and Arrival date	Time to be seen by a doctor	(ED Clinician time- Arrival date	
Triage Date and Arrival date	Time to triage	(Triage Date- arrival date)	
Time into Department and arrival time	Time to be assigned to a care group (e.g. major)	(Time into Department - arrival time)	

6.3.2.1 Descriptive Analytics

The analysis of empirical data is essential to develop a robust modelling that considers the time features of the system regarding demand volume, patterns, and profiles of patients. A thorough analysis of data enables the discovery of a different type of patterns (i.e., clustering) that are essential to reduce the complexity of the simulated system regarding patient groupings and patient allocation and routing analysis. This valuable information is needed to build a comprehensive and representative dynamic model for the underpinned healthcare system.

Volume- and Pattern-based Demand Analysis.

Due to the skewed nature of the data, the confidence intervals are measured based on nonparametric bootstrapping for the mean daily and hourly arrivals of patients without assuming normality. All the ranges use 95% confidence level where the lower and upper limits estimates are 0.025 and 0.975 quantiles. Number of resamples used is fixed for analysis (B = 1000). Different analysis scales have been used to interpret the daily arrival patterns of the patients to the ED. Figure 6.4a displays the average daily demand volume across the month of year and day of the week and hour of the day for 47,433 ED visits included in the analysis. The average daily volume 3,951 (sd = 271). September has witnessed the highest average daily arrivals (mean = 140 visits, sd = 24) followed by July (mean = 135, sd = 22.6) while the lowest average daily arrivals across the months were in February (mean = 121, sd = 21.4) followed by August (Mean = 126.8, sd = 19.9). Although there are clear differences between the average daily arrivals across months, it is hard to detect a monthly pattern in 12 months sample data. It requires more data across multiple years to identify seasonality patterns. Over the day of the week, it is undeniable that the data show a seasonality cycle (Figure 6.4b). Mondays and Tuesdays are the busiest days in a given week (mean 150.2 and 143.7, sd 19.6 and 13.4), while Saturday and Sunday (weekends) are a lot quieter days (105.6 and 107.3, sd 12 and 12.7). During the day, the demand increases, where the peak demand is around 12 none (mean = 9.7, sd = 3.66), which then declines slowly to its lowest levels during the night time, particular at five in the morning, mean = 1.89 and sd = 1.01, (Figure 6.4c).

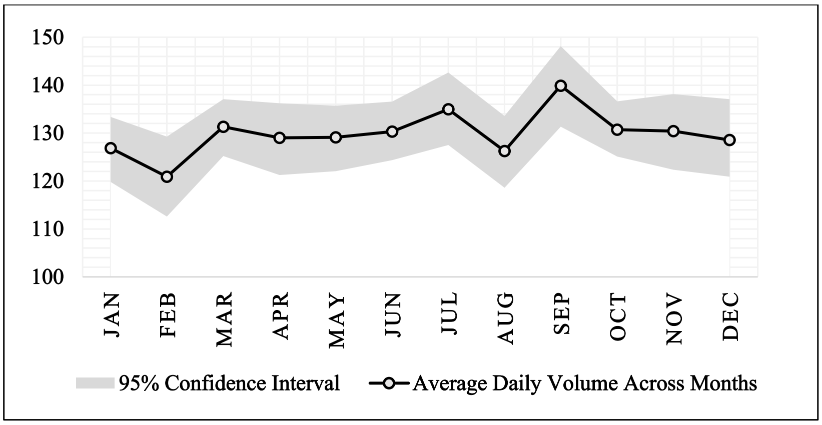
These patterns give an overview regarding demand volumes for services in the ED and different temporal scales for the patient arrival characteristics. From the simulation perspective, the inter-arrival times' data is required, not the arrival time, which is described as the time delay between two consecutive patient arrivals. To do so, the difference between the arrival times of patients is obtained for each group.

The ED hourly arrival data are consolidated by day of the week and hour of the day to construct the arrival rates that are required inputs to the model. This is followed by the determination of a proper distribution for each inter-arrival histogram. In this study, 168 (24 hours in 7 days) different inter-arrival times have been used for week-hour to consider the volumes of demand for care in ED. The impact of months' variation has been smoothed. The inter-arrival times for each week hour are used to fit the exponential distribution using the maximum likelihood estimator (MLE). This analysis results in 168 different exponentially fitted distributions.

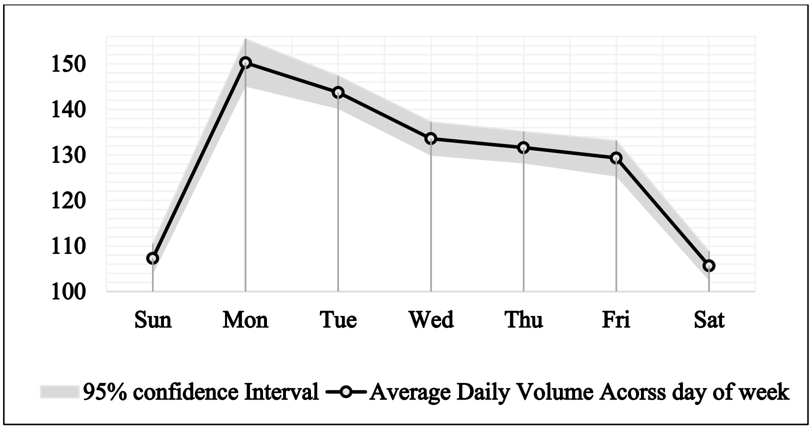
The demand fluctuates during the day, and there is a significant difference between the arrival rates during weekdays and weekends. However, the demand patterns are repeatable across the hour of a day or even across days of a week. It is evident that the volume demand patterns are highly predictable in the ED. Therefore, this should inform staffing and schedule accordingly to avoid the long waiting times, the safety issues and burn-out among the staff. Also, this can help to optimise the staffing patterns to meet the required demand which can lead to informed staffing and scheduling decisions.

Aging and Frailty

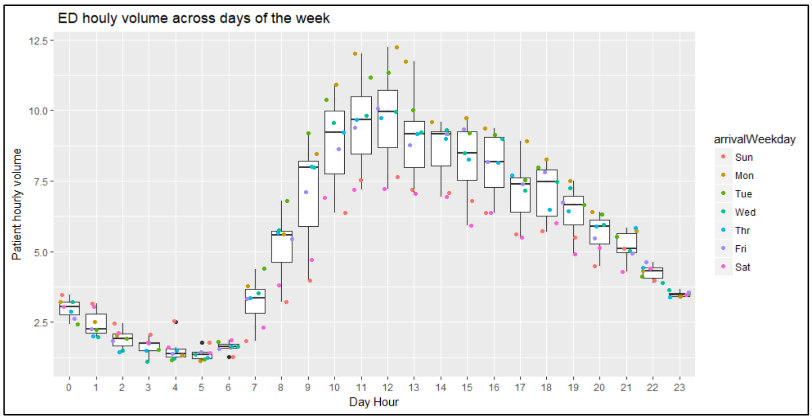
Elderly patients represent a significant percentage of patients in Tallaght hospital. Elderly patients differ according to the type and severity of their needs. They were grouped into frail and non-frail categories according to their in-patient's LOSs in acute hospitals. This



(a) Monthly pattern.



(b) Weekly pattern.



(c) Hourly patterns.

Fig. 6.4 Temporal Volumes and patterns of demand for care.

classification represents the degree of complexity (DOC) of their needs, based on the validated assumption that the most complex cases spend more time in hospitals which confirms the fact that older people - particularly frail patients - require more care and treatment than non-frail patients. The majority of elderly patients (about 82%) are classified as non-frail (with little or no complexity), and the remaining 18% are classified as frail patients (with complex needs). This study assumes the same proportion is applied to the ED and AMAU patients. The likelihood of patient admission is higher in the older demographic compared to the younger one (Figure 6.5).

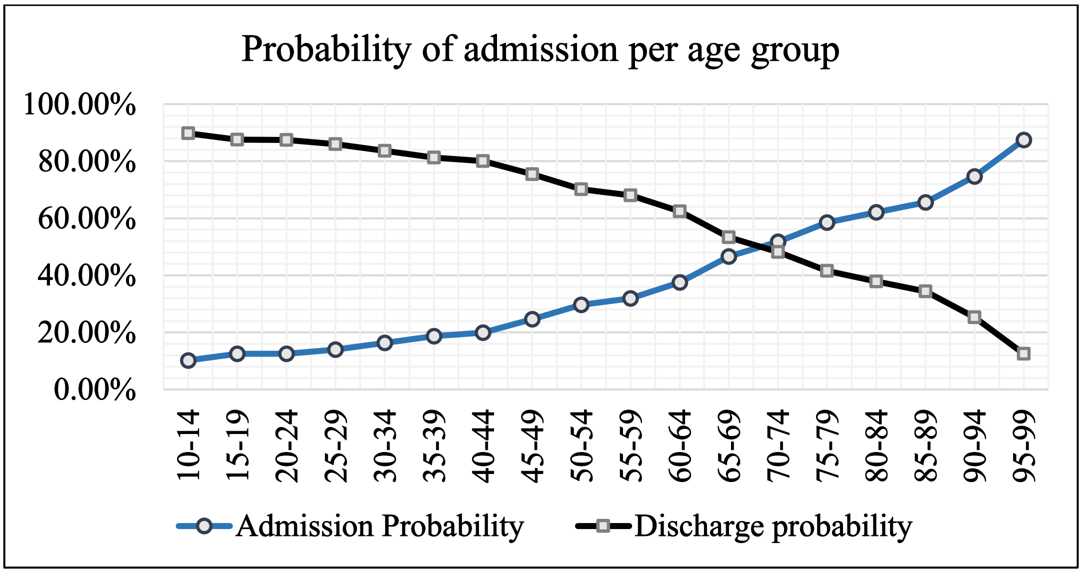


Fig. 6.5 Likelihood of admission per age group.

Arrival Mode

The mode of arrival for each group is then extracted from the dataset, which is essential to determine the distribution of walk-in patients and those who arrive by ambulance (Figure 6.6). This will be used in the simulation model to determine the percentage of a patient that will go through the registration and triage process. Also, the arrival mode of patients reflects the complexity of care needed as the likelihood of admission of patients who arrived by ambulance is higher than who in-walk. 23% of the patients arrived by ambulance, and

77% are walk-ins. Of the total patients, 90% are new patients, and 10% are unscheduled return. Referral from GP with a letter represents 70% of patients while 23% are self-referred. All diagnostic and procedure types were considered, and no exclusions were made.

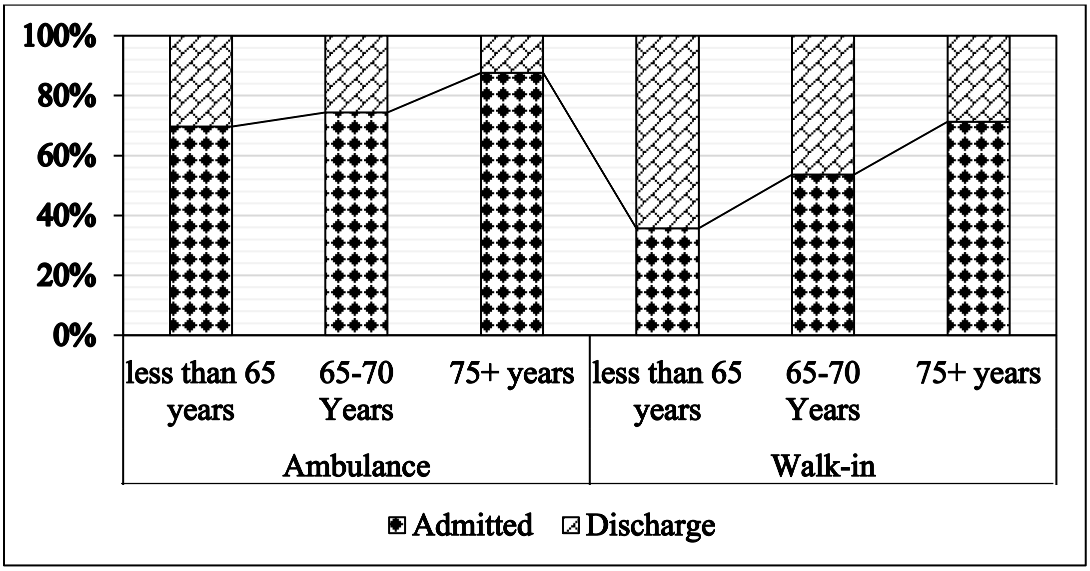


Fig. 6.6 Mode of arrivals per age group.

Severity mix/patient acuity

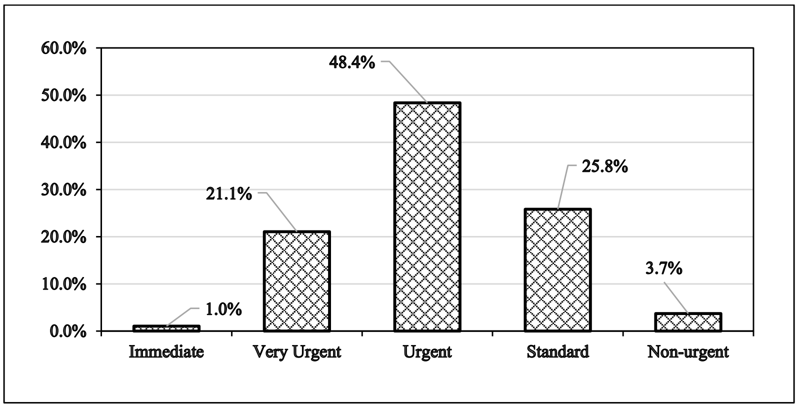
Patients differ according to the medical complaints and severity of their needs, so it is essential to understand their different arrival patterns to reflect the characteristics and needs of various groups of patients. There are two ways to categorise patients: triage category and medical complaint. The triage category has been selected to classify patients over the medical claim. This selection was for three main reasons; firstly, the number of triage categories is minimal (five triage categories are used in the ED). Secondly, patients usually have more than one medical complaint, for example, a patient with chest pain can also suffer from respiratory problems. Consequently, there is an infinite number of combinations of medical claims and hence it cannot be used to categorise patients. Finally, to be able to differentiate those patients who will be directed to the AMAU path based on their triage category. As shown in Figure 6.7, urgent patients (triage category3) represent the largest group of new attendees to the ED annually (48.4% on average) who are presented to the hospital with a broad range of medical complaints and ageing conditions.

Upon presentation in the ED, patients are triaged and categorised into different into different clinical groups based on their complaints. The clinical groups can be classified as either medical or nonmedical; the latter would have different sub-categories such as assault, ENT, trauma, dental. The majority of patients in the AMAU are medical patients, accounting 96% of patients presented to the unit. However, the same clinical group accounts for 41% of patients submitted to the ED because AMAUs is designed to deal only with medical patients. However, the ED and AMAU do not deal with the same percentage of those patients. Data analysis showed that the AMAU deal with more elderly patients compared with ED, those patients are characterised to be frail and need extra care. Also, the study of patient experience time (PET) in ED and AMAU showed that patients spend around 6-7 hours in the ED while compared to 2-3 hours for patients in the AMAU.

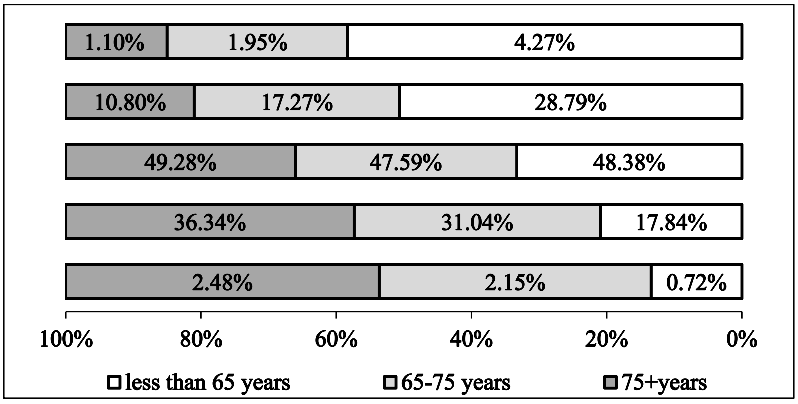
6.3.2.2 Learning Decision- Rules Using CART

As pointed out in chapter 5 (section 5.3.3), Machine Learning component adds the capability to learn from data in order to improve the accuracy of the workload prediction. The medical staff makes important decisions during the patients stay in the emergency department such as:

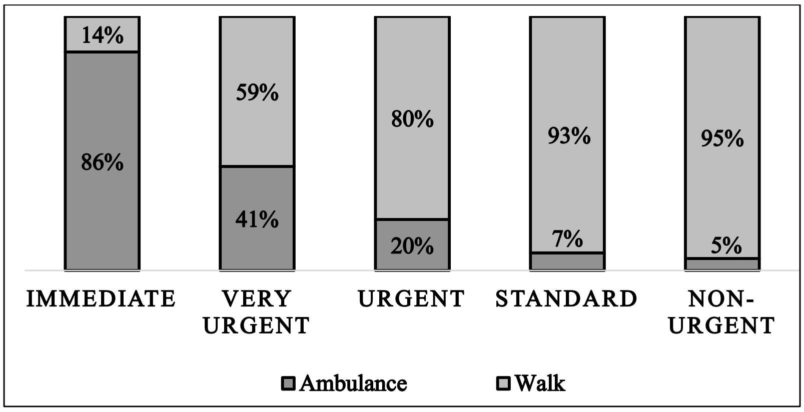
- Predict patient's acuity;
- Predict the patient need for a speciality team referral;
- Assigning a patient to a care group; and
- Predicting the patient disposition decision.



(a) Triage category.



(b) Triage per age group
X-squared = 1893.9, df = 8, p-value < 0.000)



(c) Triage Category vs Mode of arrival
(X-squared = 5379.7, df = 4, p-value < 2.2e-16)

Fig. 6.7 Distribution of patients based on their triage category.

These decisions are made by the staff nurses or physicians. The CART algorithm has been used as a predictive model for the following decisions based on patients' characteristics:

- Triage Category is five classes (very urgent, urgent, immediate, standard, or not-urgent) that reflect the patient acuity.
- Care Group is three classes (resuscitation, major, or Ambulatory)
- Need speciality referral is two classes (yes or no).
- Disposition Decision is two classes (admit or discharge).

For each of those variables, various probabilistic CART predictive model was evaluated over a defined set of tuning parameters (grid search). The performance metric was assessed using five repeats of 10-fold cross-validation to select the best model with minimum misclassification rate for each variable.

The patient clinical group, arrival mode and patient age, respectively, are the most significant predictors for predicting the triage group with accuracy 63% (Figure 6.8). Assigning a patient to a care group is mainly depends on the clinical group, arrival mode, triage category and patient age with accuracy 76% (Figure 6.9). Similarly, deciding whether a patient needs a speciality referral depends on triage category, age, and clinical group, respectively (Figure 6.10). Subsequently, with knowledge regarding the patient need for a speciality referral, clinical group, mode of arrival and triage category, the disposition decision can be predicted with accuracy 87% (Figure 6.11). These four predictive models are integrated into the simulation model. Based on the patient attributes, the decision can be predicted by sampling from the class probabilities at the leaf nodes.

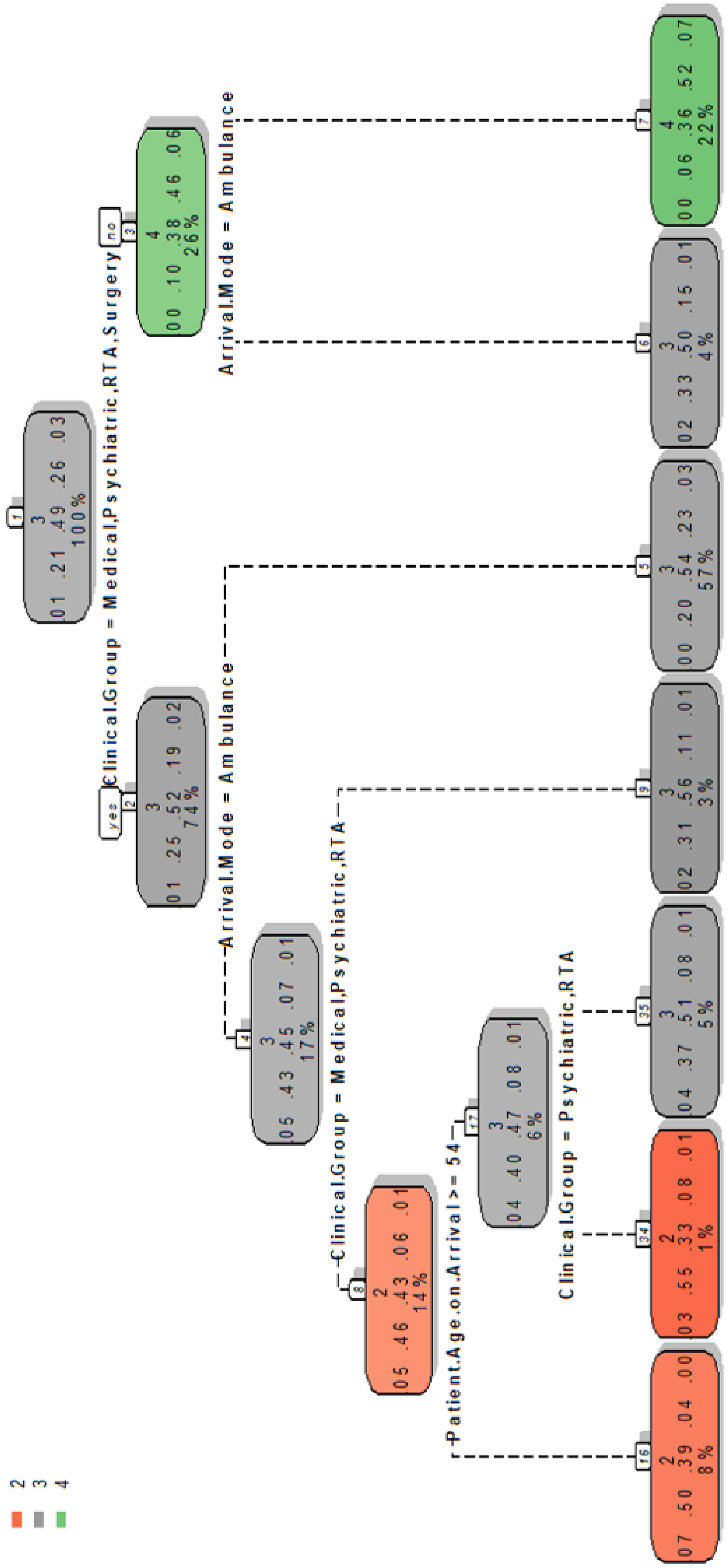


Fig. 6.8 Triage Category CART model (accuracy=63%).

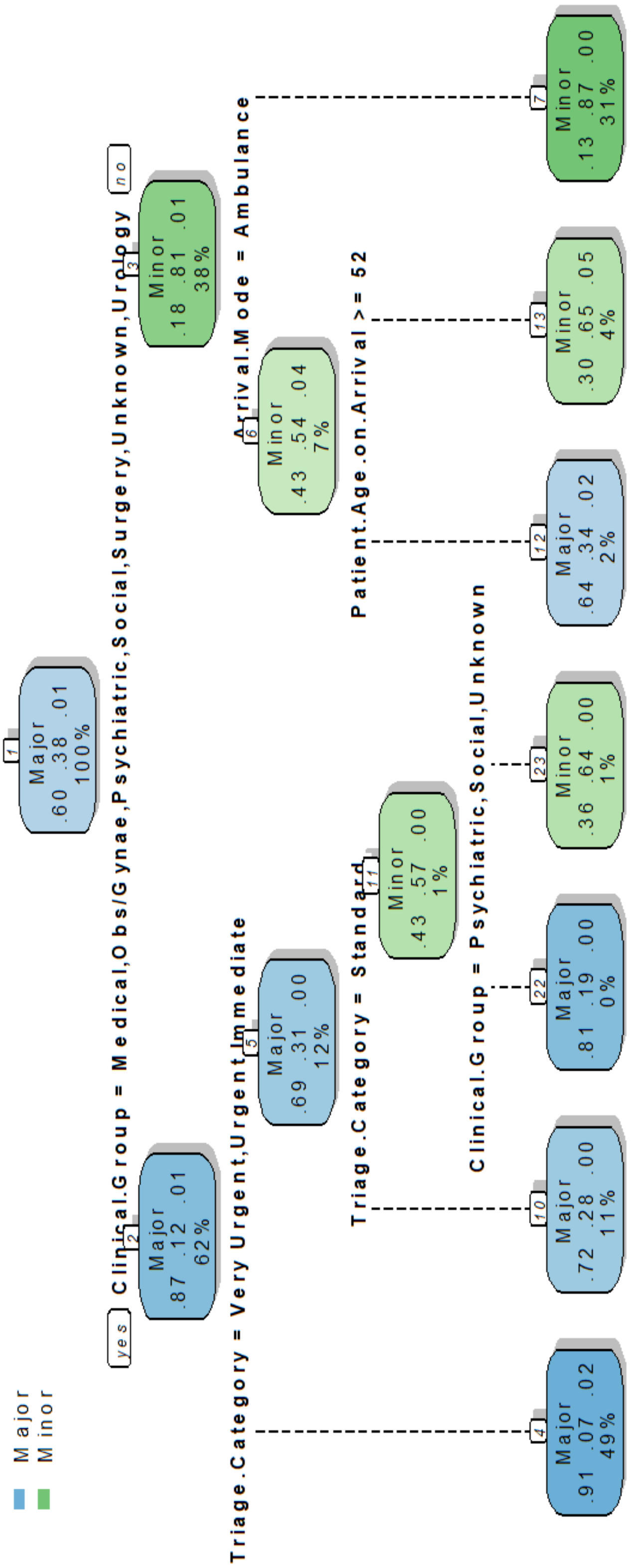


Fig. 6.9 Care group allocation CART model (accuracy=76%).

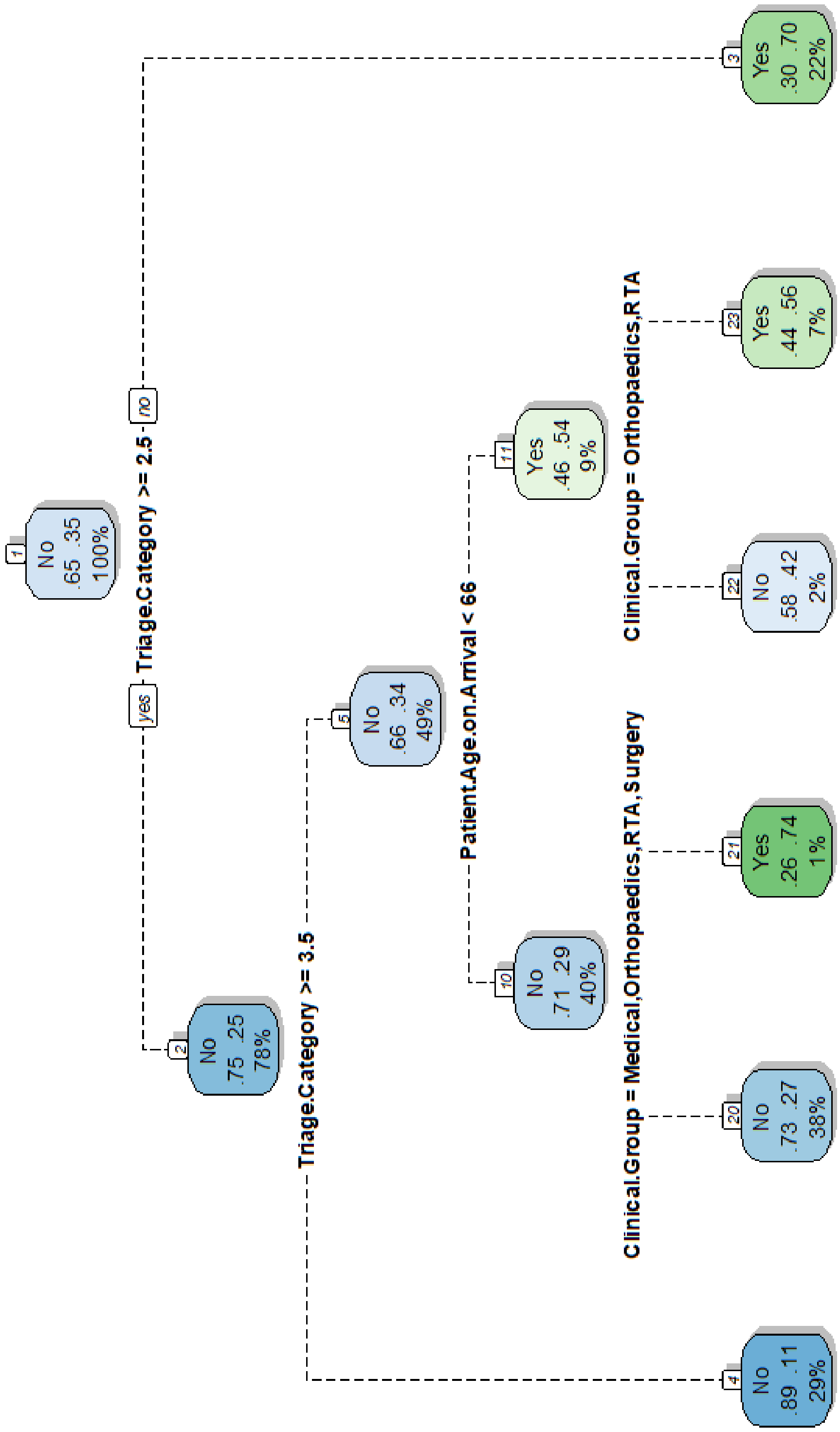


Fig. 6.10 Need Speciality referral CART model (accuracy=83%).

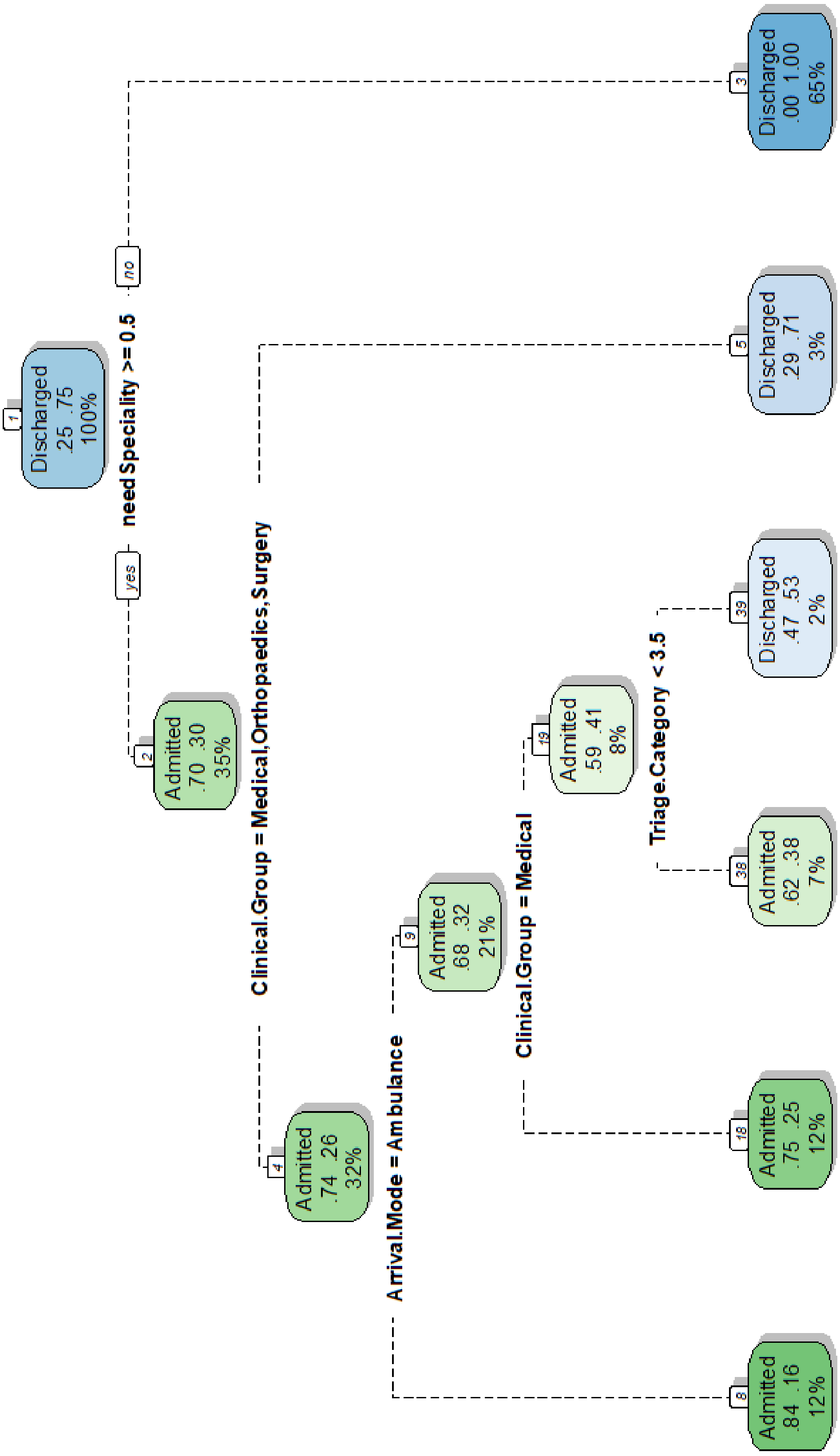


Fig. 6.11 Disposition decision CART model (accuracy=86%).

6.3.3 Phase 2: Understanding Dynamics

6.3.3.1 Organisational Characteristics - Process Mapping

There are two main ways for patient's arrival to EDs, ambulance or walk-ins (Figure 6.12). Patients arriving via ambulance are always given priority as they are considered urgent and need to be triaged immediately. Upon arrival at the ED's registration, walk-in patients (self-referral or general practitioner (GP) referral) remain in the waiting area to be triaged. When a patient's name is called, depending on staff availability, a triage nurse assesses the patient. Based on the patient's condition and triage assessment, each patient is assigned a clinical priority (triage category) according to the Manchester Triage System (MTS). The MTS uses a five-level scale for classifying patients according to their care requirements; immediate, very urgent, urgent, standard, and non-urgent. Once a triage category is assigned, the patient may be sent back to the waiting room until a bed or trolley is available in an appropriate treatment area, based on the type and intensity of their care requirements.

The patients waiting time depends on the triage category of patient, the availability of both medical staffs (i.e. ED physician or advanced nurse practitioner (ANP)) and empty trolleys, which are a prerequisite for a complete and accurate assessment. Following the patient's evaluation by an ED clinician, a decision is made: either the patient is to be discharged or admitted to the hospital. Secondary patient stages are those steps involved in the care of some but not all patients such as diagnostics (e.g. X-Ray and blood test), and second patient assessment by ED doctor. Consultation may be requested by ED staff from a medical/surgical speciality doctor to confirm that a patient should be admitted or to obtain advice on the best possible treatment for the patient who is to be discharged.

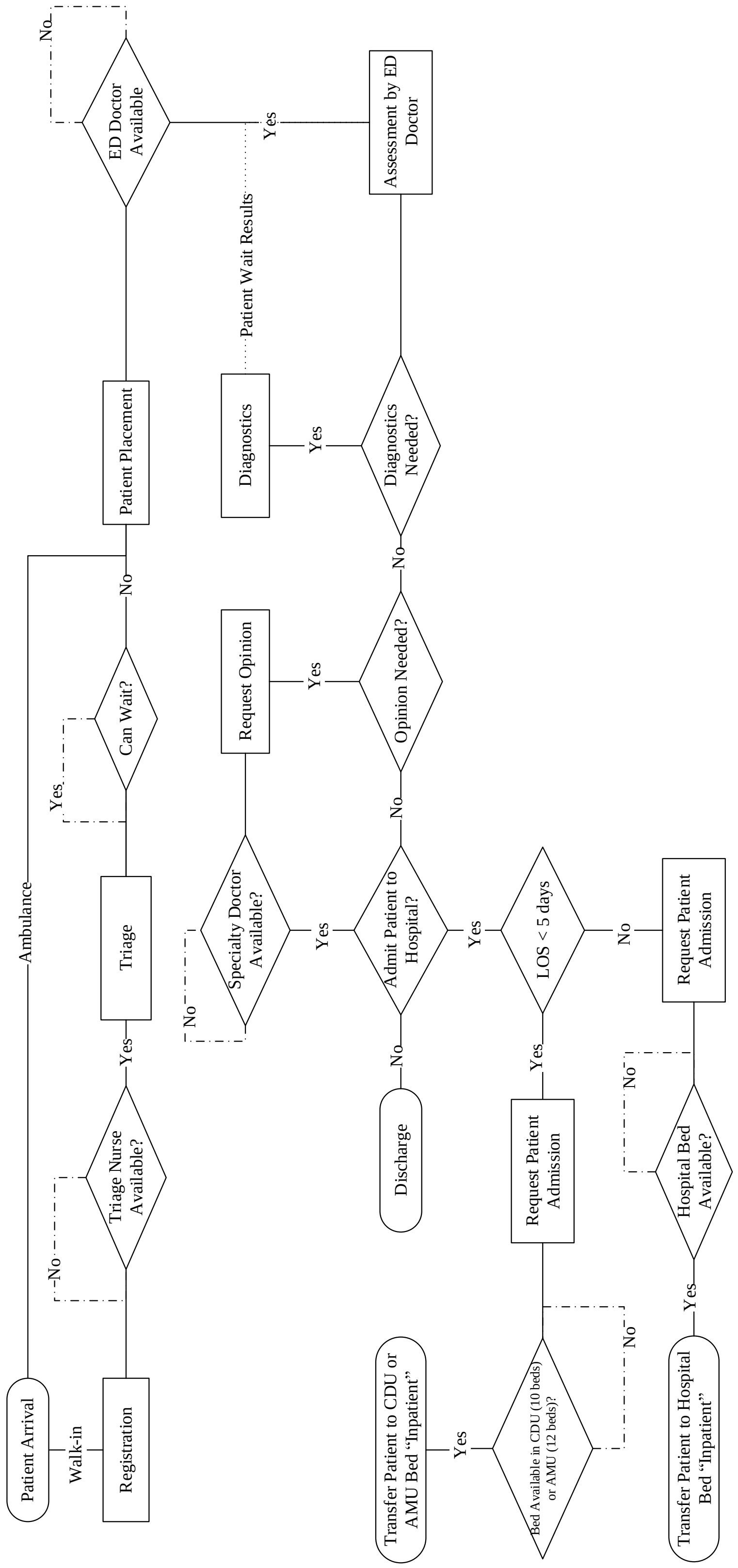


Fig. 6.12 Patient's Journey through the ED.

Moreover, after triage patients can be routed to the AMAU if they meet certain conditions (Figure 6.13): 1- to be a medical patient, 2- the patient 's triage category falls under "very urgent" or "urgent", 3- if the AMAU is open, i.e. it is a weekday, and the patient is triaged between 9:00 - 18:00. If these conditions are met, the triage nurse rings the AMAU to check if there is a bed available and if the AMAU consultant accepts the case. AMAU consultant can reject the case if the patient needs resuscitation or isolation facilities.

There are three possible paths for patients in AMAU after the doctor reviews the diagnostic test results and commence follow up or begin treatment of the patient. These paths are:

- The patient needs further diagnostic tests but is still under AMAU physician care. The average process time from arrival to AMAU to discharge or admission is between 110-177 minutes compared to 116-285 minutes average waiting time.
- Patient treatment is finished and is to be discharged. The average process time from arrival to AMAU to be discharged is 65-85 minutes while the mean waiting time is between 96-275 minutes.
- Finally, if the patient required a medical/surgical consultation, the average process time is between 17-80 minutes while the mean waiting time is between 90-240 minutes.

6.3.3.2 Burnout Causal Loop Diagram (CLD)

Hospital systems are complex with high workload pressure. To alleviate some of the workload pressure, staff capacity increase and process redesign can lead to improvements. Nevertheless, increasing capacity by appointing new nursing staff is a slow process in most hospitals, even after management have agreed that additional staff are required. Hence, the unit waiting for a response from management to increase capacity will see the nurses adjusting to the high pressures at work by different behavioural approaches. In the case of excess workload

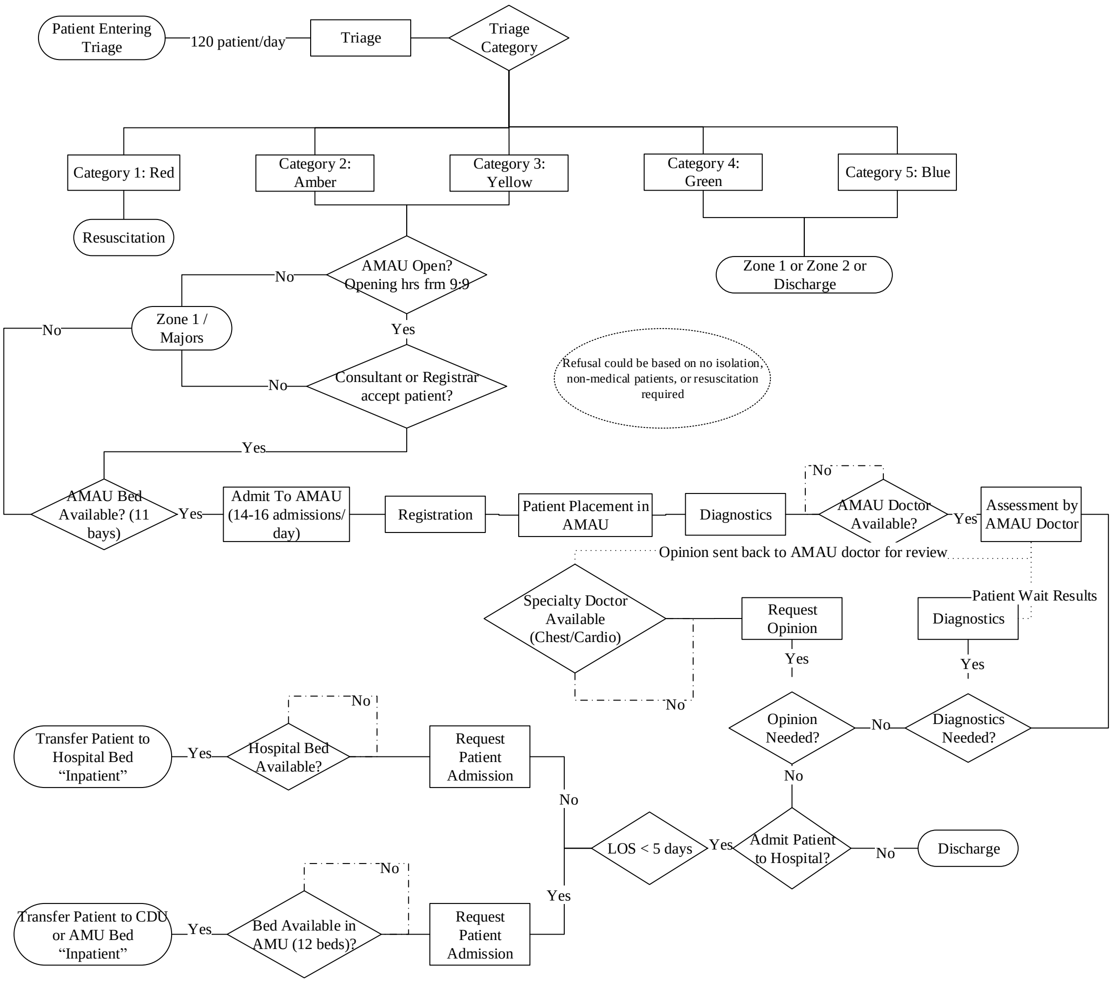


Fig. 6.13 Patient's Journey through the AMAU.

pressure, there is a high demand for beds that creates a pressure to speed up the discharge process. On the other hand, the professional experience and knowledge are likely to affect the response of medical staff to the high workload. Empirical analysis of ED staff shows that medical staff adjust their work pace in response to increased workload and speed up processes (Kuntz & Solz, 2013).This behavioural hypothesis causes a reduction in the LOS. Two possible behavioural responses can result from staff to reduce the work pressure (2001). The first adaptive response is working harder, and this will swiftly lead to burnout in a shorter time. The second is reducing the time allocated to the customer-e.g. medical staff may spend less time in nonclinical activities such as administrative work to free up time to treat patients. For instance, speeding up the work rate may increase productivity and reduce delay, but may reduce quality (Kostami & Rajagopalan, 2014). The literature provided support to theses hypothesis, and also, these possible reactions have been validated through nurses' interviews and focus groups.

In the short run, such adaptive behaviour may appear desirable, but it has substantial staff's adverse outcomes (e.g. stress, burnout and job dissatisfaction) and adverse patients' outcomes (e.g. quality of care and patient's safety). This could lead to a total net decline in performance. Decision makers should thus take into consideration the full set of possible implications of a temporary increase in service rates (Kc & Terwiesch, 2009).

The long run impact of increasing the productivity is not sustainable. Sustained working close to full utilisation to fulfil the excess workload with minimal cost leads to substantial implications and ultimately reduces the productivity and may increase the operating costs. These are in addition to the quality considerations that result from these adaptive behaviours.

Figure 6.14 presents a simplified causal loop diagram of workload pressure in nursing staff. The SD component assumes that all staff are homogeneous in their perception of both the workload and service level pressures. The nurses' burnout process begins when the staff attempts to fulfil the high workload by working intensively and for long hours which increases the stress exposure, in turn, draining their energy. Therefore, draining the nurses' energy level reduces the nurses' productivity, thus reducing the effective nurse capacity and increasing the pressure. In turn, it depletes their energy further and increasing the opportunity of nurses' burnout to happen. The unintended consequences create a reinforcement feedback loop (R1). Growing the staff fatigue (depleted energy) increases the exposure to constant work stress, and the energy drained more rapidly creating a reinforcement loop R2 (frustration-exhaustion).

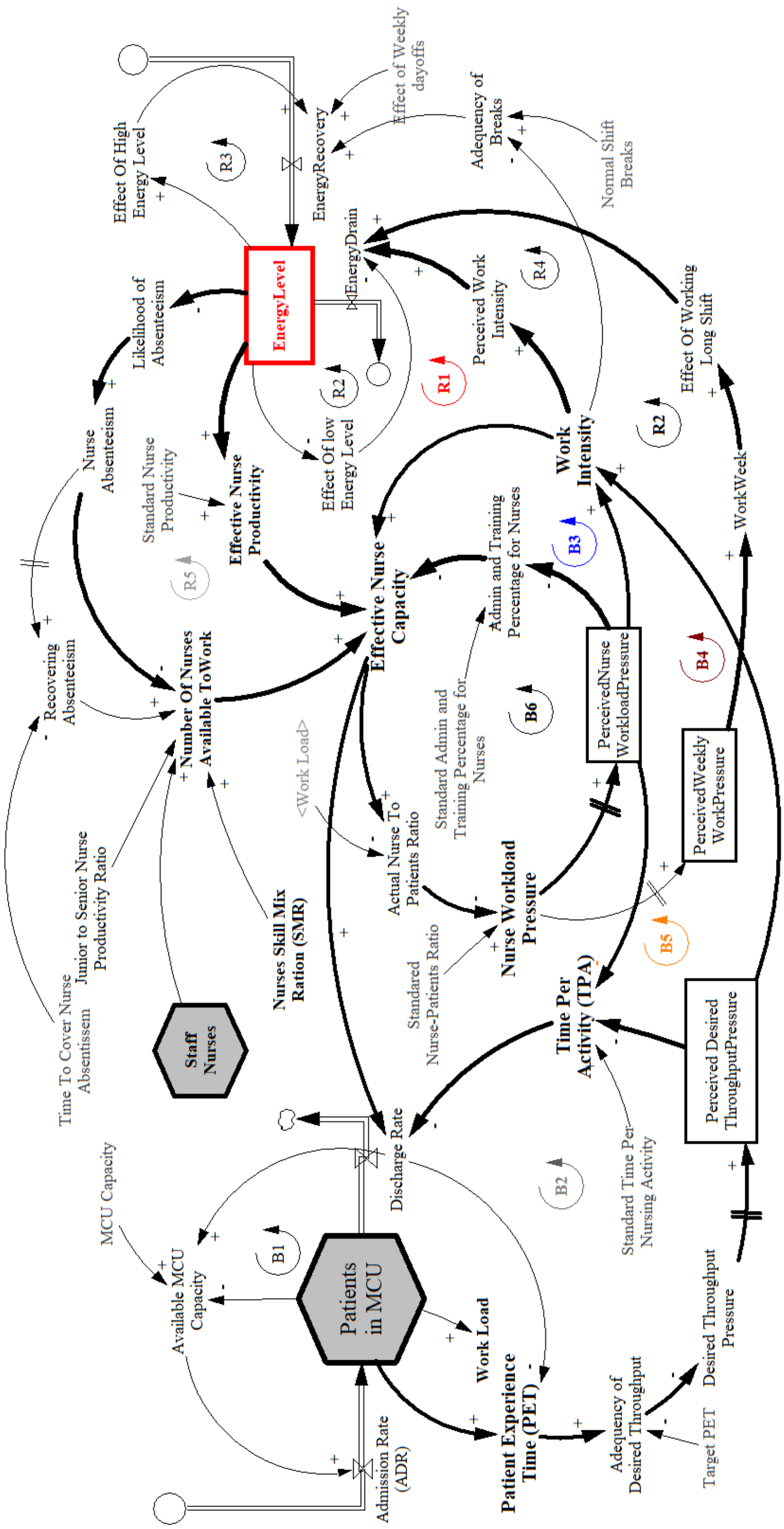


Fig. 6.14 A simplified Causal Loop Diagram for burnout.

This is unlike with high energy levels, which enhance individual morale and satisfaction. This, in turn, assists in recovery much sooner from temporary fatigue (loop R3) resulting from burnout. The failure to fulfil the desired goal (desired PET) is an additional stressor that creates pressure from management that pushes staff to work hard to achieve the service level and, in turn, undermines the energy.

Recovery from burnout can be reached by reducing workload and some management expectations, which support staff. Also, shift breaks and days off help to recover the energy decay during the day and the week. Without adequate breaks to recuperate, energy will deplete faster. However, when the unit is under work stress, the nurses may not take appropriate breaks during their duty hours, if there are insufficient staff on duty to cover breaks. Thus, the inadequacy of shifts breaks delay the fatigue recovery and increases exhaustion. This behaviour creates a reinforcement mechanism loop (R4). Another implication of burnout is the likelihood of random absenteeism associated with low energy levels. High workload due to irregularities in scheduling, unpredictable demand and adverse working conditions have a direct impact on absenteeism behaviour (Green, Savin, & Savva, 2013). Increasing absenteeism reduces the number of staff nurses available to work, thus reducing the effective productivity, which in turn raises workload pressure and eventually fatigue. Reinforcement loop R5 depicts this unintended implication. The impact of unplanned staff absenteeism continues temporarily (time delay) until the nurse manager can find a replacement.

The mathematical formulation of the SD model and samples of stock and flow diagrams are described in Chapter 5.

6.3.4 DES Simulation Model

Based on the analysis of phase 1 and phase 2, a comprehensive simulation model for the ED and AMAU is constructed using the Anylogic simulation package. As described in chapter 5, DES component includes all the factors mentioned from the patient, staff and organisational aspects. Modules of the simulation model are connected to resemble the ED business process model, where blocks are connected similarly to the conceptual flow chart, which makes the construction phase of the model straightforward. The four CART models are integrated into the model in the form of decision-rules. All model inputs are stored in a database attached to the simulation model. The model output is exported to an excel database for further analysis and validation.

The simulation model considers different types of medical staff including nurses, Advanced Nurse Practitioners (ANP), Senior House Officers (SHOs), registrars, and consultants in the ED and AMAU. Also, non-staff resources have also been included such as beds, physical spaces, and diagnosis rooms. The access to diagnostic services and inpatient care has also been modelled. The model was developed to track the individual patients through their journey to the hospital to quantify the amount of care required for his/her interactions with the staff.

6.3.5 Model Validation & Verification

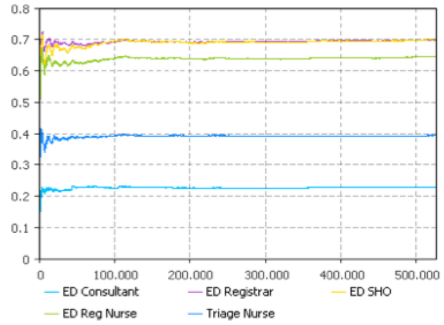
To reduce the model development cycle time and to increase the confidence in the results, verification and validation are executed throughout the development phases of the simulation model. After each development phase, the model was verified and validated in conjunction with completed phases. For the verification process, the model logic is verified to ensure that patients follow the correct care path as expected. This was achieved by tracing and debugging functions besides the visual tracking of patients. It was also achieved through checking intermediate output values such as queue lengths and waiting times between processes.The conceptual model was documented and validated by circulating the document among ED and AMAU senior consultants and senior nursing staff.

The final results of the simulation model were validated using two techniques; face validation and comparison testing. Face validation is performed by interviewing ED and

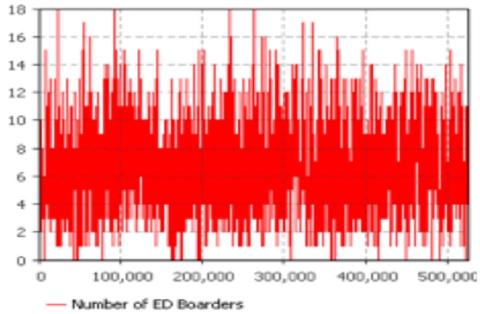
AMAU senior consultants and nursing staff to validate the final results of the simulation model. The second approach was 'Comparison Testing' by comparing the output of the simulation model with the real output of the system under identical input conditions. A sample output of four selected KPIs for the ED and AMAU is given in . Most of the times, the hospital has no available in-patient beds either in the ED (Figure 6.15b) and the AMAU (Figure 6.15f). Patients experience long waiting times to be transferred to an in-patient bed. This in turn increases workloads for medical staff, and in particular, nurses. This partially explains the significant increase in the average PET of the admitted patients in both ED and AMAU.

To validate the simulation model results, nine KPIs were used:

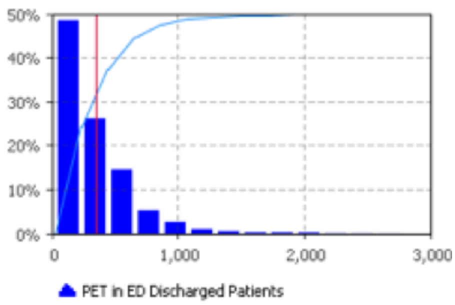
- Patient experience time for all patients in ED (ED PET),
- Patient experience time for admitted patients in ED (ED PET Admitted),
- Patient experience time for discharged patients in ED (ED_PET_Discharged),
- Percent of ED patients admitted to inpatient ward (ED admission rate),
- Patient experience time for all medical patients in AMAU (PET All-AMAU),
- Number of medical patients directed to the AMAU (AMAU Access),
- The percentage of AMAU patients admitted to inpatient ward (AMAU admission Rate).
- Patient experience time for all patients in AMAU (AMAU PET),
- Proportion of patients that spent less than 6 hours in ED (%<6hrs),
- Finally, the percentage of patients that spent less than 9 hours in ED (%< 9hrs).



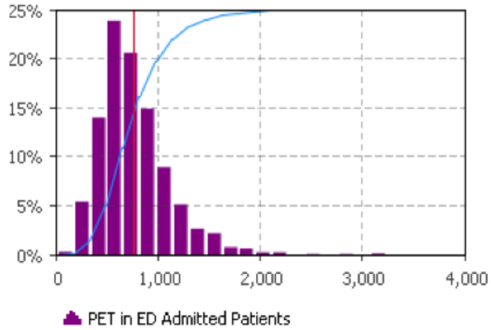
(a) Utilisation in ED.



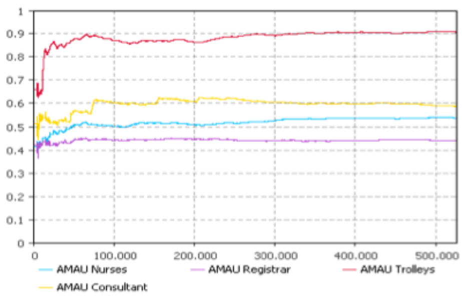
(b) Boarded patients in ED.



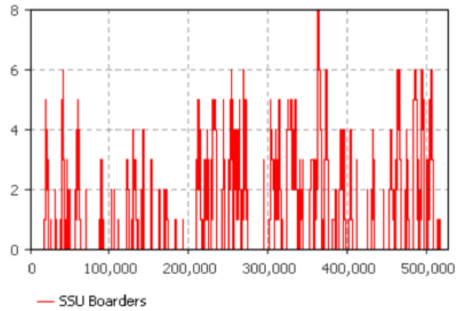
(c) PET of all patients in ED.



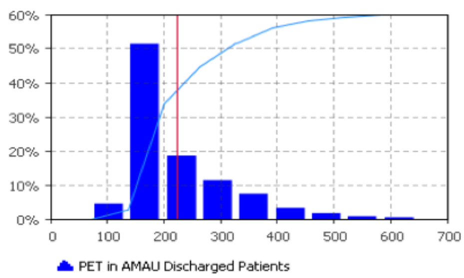
(d) PET of admitted patients in ED.



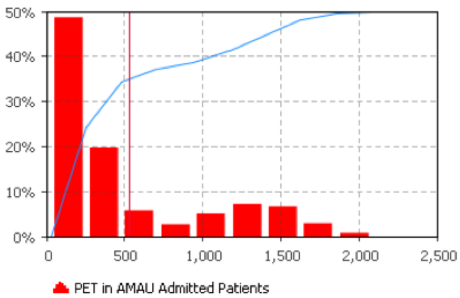
(e) Utilisation in AMAU.



(f) Boarded patients in AMAU.



(g) PET of all patients in AMAU.



(h) PET of admitted patients in AMAU.

Fig. 6.15 Distribution of patients based on their triage category.

The actual values of these KPIs were calculated from the analysis of the collected patients' records. The actual averages are calculated after removing the outliers using the 10th and 90th percentiles as the cut-off. The simulation model was run for n=20 independent replications to obtain independent and identically distributed (iid) of KPIs above, with each replicate re-initialised by a different pseudorandom number seed.

Table 6.4 summarises the percentage change between the values of the KPIs calculated from the analysis of the patients' records and the output of the simulation model. It clear that the simulated average results for all KPIs are not significantly different across the 20 replications. For each KPI, 95% confidence intervals based on the t-distribution are estimated. Since a simulation model of a real-world system is only an approximation to the actual system, one should not speak of absolute validity or invalidity of a model, but rather of the degree to which the model reflects the system. The relative differences between the actual the simulated reveal that there are some over-/under-estimations. However, the discrepancies are practically insignificant, and they are in acceptable range ($\pm 5\%$). Thus, the difference between the model and the system is statistically insignificant. The model, for all practical purposes, is a reasonably valid representation of the real system.

6.3.6 Scenario Analysis: Factors Implications

6.3.6.1 Demand Inappropriateness

From the exploratory study in chapter 4, managers consider that patients of triage categories four and five (standard and non-urgent) should not present to the emergency department. Triage categories four and five represent about 30% of the patients given in the ED. This scenario explores the impact of not serving those patients group on the service level and staff utilisation. In other words, redirecting those patients to a new pathway (e.g. their GPs or community care after triage).

Table 6.4 Simulation output vs actual (one-year simulation).

Run	ED PET	ED PET Admitted	ED PET Discharged	ED Admission Rate	AMAU Access	AMAU Admission Rate	AMAU PET	%< 6hrs	%< 9hrs
1	512.8	766.34	334.71	0.23	2909	0.55	242.9	0.49	0.66
2	537.4	776.08	363.86	0.24	2977	0.55	240.5	0.49	0.66
3	522.7	770.28	341.08	0.24	2988	0.55	255.2	0.49	0.66
4	551.2	792.26	378.45	0.23	2758	0.57	257.5	0.51	0.68
5	531.3	776.89	354.64	0.24	3117	0.54	249.0	0.50	0.66
6	522.1	771.89	345.01	0.23	2862	0.55	248.6	0.49	0.66
7	517.1	760.73	343.08	0.23	2911	0.55	241.5	0.48	0.65
8	535.5	776.13	364.57	0.23	2961	0.54	236.0	0.51	0.67
9	526.5	774.10	349.33	0.23	2944	0.55	245.6	0.48	0.65
10	546.8	787.19	373.79	0.24	2907	0.56	248.8	0.52	0.68
11	542.1	781.19	370.03	0.24	2805	0.56	262.8	0.49	0.66
12	510.2	762.60	330.79	0.23	2991	0.55	244.1	0.50	0.67
13	534.4	775.66	360.44	0.24	2955	0.55	246.1	0.50	0.66
14	529.5	778.55	349.21	0.24	2953	0.55	253.8	0.50	0.67
15	553.7	791.71	383.79	0.23	2971	0.55	262.4	0.49	0.66
16	524.0	769.37	343.75	0.24	2937	0.56	268.9	0.49	0.66
17	517.3	763.95	340.40	0.23	2945	0.54	252.3	0.49	0.66
18	528.8	777.74	350.19	0.23	2962	0.55	242.3	0.49	0.65
19	523.7	771.73	344.87	0.24	2975	0.54	250.8	0.49	0.65
20	539.8	805.01	349.29	0.24	2799	0.56	248.1	0.50	0.67
Summary Statistics									
Mean	530.36	776.47	353.57	0.24	2931.4	0.55	249.9	0.49	0.66
Stdev.	12.27	10.95	14.71	0.002	79.43	0.01	8.35	0.008	0.009
Half CI	5.74	5.12	6.89	0.001	37.17	0.004	3.91	0.004	0.004
LB	524.6	771.35	346.68	0.23	2894.2	0.55	246.0	0.49	0.65
UB	536.1	781.6	360.5	0.24	2968.5	0.56	253.8	0.498	0.66
Actual	514.0	790	371.00	0.23	2980.	0.53	258.0	0.47	0.66
% diff	**-3%**	**2%**	**5%**	**-1%**	**2%**	**-4%**	**3%**	**5.3%**	**.34%**

Table 6.5 compares the base results and this scenario across a set of selected performance criteria. Not surprisingly, less acute patients have limited impact on the PET (-3%) of all patients in ED. This can be explained as the majority of those patients are not admitted. There is a significant reduction in the PET of discharged ED patients (-19%) due to the drop down of the waiting time of discharged patients (-46%). However, the utilisation of medical staff has decreased significantly for all staff. Similarly, this patients group (category 4 and 5) has a negligible impact on the AMAU because most of AMAU patients are from category four and five.

This Scenario reveals that patients with standard and non-urgent care needs create pressure on medical staff and results in inappropriate overcrowding in the ED. The staff time saved are utilised by the patients with higher acuity which results in a significant decrease in patients' waiting time and reduce staff workload.

6.3.6.2 Lack of Coordination between Hospital Facilities

Management in Tallaght hospital considers that the lack of coordination between the upstream and downstream is one of the most significant problems they are facing. The lack of coordination results in the increase in the number of boarding patients who need to be admitted.

However, due to a lack of bed availability, they are required to board in the ED or the AMAU. Although they completed their emergency treatment, ED and AMAU staff have to provide inpatient care which is not in their responsibilities. This generates additional workload and resentment on the staff and at the same time leads to patient dissatisfaction as they are waiting on trolleys. Also, nursing staff in the ED and AMAU have to communicate and coordinate with the bed management staff to move the patients who are causing additional pressure on the medical staff.

Table 6.5 Impact of inappropriate demand.

Performance Measures		Base		Inappropriate Demand Scenario.			
		Mean	**Stdev.**	**Mean**	**Stdev**	**% change**	**p-value**
Emergency Department							
Patient Related	ED PET ALL	548.102	13.938	529.551	4.612	-3%	**0.036**
	ED PET Admitted	790.425	12.653	757.142	7.454	-4%	**0.009**
	ED PET Discharged	372.922	15.894	300.764	2.924	-19%	**0.001**
	ED Proportion of Admission	0.237	0.001	0.297	0.002	26%	**0.000**
	% Pts<6hrs	0.488	0.007	0.486	0.005	0%	0.476
	% pts<9hrs	0.655	0.006	0.660	0.005	1%	0.107
	WT Disch. ED	182	4.086	98.2	9.08	-46%	**0.000**
Staff Related	ED SHO Util.	0.726	0.008	0.484	0.004	-33%	**0.000**
	ED Registrar Util.	0.708	0.005	0.621	0.002	-12%	**0.000**
	ED Nurse Util.	0.723	0.006	0.555	0.002	-23%	**0.000**
	Triage Nurse Util.	0.396	0.002	0.397	0.003	0%	0.794
	ED ANP Util.	0.614	0.006	0.393	0.005	-36%	**0.000**
	ED Consult. Util.	0.280	0.005	0.251	0.002	-10%	**0.000**
	ED Doc. Pts. Ratio	21.638	0.672	14.866	0.052	-31%	**0.000**
	ED Nurse Pts. Ratio	21.638	0.672	14.866	0.052	-31%	**0.000**
Acute Medical Assessment Unit. Department							
Patient Related	AMAU Access	3100.200	77.202	3114.200	76.231	0%	0.614
	AMAU Admission Rate	0.546	0.004	0.552	0.007	1%	0.230
	AMAU PET	251.018	1.198	249.774	1.744	0%	0.233
Staff Related	WT Disch. AMAU	106.2	6.79	106.2	7.259	0%	1.000
	AMAU SHO Util	0.167	0.006	0.165	0.006	-1%	0.499
	AMAU Registrar Util	0.484	0.009	0.487	0.007	1%	0.156
	AMAU Nurse Util	0.633	0.007	0.636	0.005	1%	0.237
	AMAU Consult Util.	0.451	0.015	0.450	0.005	0%	0.882

Note Disch.: Discharge; pts: Patients; hrs: Hours; Stdev: Standard Deviation; Util.: Utilisation The p-value for paired t-test at 95% confidence level (null hypothesis H0: two samples have same average and alternative hypothesis H1: two samples have different average).

This scenario aims to explore the implication of the lack of management coordination regarding the boarding patients. Four factors are related to this situation:

- Allow Boarding Care: this factor has two levels: either to allow ED and AMAU staff to provide inpatient care to boarded patients or not.
- The intensity of boarding care: this factor reflects the power of nursing work required to care for boarded patients. This factor is two level (low and high)
- Priority of boarded inpatient care: this factor reflects the implication of prioritisation of care provided to boarded patients compared to normal patients. This factor has two levels: low and high.
- Finally, Boarding time: the time patients wait for an inpatient bed which has three levels: High (current setting), medium (-25% of the current) and low (50% of the current).

The design of experiments used an orthogonal array for this scenario analysis (Table 6.6) instead of using full factorial to reduce the computational time.

Table 6.6 Designs levels.

Design	Allow Boarding Care	Intensity of Care	Priority	Boarding Time
D1	Yes	High	Low	Medium
D2	Yes	Low	High	High
D3	No	High	Low	High
D4	Yes	High	High	Low
D5	Yes	Low	Low	Medium
D6	No	Low	High	Low
D7	No	Low	High	Medium
D8	Yes	Low	Low	Low
D9	No	Low	Low	High
D10	No	High	High	Medium
D11	NO	High	Low	Low
D12	Yes	High	High	High

This scenario has 12 different designs which have been simulated for one year using five replications each. Five replications were used instead of 20 as they were sufficient in this experiment and no need to do useless replications. The results of the simulation are given in Table C.7 (Appendix C) which represent the data set for further analysis.

Following the retrieval of the DOE dataset, as given in Table D.7, analysis of variance (ANOVA) has been applied for each one of the performance measures to explore the significance of the boarded patients. The ANOVA analysis is given in Table 6.7 that show the p-value (probability of being greater than the F-statistic).

Table 6.7 ANOVA type II analysis for the DOE results.

KPI	**ANOVA Analysis**			
	Allow Boarding Care	**Intensity of Care**	**Priority**	**Boarding Time**
ED PET ALL	0.06	0.15	0.22	**0.01**
ED PET Admitted	0.17	0.21	0.40	**0.00**
ED PET Discharged	0.10	0.21	0.22	0.25
ED Proportion of Admission	0.24	0.09	0.07	0.48
% Pts<6hrs	0.07	0.12	0.16	0.08
% pts<9hrs	0.08	0.15	0.20	**0.02**
ED SHO Util.	0.54	0.68	0.78	0.19
ED Reg. Util.	0.10	**0.05**	0.23	0.61
ED Nurse Util.	**0.01**	0.10	0.51	0.68
Tri.Nurse Util.	0.12	**0.01**	0.84	
ED ANP Util.	**0.01**	0.12	0.78	0.87
ED Consult. Util.	0.98	0.21	0.49	0.32
AMAU Access	**0.01**	**0.00**	**0.01**	**0.03**
AMAU Admission Rate	0.94	0.71	0.94	0.94
AMAU PET	**0.01**	**0.01**	0.65	0.44
AMAU SHO Util	**0.00**	**0.03**	0.59	0.89
AMAU Reg Util	1.00	**0.03**	0.06	0.06
AMAU Nurse Util	**0.00**	0.05	0.42	0.95
AMAU Consult Util.	0.40	**0.04**	0.76	0.08
WT Disch. in ED	**0.05**	0.11	0.16	0.14
WT Disch. in AMAU	**0.01**	**0.01**	0.29	0.89

Bold means the factor is statistically significant with the corresponding KPIwith $\alpha = 0.05$.

It is apparent that providing care to the boarded patients and the intensity of care required has a significant impact at 95% confidence level on the staff workload (Figure 6.16). The effect of priority of care provided to boarded patients is limited to AMAU Access because the AMAU has demand control and can reject patients due to the unavailability of beds or staff. All the four factors have insignificant influence on PET of discharged patients, ED Proportion of Admission, %pts<6hrs. As expected, boarding time has significant impact on the PET of all patients, PET of the admitted patients, and % pts<9hrs.

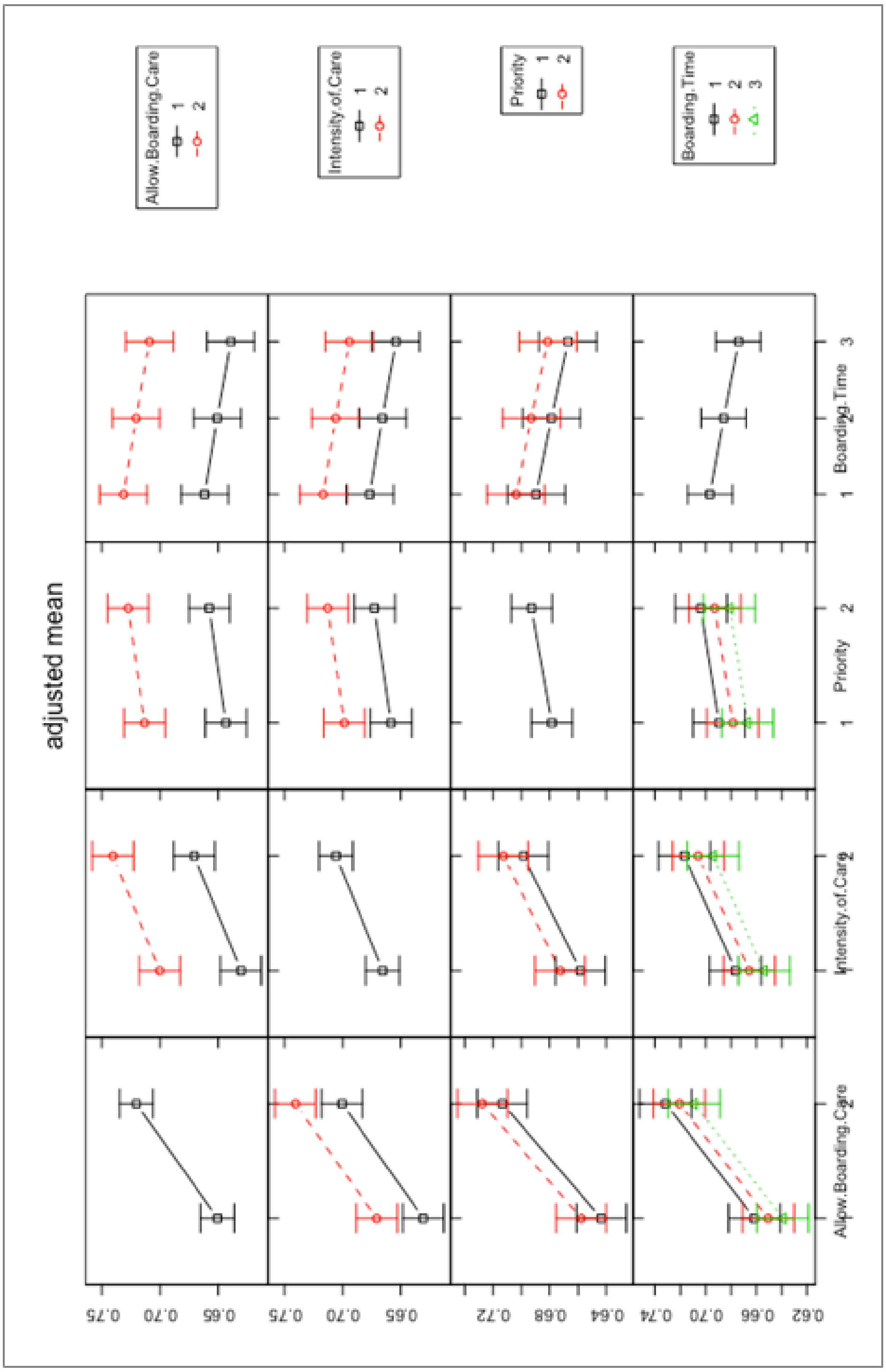


Fig. 6.16 Interaction plot for the ED Nurse Utilisation.

This scenario analysis confirms management perceptions about the problem of boarding and the lack of coordination with the downstream resources (i.e. inpatient wards). This creates more unnecessary workload on the staff besides the overcrowding that makes the work environment not suitable to provide emergency care.

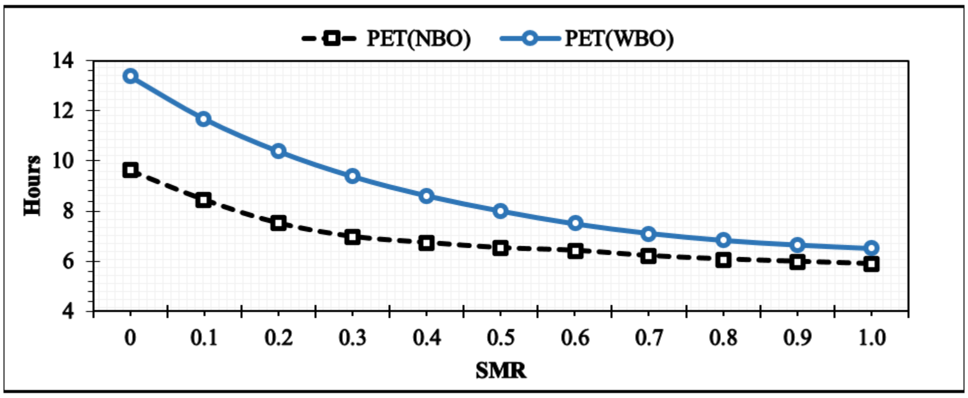
6.3.6.3 Environment Complexity (Burnout Implications)

This set of experiments utilises the burnout component-based system dynamics model, which was explained in chapter 5, to explore the influence of nurse adaptive behaviour in a heavy workload environment. The system dynamics mathematical formulation and stock and flow model are provided in Appendix C.1. The focus here is on AMAU nursing staff, as both the literature revealed that nurses are more vulnerable to burnout. The analysis of this scenario is based on sensitivity analysis of three parameters (skill mix ratio, work intensity, and time per activity) as requested by the hospital management under investigation. The analysis has been classified into three sets of experiments. Each experiment has two key settings; one setting assumes the burnout has not taken place yet (no burnout; NBO) on the nurses' behaviour. While the second case considers the burnout has taken effect (with burnout; WBO). The sensitivity of these parameters was assessed using: AMAU PET, the percentage of administrative work reduction (AWR) and percentage of admission rate (ADR). ADR is the proportion of the ED medical patients that are admitted by the AMAU while AWR calculates the percentage of administrative work reduction as a response to high workload and service level pressures as discussed in chapter 5.

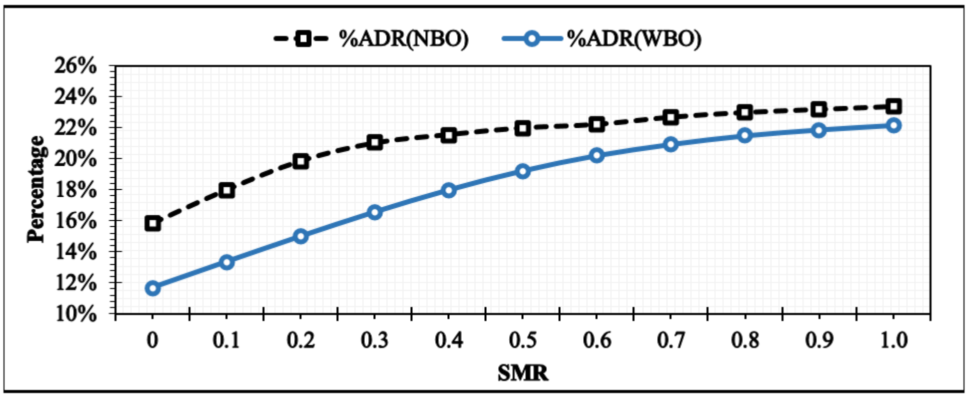
Skill-Mix Ratio (SMR) Implications

Mismanagement of nurse shift schedules carries risks. This can lead to fatigue and burn-out that eventually impacts negatively on service quality. The imbalanced skill-mix shift is one of the characteristics of weak scheduling decisions (Alistair Clark et al., 2015). The first set of experiments recommended by management is to examine changing the shift skill-mix ratio (SMR) for nurses and its effect on the unit performance. Striking the right balance between work distribution and fair work schedules while distributing the workload as fair as possible is a challenging task for the unit manager. Not to mention the unforeseen events of staff sickness, epidemic infections, or personal holiday requests that feature extra burden on managers to optimise the resources and the productivity of the unit. The standard clinical skill-mix ratio in the units is three experienced nurses to one junior nurse. In this analysis, SMR can take a value from zero to one, where zero means that all staff nurses in a shift are inexperienced, and one states that each member of the team is experienced. The model simulates the behaviour of the levels of SMR between zero and one; with an increment of 0.1 in every set of runs. Results reveal the significant implications of SMR on the performance measures. The baseline value of SMR is 0.75. In both cases, NBO and WBO, the LOS and percentage of administrative work reduction are decreasing as the proportion of experienced nurses increases, while the PET decreases significantly (Figure 6.17a).

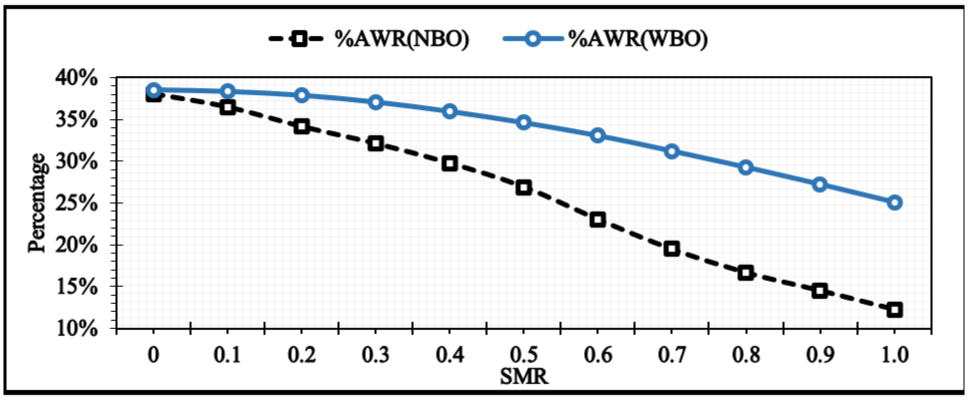
If all staff nurses are experienced (high skill grade), the PET dramatically reduced by more than 63% in the case NBO and by more than 100% in case WBO. Similarly, Figure 6.17b shows that the ADR has increased by 16% reaching 23% when no burn-out is considered and from 12% to 22% when nursing burned-out. Imbalanced case mix (i.e. small SMR) has a greater impact on the nurses' productivity that creates additional pressure on the staff nurses. They have to work hard to meet the demand imposed on them by reducing their administrative tasks and also in reducing the shift breaks length. When SMR is 0 (all staff nurses are junior), the amount of administration work reduction (AWR) is 38% and 39% in case of NBO and WBO, respectively (Figure 6.17c). These percentages reach 12% and 25% when all nurses are experienced for NBO and WBO respectively. When the nurses are burnt-out, AWR still records a high value even though all nurses in the shift are seniors. This can be explained by looking at the causal loop B6 in chapter 5, where the continuous



(a) The implications on PET.



(b) (The implications on ADR.



(c) The implications on AWR.

Fig. 6.17 Sensitivity analysis of the SMR.

workload pressure impacts negatively on the productivity of nurses, and they respond by increasing AWR, which in turn reduces the energy level.

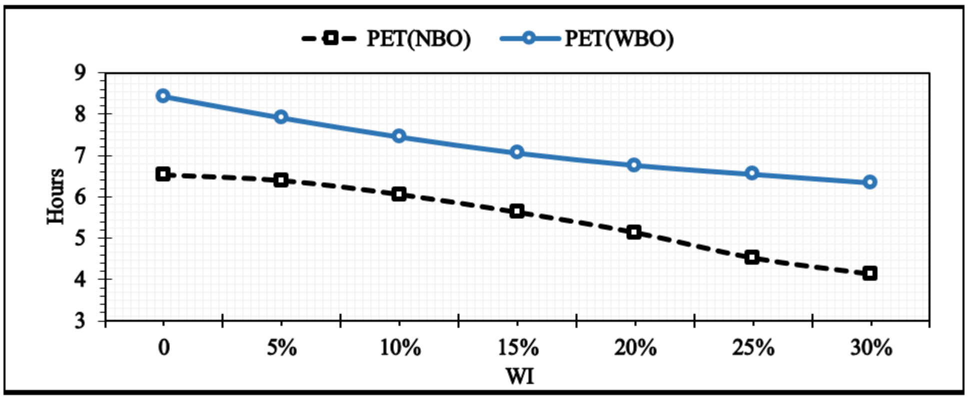
Work Intensity (WI) Implications

Work intensity (WI) is positively correlated with indicators of work demands, long working hours, job stresses and high perception of workload (Burke, Singh, & Fiksenbaum, 2010). The response of staff nurses to high workload and service level pressures are also examined. This experiment demonstrates the sensitivity analysis results of changing the work intensity of the nurses as a reaction to the increase in workload demands. WI enhances the productivity of staff nurses because they reduce the length of their breaks, show more dedications, reduce their admin work, and sometimes work overtime voluntarily.

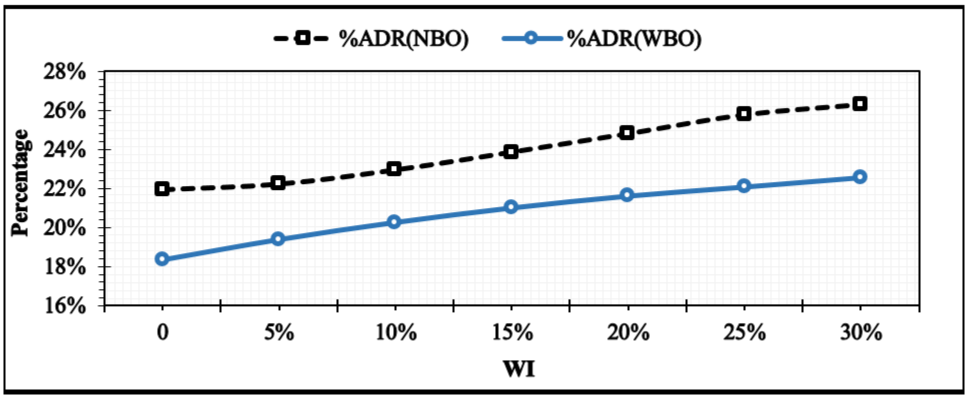
The Implications of WI is tested over seven levels from 0% to 30% with 5% increment factor. WI has a significant positive effect on the three performance measures. An increased workload or work level has series of unexpected consequences. For example, results show that with a WI equal to nearly 30%, a noticeable reduction in the admin work (AWR) by 83% is recorded (Figure 6.18). Firstly, consistent WI induces cases of fatigue and burn-out exponentially while reducing productivity and concentration. It also increases absenteeism and medical errors. Secondly, continuous patterns of WI will reduce administrative work of patients' records. This can result in a slowdown in other activities related to the treatment or error that can lead to worse consequences. This can also easily interrupt training and improvement programs. From interviews with nurses, shortening or cancelling their breaks creates an adverse effect on their mental health, and in the long-term can lead to a breakdown. In fact, the unintended consequences of this behaviour on the quality of care (i.e., medical errors) are more critical than what this experiment may reveal. Recording errors (medical or administrative) appear as a serious problem in most of the healthcare systems.

Time per Activity (TPA) Implications

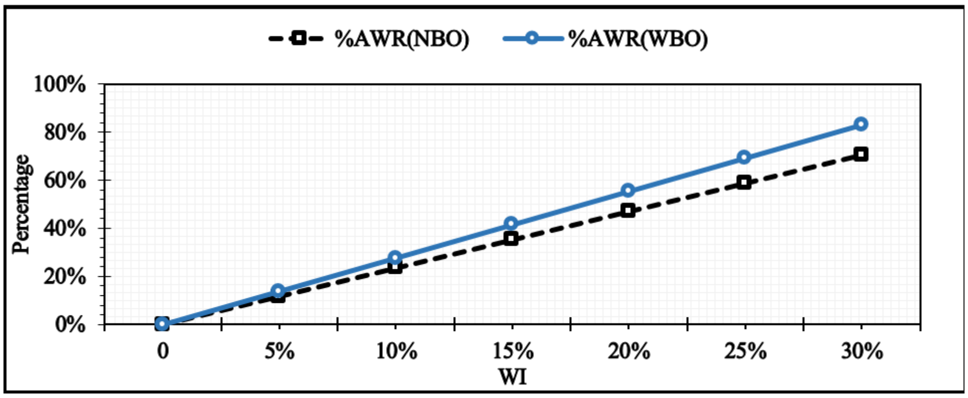
Research reported that nurses sometimes tend to reduce time allocated to some activities to cope with the high demand imposed on them (Kalisch et al., 2009). This is referred as missed



(a) The implications on PET.



(b) (The implications on ADR.



(c) The implications on AWR.

Fig. 6.18 Sensitivity analysis of the WI.

nursing care or care left undone regarding delayed, partially completed, or not completed care. This behaviour is reflected in this experiment through adjusting (shortening) the time allocated to nursing activities to speed up the process.

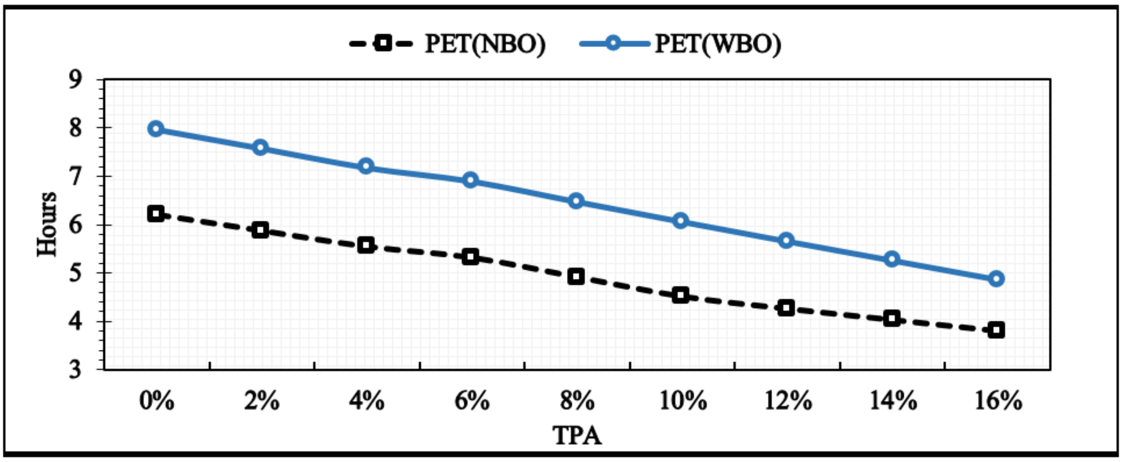
In the model (i.e., balanced feedback loops B2 and B5 in chapter 5), the TPA is dynamically adjusted based on the perceived workload pressure and desired service level pressure (i.e., desired PET). This behaviour is simulated by reasonable reduction of the standard TPA ranging from 0% to 16% by 2% increments. As expected, reduction in the TPA has a considerable impact on performance measures. A reduction of PET and an increase in the ADR takes place when the TPA is reduced by 16% comparing to the standard TPA (i.e., without reduction). The PET dropped by more than 38% in NBO case and by 31.9% in WBO case while the ADR is increased by 17% and 31.7% in the cases of NBO and WBO respectively (Figure 6.19)).

However, this behaviour has unintended consequences such as compromising service quality and undermining patient experience. Patient safety is at the heart of medical practice and is influenced by errors which result in substandard care. Human behaviour altered by workload pressure creates risks to patient safety. The possible deterioration in the quality of care and medication errors is not considered in this experiment.

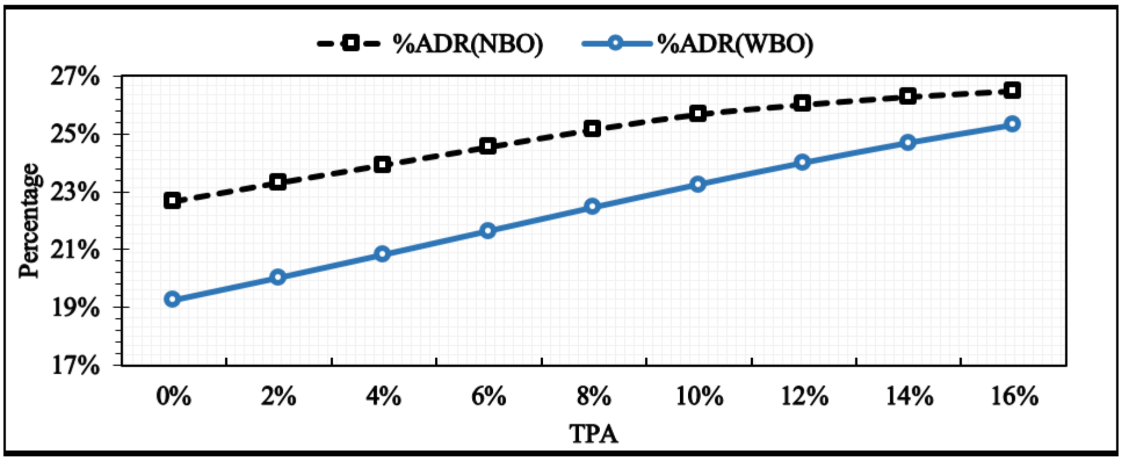
6.3.7 Phase 3: Optimisation

Several factors can have an impact on ED's operational performance. From the supply and demand perspective, patients demand patterns and staffing levels during the day determines the performance of the ED. The patient demand patterns are mostly out of management's control and the only way to improve operational performance regarding waiting time and PET is to establish an appropriate work shift schedule which matches the patient demand patterns.Adding more staff capacity, rescheduling work shifts through modifying the team patterns are useful strategies to improve the operational performance. ED demand patterns are also independent of staffing patterns.

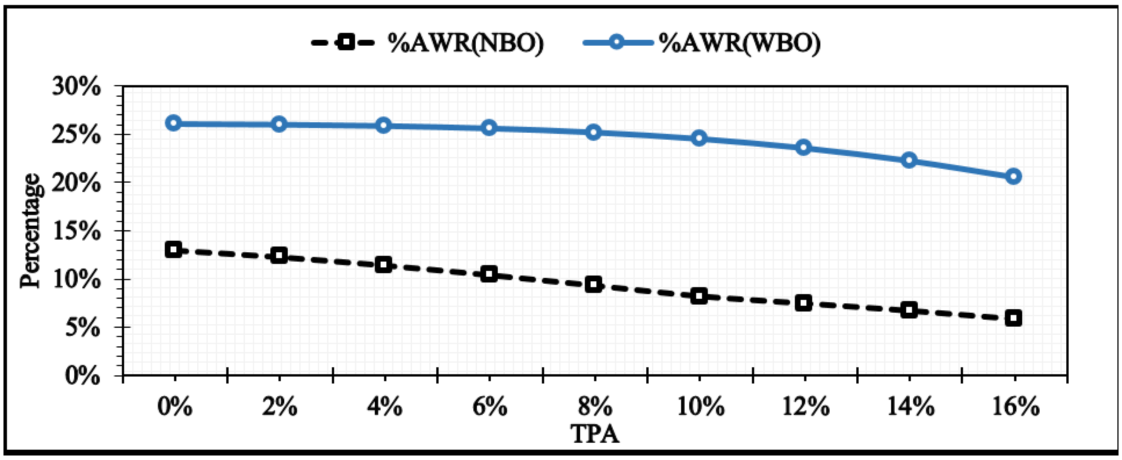
Therefore, inappropriate staffing results in long queues, increases in waiting time, poor patient experience and unbalanced workload on the staff. In this phase of the study as



(a) The implications on PET.



(b) (The implications on ADR.



(c) The implications on AWR.

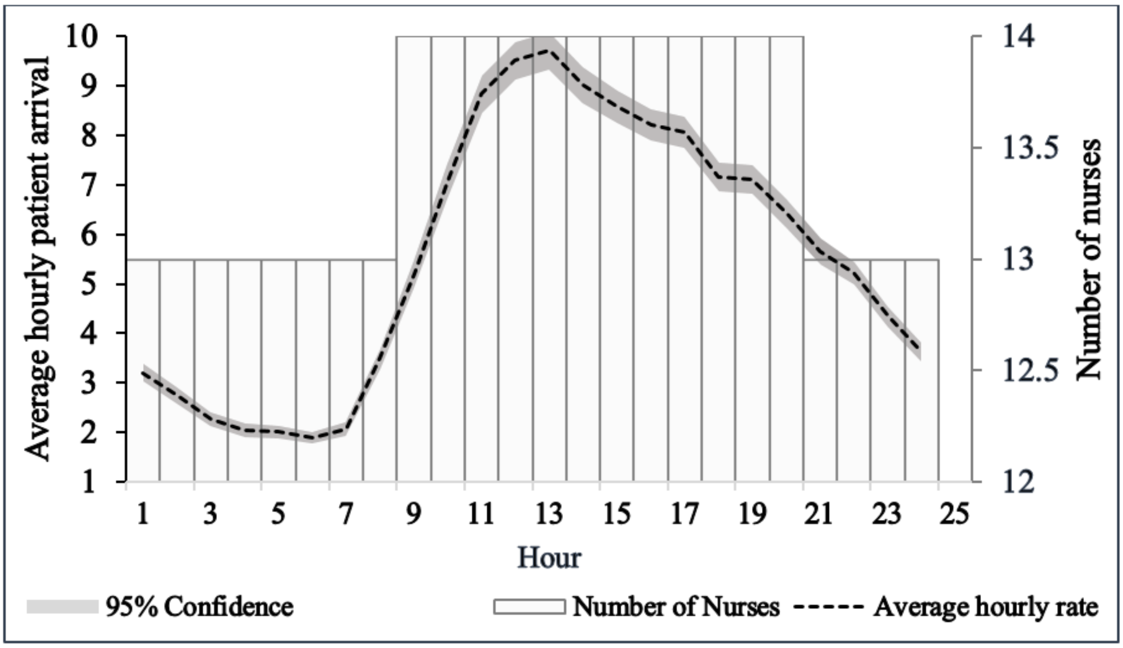
Fig. 6.19 Sensitivity analysis of the TPA.

discussed Chapter 5, simulation and optimisation are applied to determine the optimal temporal staffing patterns to meet patients demand. Then, staffing patterns obtained from solving the staffing problem are used to generate shift schedule patterns that satisfy the staffing requirements with minimum under-/over-staffing.

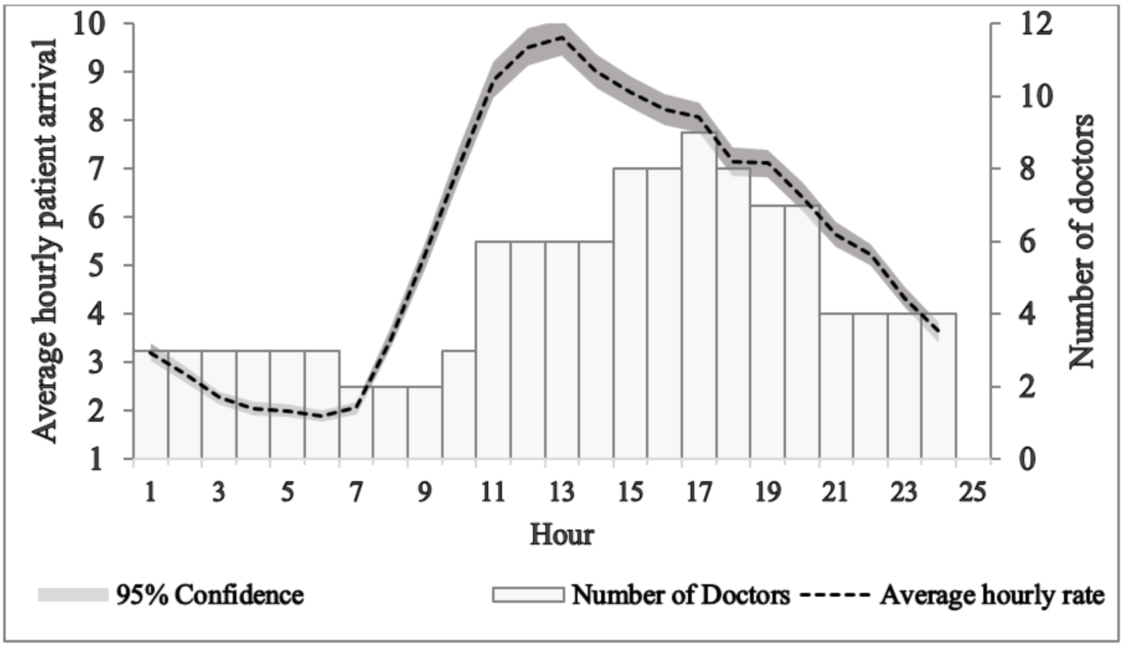
This analysis focused on five types of ED staff: Triage Nurse, Advanced Nurse Practitioner (ANP), ED registered nurse, ED SHO and ED Registrar. The ED staff in Tallaght hospital are dedicated to the ED. Nurses work two long shifts 8 AM to 8 PM and 8 PM to 8 AM. The SHO team has six different shifts during the day, and the Registrar staff have five. Nurses shift length is fixed at 12 hours. Similarly, the shift duration of doctors is set at 10 hours. Fixed length shifts with predetermined starts are inflexible to meet the demand patterns that change from moment to another.

However, when comparing the volume demand pattern during the day with the current staffing levels, results demonstrated that staffing patterns are partially informed by the demand (Figure 6.20). The department managers often use simple formulae of total and average for doing staffing calculations which are misleading and usually ends up with suboptimal decisions.

The simulation base scenario runs to provide insights regarding the current staff schedule workload and staff utilisation. The average staff workload over the simulation run is given in Figure 6.21. The workload for nurses, SHO and registrars are nearly 70%, with high standard deviations due to the demand fluctuations during the day. The figure shows the change of the staff workload during the hour which reveals the workload peak of all ED staff starts at 11 AM till 6 PM.



(a) Nurse Schedule vs. demand volume patterns.



(b) Doctor Schedule vs demand volume patterns.

Fig. 6.20 Temporal workloads vs current ED staffing.

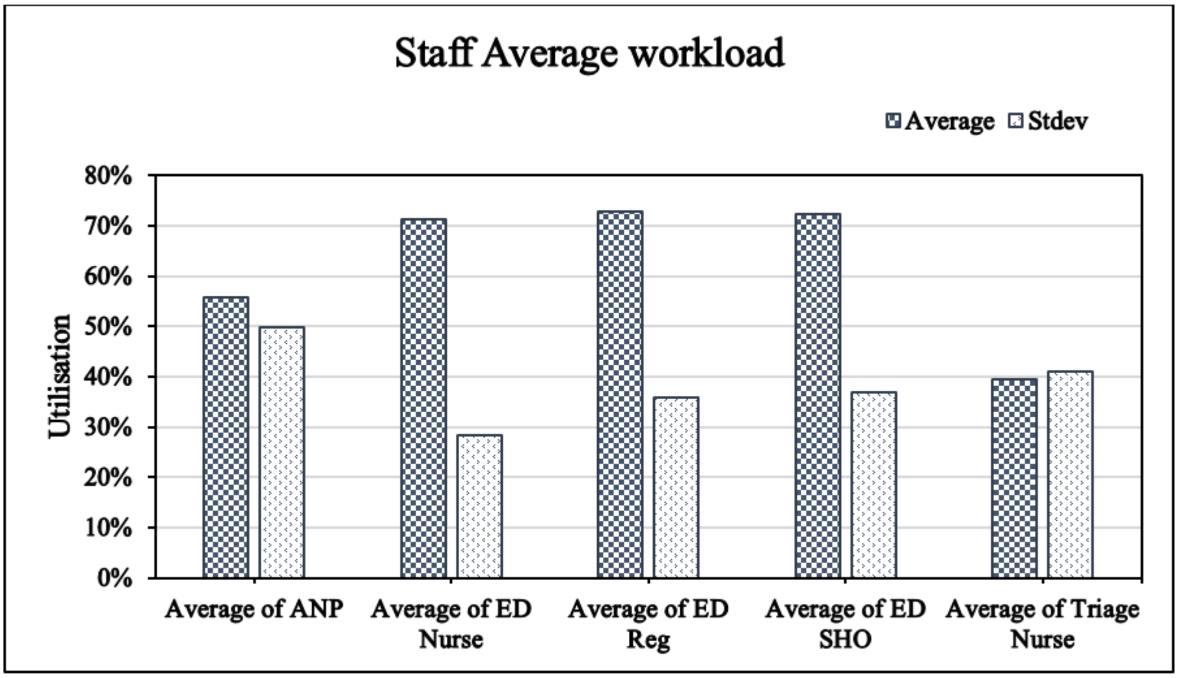


Fig. 6.21 The averaged staff workloads.

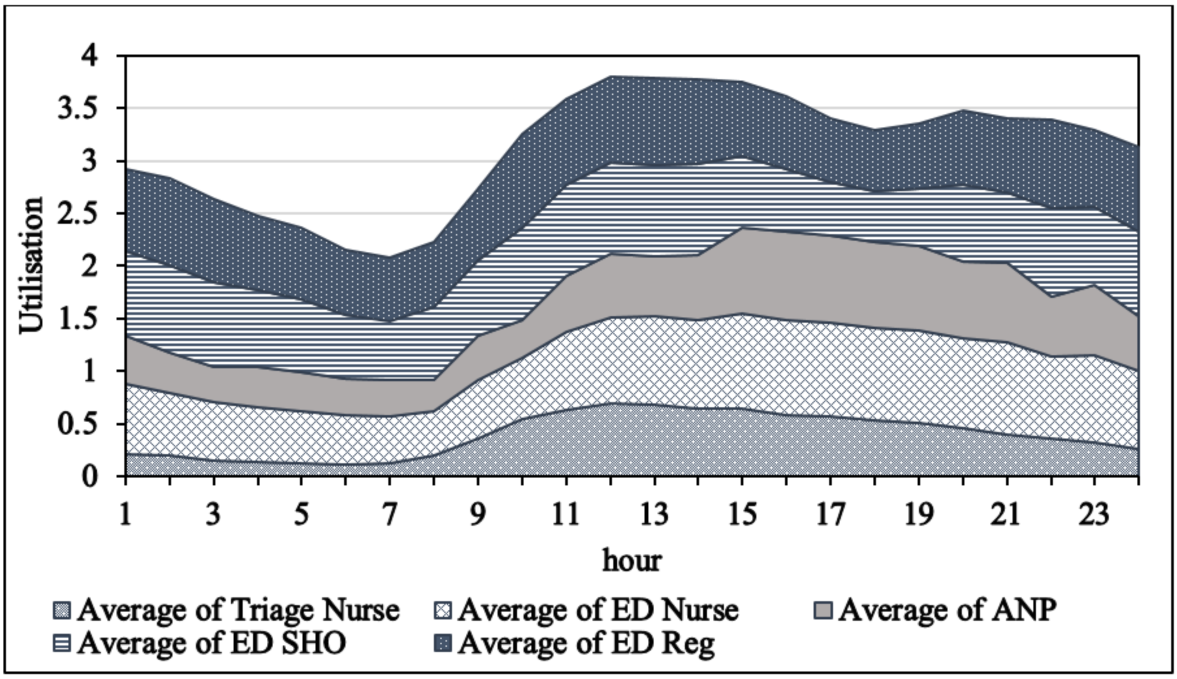


Fig. 6.22 Average staff workload per hour for the base schedule.

6.3.7.1 Base staffing Experiment

Management has selected two main criteria that determine the quality of service. The average waiting time for patients and the percent of patients whose LOS is less than six hours are both reflections of the patient experience time. Both performance indicators are aligned with the national strategy that aims to improve the safety and quality of care as stated by of the Emergency Medicine Programme (EMP).

From the staff perspective, sustained working close to full utilisation to fulfil the excess workload with minimal cost leads to substantial implications and ultimately reduces the productivity and may increase the operating costs, in addition to the quality issues that result from these adaptive behaviours. Therefore, an efficient schedule should keep the staff utilisation less than a threshold as recommended by the SD component. At the same time, management suggested a lower bound for staff utilisation to minimise the improper underutilisation.

The three criteria are evaluated using the simulation model, therefore obtaining the (near) optimal staffing patterns requires solving a stochastic multi-objective simulation optimisation problem with integer variables. The Desirability approach was used to optimise multiple simultaneous objectives by transforming the estimated response(by simulation) into a unified scale called a desirability index (section 5.5.2). The desirability function for minimisation is smaller-the best (STB type), maximisation is larger-the-best (LTB type), and a target is nominal-the-best (NTB type). Their mathematical equation is given in Appendix C.2. Therefore, average waiting time, percent of patient with LOS less than 6 hours, and average utilisation criteria are transformed by STB, LTB, and NTB desirability functions, respectively. The shape parameters are set to 0.5 for the three types to obtain a convex transformation and to make it easier to get a desirable solution (this set with the coordination with the management). The preferences of the management regarding the lower and upper bounds of the three objectives are given in Table 6.8. The overall desirability is determined using the equation illustrated in section 5.5.2 using equal weights geometric mean.

A staffing optimiser determines the optimal staffing for each staff type by applying a simulation. Staffing optimiser searches for a near-(optimal) staffing patterns that match the patients' demand. The objective function is minimising the patient waiting time. The results of this stage are summarised in Table 6.9.

Table 6.8 Desirability Approach parameters

			Lower bound	**Upper bound**	**Target**	**Shape parameter**	
		Type	L	U	T	a	b
Waiting time (W)	Smaller is The Best	STB	60	200	-	.5	-
Percent of patients with LOS <6 hrs	Larger is The Best	LTB	30%	75%	-	.5	-
Staff Utilisation	Nominal is the Best	NTB	30%	75%	60%	.5	.5

The staffing optimiser has achieved a significant reduction in required daily staffing hours. Nursing and triage hours were reduced by 36 and 14 respectively, while ANP hours increased by 11 hours. Registrar hours increased significantly from 58 hours to 81 hours (23 extra hours are required). This has been compensated by a substantial reduction in the SHO hours (16 hours).

The staffing patterns of each staff type are presented in Figure 6.23 for nursing staff and Figure 6.24 for doctors. The staffing patterns in both figures seek to match the demand patterns at peak periods.

However, the adopted fixed shifts by the department do not help management to benefit from this reduction. For example, nurses are working single length shift (12-hours) with the fixed start time (at 8 AM and PM). Therefore, the shift schedule that satisfies the staffing requirements is the maximum staff required during the first shift, which is ten nurses. Similarly, the second shift will be allocated with ten nurses. This simple schedule is inefficient regarding overstaffing and unfair regarding workloads. The flexibility of shifts with variable length and start time enable management to better respond to the demand efficiently and reflectively. In stage two of the optimisation phase, various shifts with variable starting times are explored to predict their implications on the over/understaffing.

Table 6.9 Results obtained from the staffing optimiser.

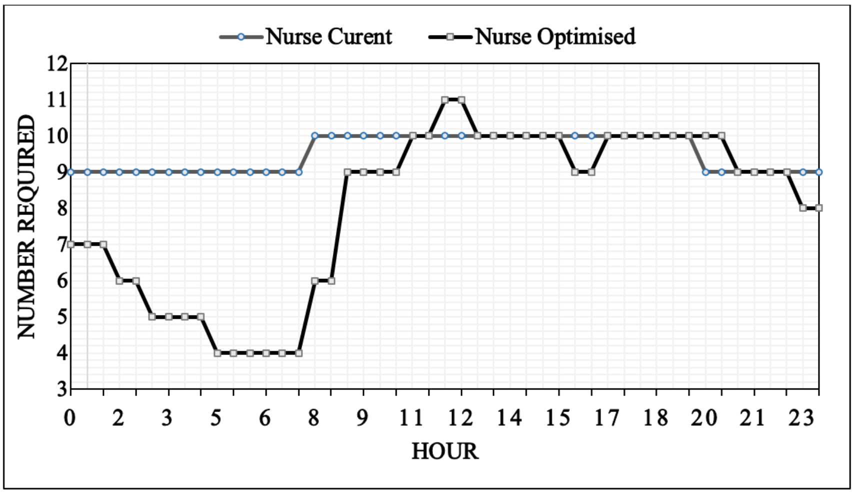
Hour	Nurse		Triage Nurse		ANP		SHO		Registrar	
	As is	**Optimised**	**As is**	**Optimised**	**As is**	**Optimised**	**As is**	**Optimised**	**As is**	**Optimised**
0	9	7	2	1	1	1	1	1	2	3
1	9	7	2	1	1	1	1	1	2	3
2	9	6	2	1	1	1	1	1	2	2
3	9	5	2	1	1	1	1	1	2	2
4	9	5	2	1	1	1	1	1	2	2
5	9	4	2	1	1	1	1	1	2	1
6	9	4	2	1	1	1	1	1	1	1
7	9	4	2	1	1	1	1	1	1	2
8	10	6	2	1	1	1	1	1	1	3
9	10	9	2	2	1	2	1	2	2	6
10	10	9	2	2	1	2	3	2	3	4
11	10	10	2	2	1	2	3	3	3	4
12	10	11	2	2	1	2	3	3	3	4
13	10	10	2	2	1	2	3	2	3	5
14	10	10	2	2	1	2	4	2	4	4
15	10	10	2	2	1	2	4	2	4	4
16	10	9	2	2	1	2	5	2	4	4
17	10	10	2	2	1	2	5	2	3	4
18	10	10	2	2	1	2	4	2	3	4
19	10	10	2	1	1	2	4	2	3	4
20	9	10	2	1	1	1	2	2	2	4
21	9	9	2	1	1	1	2	2	2	4
22	9	9	2	1	1	1	2	2	2	4
23	9	8	2	1	1	1	2	1	2	3
Total hours	228	192	48	34	24	35	56	40	58	81
change	**-36**		**-14**		**11**		**-16**		**23**	

Results obtained from the staffing optimiser feed into the shift schedule to determine the optimal shift starts for each staff type. In this experiment, four types of shifts are used 12, 10, 8, and 6 hours for nurses, and three shifts 10, 8, and 6 for doctors. As described in chapter 5, formulation three is applied to obtain the staff shift schedule that minimises the understaffing and overstaffing for each staff type with more weight given to the understaffing to maintain both qualities of care and improve staff satisfaction. As advised by the management, starting a work shift from 1 AM to 6 AM is not allowed for all personnel types. These time blocks are added to the prohibition set to prevent starting a work shift at these times.

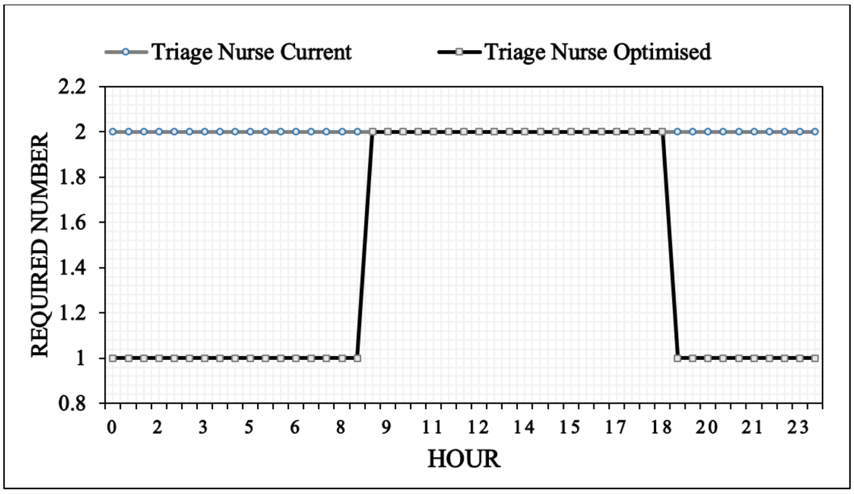
Results of shift schedule for nursing staff is shown in Table 6-10 and Figure 6.25a. For nurses, their schedules consist of working the four shifts. The first shift is 12 -hour shift that is set as follows: three nurses start at 7 AM and 7 PM while only one nurse at 1 PM, 3 PM, 4 PM and 8 PM. The 10-hour shift is registered with three nurses; two at 10 AM and one at 12 PM. Only one nurse is planned for 8-hour shift that starts at 9 AM. The last scheduled shift for nurses is the 6-hour shift which is scheduled for three nurses; one nurse starts at 8 AM, 9 AM, and 10 AM. The nurse schedule results in 192 nursing hour schedule that covers the demand requirement with zero planned under/overstaffing.

Two shifts have been proposed for scheduling triage nurse. One triage nurse is scheduled for 12-hour shift at 8 AM and 8 PM, while one extra nurse is scheduled for 10-hour shift at 10 AM to cover the demand peak. Triage nurse shift schedule includes all 34 hours of triage nurse staffing without any extra staffing hours. Likewise, the ANP has scheduled for only 12-hour shift where one starts at 7 AM, 9 AM and 7 PM. ANP schedule covers 36 hours with one hour overstaffing.

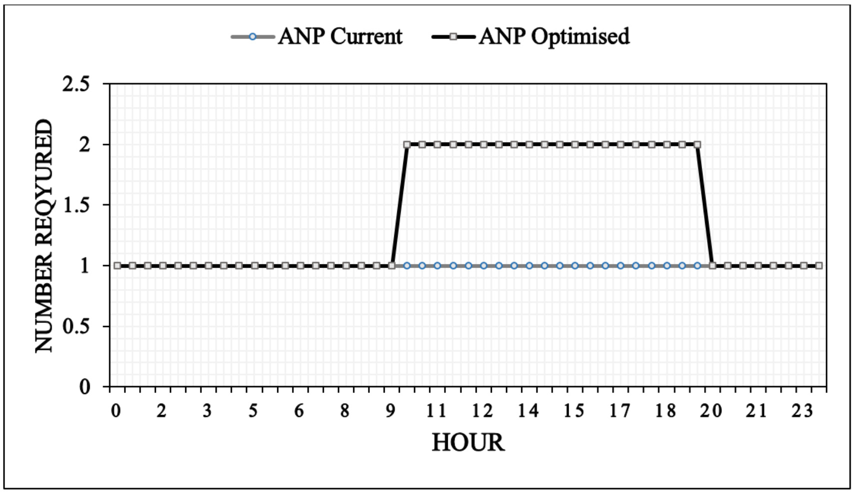
The proposed SHO schedules include overlapping five shifts with total 40 hours without overstaffing. Two SHOs are scheduled for 10-hour shift with one SHO at 12 PM and one at 10 PM. The 8-hour shift is allocated with one SHO at 4 PM, while 6-hour shift is assigned with two SHO; one at 8 AM and one at 10 AM.



(a) Registered Nurse.

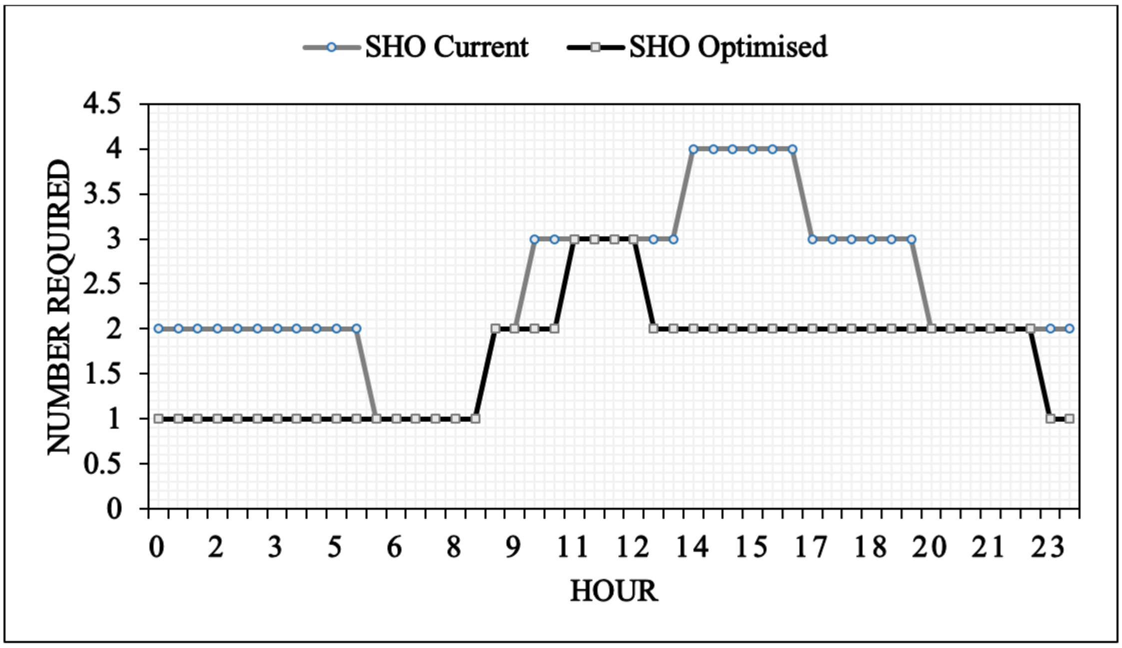


(b) Triage Nurse.

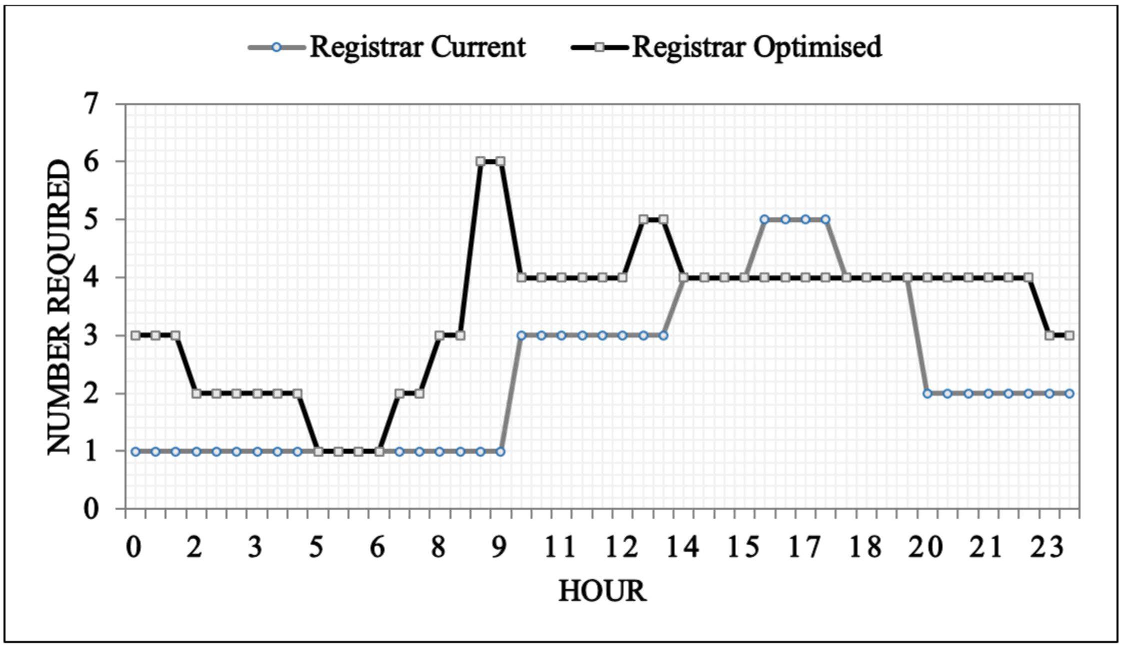


(c) Advanced Nurse Practitioner (ANP).

Fig. 6.23 Current vs optimised nursing staffing patterns.



(a) Senior House Officer (SHO).



(b) Registrar.

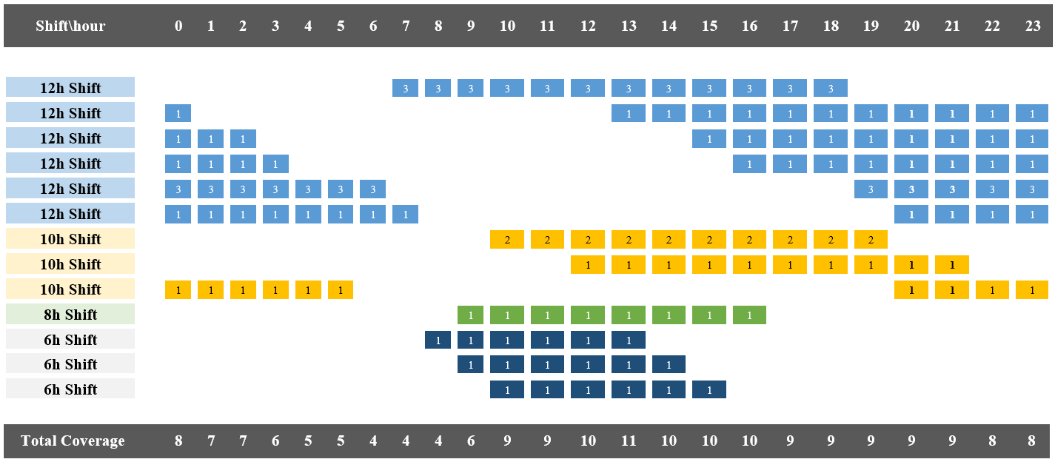
Fig. 6.24 Current vs optimised staffing patterns for doctors.

Table 6.10 The proposed shift schedules for nursing staff.

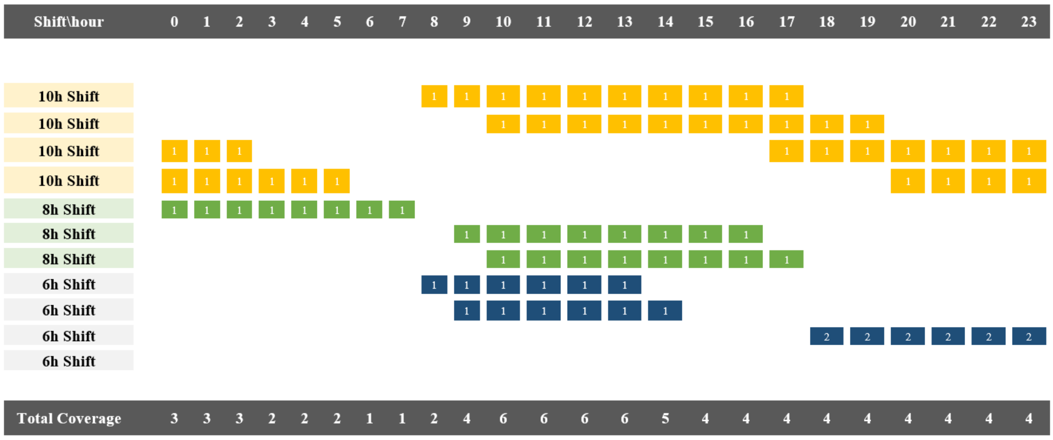
	Nurse Schedule																								
	hour	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**Total**
	Req.	**7**	**7**	**7**	**6**	**5**	**5**	**4**	**4**	**4**	**6**	**9**	**9**	**10**	**11**	**10**	**10**	**10**	**9**	**10**	**10**	**10**	**10**	**9**	**9**	**192**
Nurse	12h Shift	0	0	0	0	0	0	0	**3**	0	0	0	0	0	**1**	0	**1**	**1**	0	0	**3**	**1**	0	0	0	
	10h Shift	0	0	0	0	0	0	0	0	0	0	**2**	0	**1**	0	0	0	0	0	0	0	**1**	0	0	0	
	8h Shift	0	0	0	0	0	0	0	0	0	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
	6h Shift	0	0	0	0	0	0	0	0	**1**	**1**	**1**	0	0	0	0	0	0	0	**1**	0	0	0	0	0	
Coverage	12h Shift	6	6	6	5	4	4	4	4	3	3	3	3	3	4	4	5	6	6	6	6	7	7	7	7	**120**
	10h Shift	1	1	1	1	1	1	0	0	0	0	2	2	3	3	3	3	3	3	3	3	2	2	1	1	**40**
	8h Shift	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	**8**
	6h Shift	0	0	0	0	0	0	0	0	1	2	3	3	3	3	2	1	0	0	1	1	1	1	1	1	**24**
	Understaffing = 0 & Overstaffing = 0																								
	Req.	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**2**	**2**	**2**	**2**	**2**	**2**	**2**	**2**	**2**	**2**	**1**	**1**	**1**	**1**	**34**
Triage Nurse	12h Shift	0	0	0	0	0	0	0	0	**1**	0	0	0	0	0	0	0	0	0	0	0	**1**	0	0	0	
	10h Shift	0	0	0	0	0	0	0	0	0	0	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	
	8h Shift	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
	6h Shift	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
Coverage	12h Shift	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	**24**
	10h Shift	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	0	0	0	0	**10**
	8h Shift	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
	6h Shift	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
	Understaffing = 0 & Overstaffing = 0																								
	Req.	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**2**	**2**	**2**	**2**	**2**	**2**	**2**	**2**	**2**	**2**	**2**	**1**	**1**	**1**	**35**
ANP	12h Shift	0	0	0	0	0	0	0	**1**	0	**1**	0	0	0	0	0	0	0	0	0	**1**	0	0	0	0	
	10h Shift	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
	8h Shift	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
	6h Shift	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
Coverage	12h Shift	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2	1	1	1	**36**
	10h Shift	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
	8h Shift	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
	6h Shift	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
	Understaffing = 0 & Overstaffing = 1																								

Table 6.11 Proposed physician shift schedule.

	Physician Schedule																								
	Hour	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**Total**
	Req.	1	1	1	1	1	1	1	1	1	1	2	2	3	3	2	2	2	2	2	2	2	2	2	2	**40**
SHO	12h Shift	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
	10h Shift	0	0	0	0	0	0	0	0	0	0	0	0	**1**	0	0	0	0	0	0	0	0	0	**1**	0	
	8h Shift	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	0	0	0	0	0	0	0	
	6h Shift	0	0	0	0	0	0	0	0	**1**	0	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	
Coverage	12h Shift	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
	10h Shift	1	1	1	1	1	1	1	1	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	**0**
	8h Shift	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	**16**
	6h Shift	0	0	0	0	0	0	0	0	1	1	2	2	2	2	1	1	0	0	0	0	0	0	0	0	**24**
Understaffing = 0 & Overstaffing = 0																										
	Req.	3	3	3	2	2	2	1	1	2	3	6	4	4	4	5	4	4	4	4	4	4	4	4	4	**81**
Registrar	12h Shift	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
	10h Shift	0	0	0	0	0	0	0	0	**1**	0	**1**	0	0	0	0	0	0	**1**	0	0	**1**	0	0	0	
	8h Shift	**1**	0	0	0	0	0	0	0	0	**1**	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0	
	6h Shift	0	0	0	0	0	0	0	0	**1**	**1**	0	0	0	0	0	0	0	0	**2**	0	0	0	0	0	
Coverage	12h Shift	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
	10h Shift	2	2	2	1	1	1	0	0	1	1	2	2	2	2	2	2	2	3	2	2	2	2	2	2	**40**
	8h Shift	1	1	1	1	1	1	1	1	0	1	2	2	2	2	2	2	2	1	0	0	0	0	0	0	**24**
	6h Shift	0	0	0	0	0	0	0	0	1	2	2	2	2	2	1	0	0	0	2	2	2	2	2	2	**24**
Understaffing = 0 & Overstaffing = 7																										



(a) Registered nurse.



(b) Registrar.

Fig. 6.25 Visual presentation of the generated schedules for selected staff types.

Registrars are scheduled across ten overlapping shifts (Figure 6.25b. Four 10-shifts are allocated with one registrar each at 8 AM, 10 AM, 5 PM and 8 PM, while three 8-hour shifts are scheduled with one registrar each at 12 AM, 9 AM and 10 AM. Also, three 6-hours shifts are added to meet the requirements with one registrar at 8 AM and 9 AM. The optimal registrar schedule results in seven hours overstaffing.

To avoid staff understaffing and minimise overstaffing, shift schedule with flexible start time enables to meet the staff requirements through the overlapping between staff shifts. Due to the consideration of the workload patterns obtained from the staffing optimiser, the resulted staff shift schedules comply with the daily patients' arrival pattern considering the main factors that impact the amount of care required.

The results of staff schedules from this stage are simulated to evaluate the predicted performance after optimising the staffing patterns and shift schedule (6.12). As expected, the performance has been improved substantially through modifying the staff patterns to match demand. Optimised staffing patterns eliminated 43% of the patients waiting time which has reflected on the performance measures. Simulation model predicted the PET of all patients had been dropped by 29%, while PET of discharge is reduced by 33%. Optimising staffing patterns to match the demand has limited impact on reducing the PET of admitted patients because most of their waiting is boarding. Percent of patients discharged or admitted in less than six hours has improved by 25%, while there is a 13% improvement in the number of patients admitted or discharged in less than nine hours.

Table 6.12 Performance comparison.

	WT	ED PET	ED PET Admitted	ED PET Discharged	%< 6hrs	%< 9hrs
Current Staffing	272	530.36	776.47	353.57	0.4949	0.6622
Optimised Staffing	155	375	733	250	0.618	0.747
% change	43%	-29%	-6%	-33%	25%	13%

6.3.7.2 Impact of Flexible Shift Experiment

As previously pointed out, nurses in the hospital under investigation are using fixed shifts with the fixed starting time. This experiment explores the impact of adding more shift with variable/flexible starting time. Four settings of shifts starts are proposed for the comparison: current, Flex1, Flex 2, and not restricted.

- Current (Restricted). This is the current shift adopted by the ED nurses, which includes two 12-hour shifts (at 8 AM and 8 PM).

- Flex1. This setting allows starting a shift only at certain time blocks. In this case, the allowed shift starts are from 7 AM to 11 AM (day) and from 6 PM to 9 PM (night).

- Flex 2. This setting is more flexible as it allows a shift to start at any time block between 7 AM and 9 PM.

- Not restricted. This configuration allows a shift to start at any time block during the planning period.

The nurse staffing patterns from the base scenario are used by shift scheduling in this experiment. Four shift policies for each setting are adopted. First shift policy assumes the only one shift is available (12H shift). The second policy uses two shift (12H and 10H shifts). The third policy uses a combination of three shifts (12H, 10H, and 8H). Finally, policy four adopts the four shifts. For each policy and shift setting, stage two optimisation (formulation 3) is used to get the optimal shift schedule. The high penalty is given to the understaffing term in the objective function to push the optimisation to eliminate any shortage. The overstaffing term is the possible way to for covering the requirements. Therefore, the overstaffing is reported across this experiment.

The results of shows that variable start has a significant impact in reducing the overstaffing (Figure ?6 24). Using a combination of shift lengths and flexible shift start time eliminates the overstaffing. This provides flexibility to the management to respond efficiently and more to the changes in the workloads. Still using single shift with some flexibility in the start time has a significant impact on reducing the overstaffing. However, single shift policy is rigid to accommodate the patterns of requirements. A substantial drop in the staff surplus for policy two. In the Flex1 setting, the surplus has reduced 70% (from 60 hours to 18 hours). Shift policy four much more efficient with 90% overstaffing reduction in Flex 1 setting and eliminate the nurse surplus in the Flex2 setting.

In summary, variable shift-length and flexible start-time are useful and practical policies that can improve the quality of schedule regarding coverage, operational efficiency, responsiveness, and flexibility.

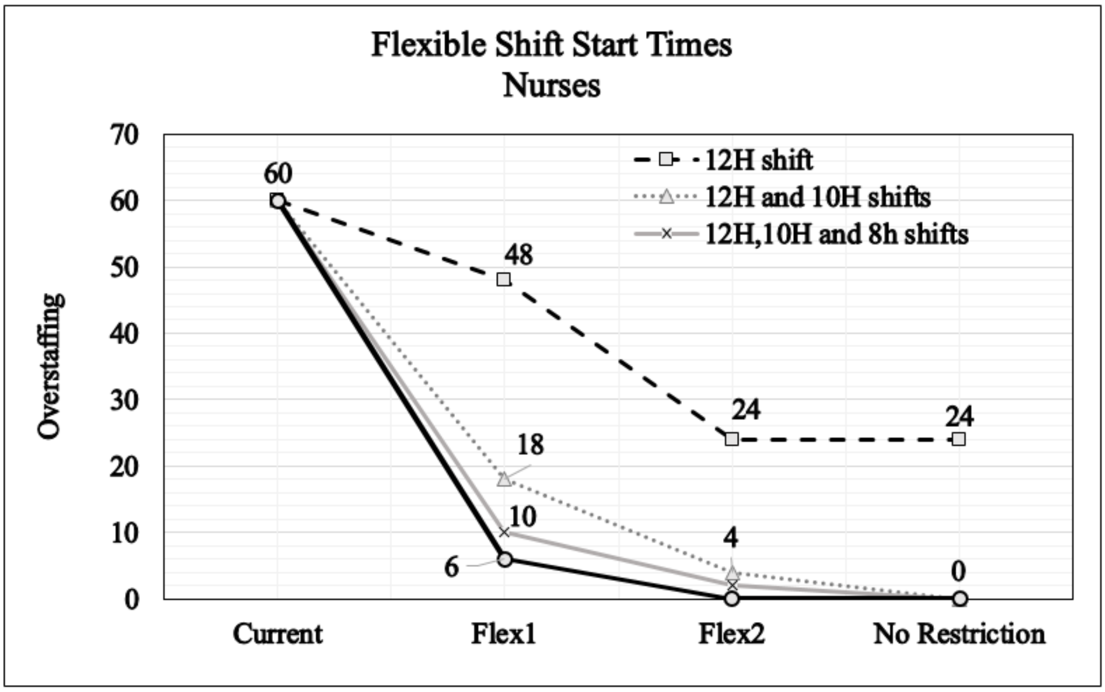


Fig. 6.26 Impact of flex start time on overstaffing.

6.3.7.3 Effect of Increase in Complexity of Care (Acuity)

The DES simulation model captures the complexity of care regarding workload intensity - the amount staff time required to provide patient care during their entire stay in the hospital. Workload intensity includes both direct and indirect care.

In this experiment, two scenarios are compared with base staffing at the standard workload intensity. Scenario one and two increase the workload intensity by 10% and 20% of the base, respectively. The staffing optimiser is employed to generate the staffing patterns for each staff type. The same parameters used for the base staffing (Table 6.7) are applied for this experiment in order to compare the change in staffing patterns due to the increase in patient care. Figure 6.27 and Figure 6.28 show near optimal staff requirements for nursing staff and physicians, respectively.

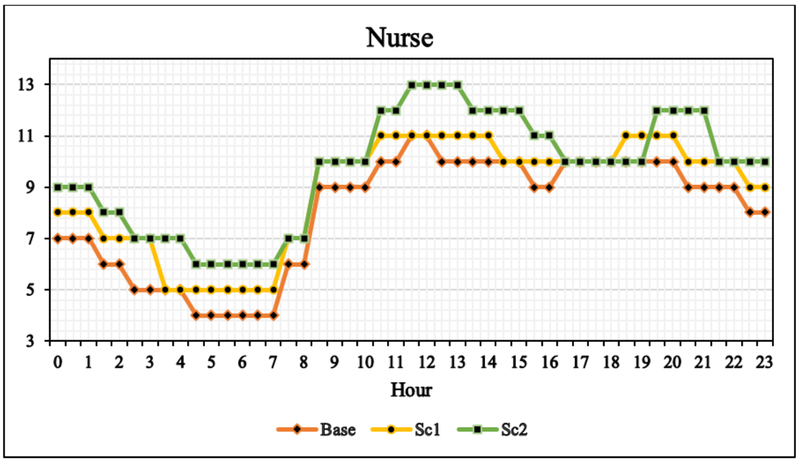
For nursing staff, a significant change in the staffing patterns of the nurses in scenario 1 and two compared to the base staffing patterns. Nursing staffing requirements are shifted up. Insignificant change in the staffing patterns of triage nurses because the simulation model assumes that the complexity of care required is an outcome of the triage activity. Similarly, for ANP staff, no change in the staffing from the base and scenario one. While in scenario 2, one extra ANP nurse is required from hour 8 AM to 2 PM and one at 3 PM with total 5 hours extra. The physician staffing patterns have shifted above the base schedule in order to compensate for the increase in workload.

Figure 6.29 compares between base, scenario 1 and scenario 2 regarding the aggregate change in the staffing. Significant increase in the nursing and physician hours are required in order to meet the increase in patient's acuity. The associated shift schedules are provided in Appendix C.4.

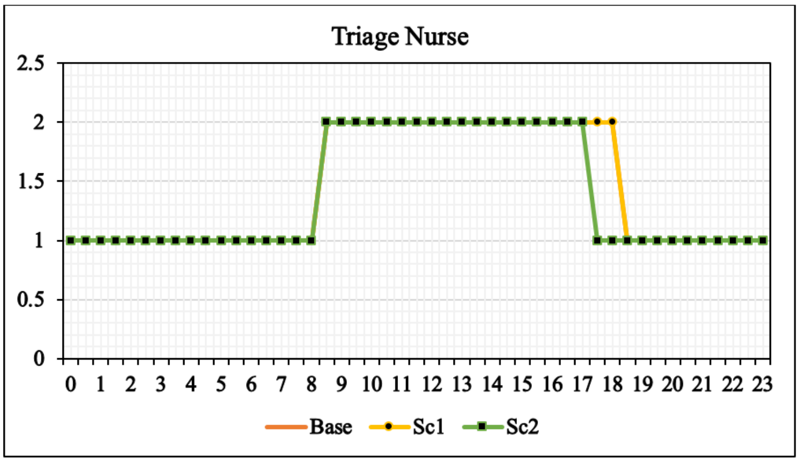
6.3.8 Findings

This case study has revealed that the developed integrated framework, when properly conceived and designed in a collaborative fashion between scientists and clinicians can provide a valid and verifiable dynamic comparator (i.e., model) to a real-life overcrowded Hospital (ED and AMAU).

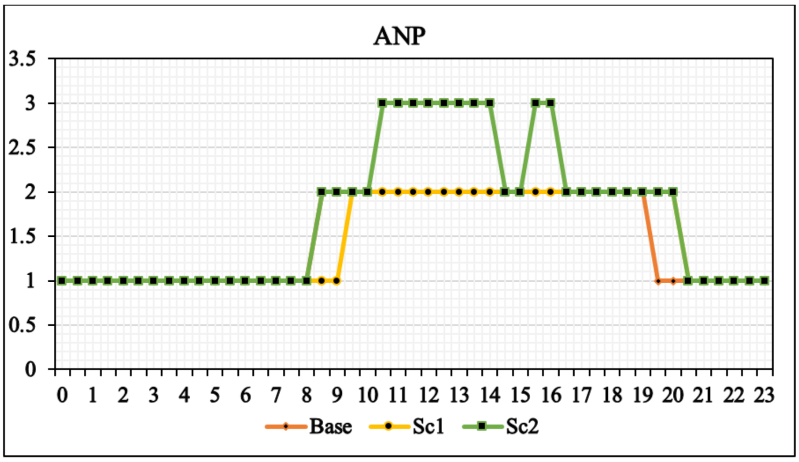
The developed framework provides a comprehensive solution that enables managers to explore and address the dynamics of factors that impact the staffing and scheduling decisions. Also, it provides a tool to enhance current decision making by considering various factors across the main aspect of the problem: patient, staff, and organisational aspects. All those factors as described in chapter 5 are incorporated into the simulation model to predict accurate staff workload. Staffing optimiser attempts to find adequate staffing patterns that meet the



(a) Registered Nurse.

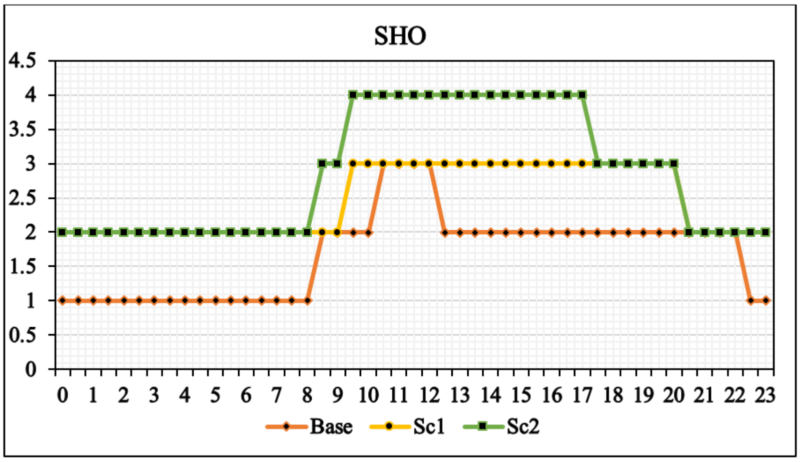


(b) Triage Nurse.

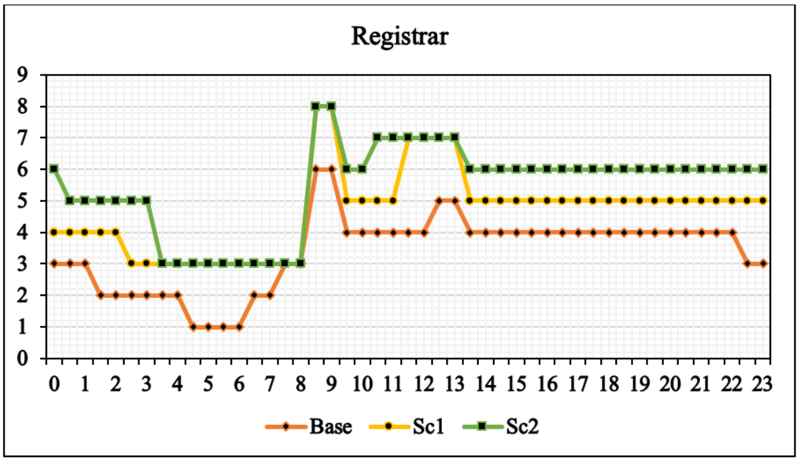


(c) Advanced Nurse Practitioner (ANP).

Fig. 6.27 Nursing staffing patterns; Base vs. Sc1 and Sc2.



(a) Senior House officer (SHO).



(b) Registrar.

Fig. 6.28 Physician staffing patterns; base vs. Sc1 and Sc2.

patients demand with near certainty and at the same time achieve a certain level of service quality. To do that, the staffing problem is cased as a multi-criteria stochastic optimisation problem. Desirability approach is introduced to consider the decision maker preferences and also to convert the multi-objective problem into single-objective. The output of staffing optimisation is utilised by shift scheduling optimiser to propose set of shifts that trade-off between understaffing and overstaffing.

The framework has been applied successfully in the Emergency Department and Acute Medical Assessment Unit in a major teaching university hospital in Dublin. Several scenarios

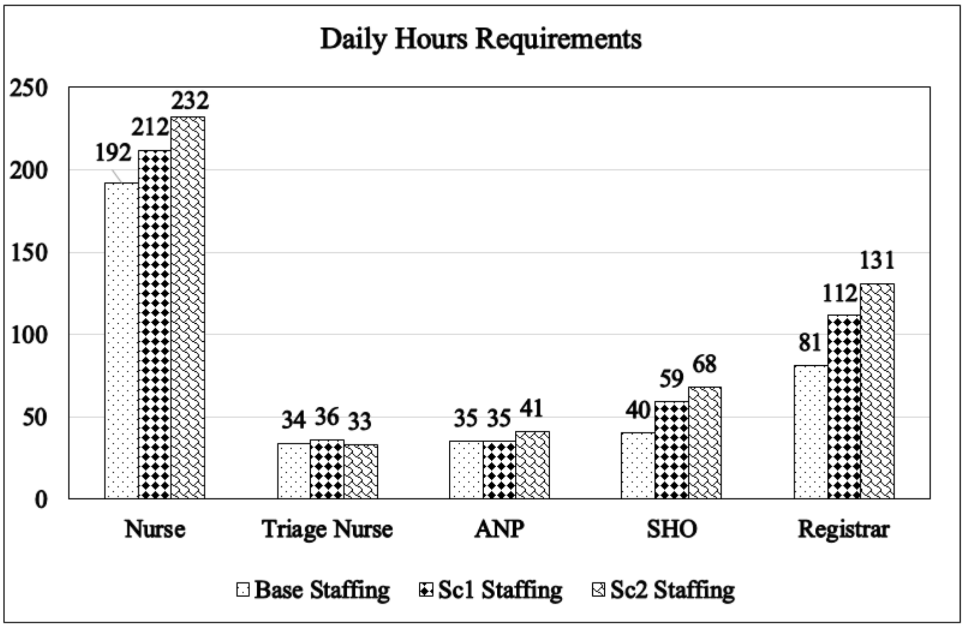


Fig. 6.29 The aggregate total staffing hours required.

have been explored such as lack of coordination with downstream, inappropriate demand, and adaptive staff behaviour. The lack of coordination among hospital facilities from the scenario analysis confirms the management perceptions about the problem of boarding and the lack of alignment of the downstream resources (i.e. inpatient wards). This increases the unnecessary workload on staff besides the overcrowding that makes the work environment not suitable to provide emergency care.

The burnout scenario has explored the impact of burnout and the adaptive staff behaviour in the AMAU nurses through investigating the three factors using SD component: Skill-Mix (SM), Work Intensity (WI), and Time per Activity (TPA). Nurses react to the burnout effect by adjusting their behaviours to cope with the fatigue, stresses, and workload pressures. This reaction can be described as a natural defence to survive the tide. Results show that the imbalanced skill-mix has a greater impact on the nurses' productivity that creates additional pressure on the staff nurses, which eventually leads to burnout. The work intensity behaviour experiment indicates that working hard mitigates the workload pressure temporarily, but eventually depletes the energy nurses' energy level which has dramatic unintended consequences.

This low-cost framework may also prevent the introduction of potentially expensive and unsuccessful strategies to improve patient care and staffing decisions. The lengthy waits for admission from the ED increase the total hospital average length of stay and impacts on the mortality of elderly patients. Access block, therefore, has been shown by the developed framework to have the greatest impact on prolonged waiting time for patients and successful strategies are available to reduce hospital access block time especially in situations of ED surge and reduced hospital bed capacity. The optimised base staffing patterns and shift schedules actively contributed to solving ED overcrowding problem and reduced the average waiting time for patients significantly by 43% compared to the current waiting time of discharged patients. That is achieved by optimising the staffing level and then determine the shift schedule that minimises the understaffing and overstaffing to meet patient demand.

Chapter 7

Conclusion

> Through all the years of experimenting and research, I never once made a discovery. I start where the last man left off.... All my work was deductive, and the results I achieved were those of invention pure and simple.
>
> *Thomas Edison(1847–1931)*

7.1 Introduction

Acute hospital systems all over the world struggle to meet patients' demands to provide a safe, high quality and timely health service. Increasing pressures on the service due to an ageing population, combined with technological and medical advances, budget constraints, shortages in medical staff, and rising patient expectations, make hospital management a complex and challenging task. Irish hospital systems, at various levels, face severe shortages of doctors and nurse. Staff experience a constant increase in their workload and workload balance of medical staff is always an issue for hospital management. This can result in medical staff often suffering 'burn-out' due to the complexity of the staff scheduling practices. Burn-out of staff can lead to mistakes in diagnosis, operational difficulties, failure to achieve hospital performance targets and most importantly, deterioration in patients' experience.

Hospital managers strive to utilise new scientific knowledge to address planning problems. However, most of the Irish hospitals still depend on basic statistical average of historical data in their planning decisions. Subject to the constrained healthcare professional supply, optimising staffing and shift scheduling decisions of the current doctors and nurses are of immense importance, particularly, to enable management's response to system dynamics efficiency. This requires systematic and advanced methods to support management with informed decisions regarding staffing and scheduling based on evidence from data. The proposed integrated framework provides managers with a simulation-optimisation solution for better staffing and shift scheduling of medical staff given various factors that determine the workload patterns.

7.2 Research Contributions

The work carried out in this research has contributed to both knowledge and application of scheduling and staffing problem in healthcare context.

Extensive literature review on staffing and scheduling of medical staff at hospitals

This contribution adds to the knowledge domain by looking at the first research question of the study; "***What are the existing models, frameworks, solution methods, and best practices used in staffing and scheduling hospital staff?***"

- The study provides a comprehensive review of methods that are used for staffing and scheduling of medical staff in hospital settings. A new four-dimension taxonomy of the problem is presented including; problem contextualisation, solution approach, uncertainty and evaluation perspective. Reviewing over than 1500 articles has given a useful insight on the implications of staffing and scheduling problems on work performance.

- Due to their importance to hospitals, the OR/MS research community has reported various methods for underpinning the challenges of medical staffing and scheduling. It shows that there is a growing trend acknowledging the potential impact of existing models, but a set of dominant characteristics were found such as:
  - A vertical separation between scheduling stages;
  - Focus on single staff and ignoring the mutual interaction between resources;
  - Paucity in coordination between hospital functions;
  - Lack of integrating practitioners view;
  - The absence of studies, which have considered staff behaviour; and
  - This study also provides a roadmap for future research and identifies areas that require further attention from researchers.

Exploratory Study: Practitioners' Perception

This contribution addresses the second research question; "***What are the key factors of management in staff planning activities (implications, regulations, and others?)***". This contribution adds to both knowledge and application of the field.

- An exploratory study is conducted in eleven major hospitals - representing 50% of healthcare service providers in Ireland) evenly distributed across Ireland covering various departments and specialities. A total of 25 experienced managers (14 consultant and 11 head nurses) are recruited purposefully where their average experience in a management role was ten years. The data was collected through in-depth interviews with hospital managers involved in staffing and scheduling decisions. The outcomes of the exploratory study have contributed to the design and engineering of the staffing and scheduling framework.

- Exploratory study findings are important to understand the staffing and scheduling problem in the Irish hospitals in particular. Several opportunities have presented themselves in this study that can improve the healthcare process not only from the management perspective but also from staff and patient perspectives.

- Practitioners' perception came precisely to assure us that the scheduling problem has similar characteristics as per the literature (i.e. multi-facets, combinatorial and highly constrained problem). Also, they mentioned some factors that challenged the problem and prevent or inhibit management from improving staffing decisions such as the lack of coordination and its implications. Four-factor aspects have identified this: Patient, Staff, Organisational and External Aspects. The designated aspects can help to reconceptualise of the staffing and scheduling problem from the practitioner point of view and how to be addressed.

Developing a new multi-method integrated framework for staffing and shift schedule

This contribution is believed to add value to both knowledge and application by addressing research questions 3 and 4 (as indicated below), and part of the second research question.

RQ3: "***How can human behaviour be modelled to impact the output of planning process?***"

RQ4:"***What should an integrated solution for staffing and schedule look like in order to be applicable for managers?***"

- The developed integrated framework has included the practitioners' views and understanding which certainly will add value to the solution and increase opportunities of implement-ability. Introducing advanced operations research approaches (e.g. machine learning, and optimisation) to solve the problem is a contribution.

- The framework has attempted to address staffing and shift schedule problem in its totality by incorporating key factors that affect decisions. Between patient, staff, and organisation issues, there are more than 25 factors to be considered, in addition to mutual interactions between staff types, coordination with downstream resources, severity mix, and integration between staffing and scheduling decisions.

- A multi-method approach is employed to consider the system complexity and the dynamism embedded in medical staffing and scheduling problem. Modelling and simulation, optimisation, data analytics and machine learning have contributed in providing the framework with flexibility and accuracy. Some of the techniques are used to envisage the impact of the schedule (i.e. simulation) while others are there to answer questions (i.e. Optimisation).

- Impact of staff burnout is modelled using a System Dynamics approach. The model represents a significant contribution to a critical problem (i.e. burn out phenomena). Management has realised the impact of burnout on medical staff behaviour and performance. Workload stresses are directly related to staff planning and scheduling and have grave implications for the service.

Staffing and Schedule Practices

This contribution is believed to add value to the application domain by addressing fourth research question RQ4: "***What should an integrated solution for staffing and schedule look like in order to be applicable for managers?***"

- Implementation of such a planning framework is not expected to be smooth and would meet with resistance to change. Simulation and Optimisation have played a significant role in easing the movement towards implementation of the proposed solutions. An excellent partnership was established with a leading university hospital serving over 600,000 of the people that live in Dublin and 400,000 of the catchment area near Dublin. Validation was agreed to take place in their Emergency Departments (one of the busiest in Ireland). Results have given insights to the management and also enabled them to address the scheduling issues differently. The framework has also recommended new shift that considers various factors incorporated in the simulation component.

- Staffing optimiser produced near optimal staggered staffing levels that significantly reduced the required daily staffing hours needed compared to the current configuration. The optimal staffing not only considers all key factors but also capture the mutual interactions between the multiple healthcare providers. It also ensures that workload does not exceed a certain threshold informed from burnout SD model.

- The generated shift schedules have substantially improved the patient experience (time-related performance) with 43% reduction in the patients waiting time, 29% drop in PET of all patients, while PET of discharged patients is reduced by 33%. Also, it helps in achieving the HSE national targets with 25%, and 13% improvement in six-hour and nine-hour targets, respectively. Furthermore, optimal shift schedules were able to efficiently and effectively align staff patterns to patients' demand where all healthcare providers' new schedules eliminated both overstaffing and understaffing except for registers (seven extra hours are required).

7.3 Limitations and Future Work

Although the outcomes of this research make significant contributions to the healthcare applications, the implications of the research are confined to a single case study. As a future work, implementations of multiple of case studies can assure the framework validity.

Promising Avenues for Future Work

- Adding more strategic decisions (i.e. hiring, cross training and outsourcing decisions) can be integrated into the proposed framework to add extra value and help policy makers.

- Automating the integration of all the components of the proposed framework. It would be beneficial to achieve this by developing a web-based technology that combines all the elements in an automated manner and facilitates communication and the data acquisition from the HIS. Web services based data acquisition is an ideal technology for the integration with hospital IT system, which allows intersystem interaction and interoperability across platforms through the use of standard data format. Alternatively, the HIS based data can be acquired regular from a flat file (e.g. CSV or JSON). Part of the required data are not stored in the HIS such the activity processing time. With the advances real-time data acquisition technologies, observational data related to processing time for different activities can be tracked through wireless technologies such as near field communication (NFC). This can be integrated with the HIS in a real-time fashion.

– Machine learning algorithms can be introduced to improve the accuracy of the demand prediction. Another direction of potential research is the enhancement of the predictability and learnability of the model. This requires experimenting with various machine learning algorithms in addition to the supervised learning algorithms (e.g. CART) that require historical data for training. It envisages to investigate the integration of unsupervised learning algorithms (e.g. reinforcement learning) for better address the staffing problem in real-time decisions. Reinforcement learning enables agents to learn from the interaction with the environment by taking actions (choices) that optimise a reward function. This allows agents (e.g. staff) to behave intelligently and it will enable to use simulation as the interaction environment to learn the optimal staffing policy.

– Intelligent-agent for incorporating staff behaviour. Although the framework utilises multi-methods of simulation, the staff are modelled as resources rather than agents without incorporating human behaviour. Agent-based modelling of different personnel types allows integrating human behaviour and decision-making components into the framework.

7.4 Recommendations for Implementation

- It is recommended that the staffing method takes account of the multiple factors outlined in the framework across the four aspects (Patient, Organisational, Staff, and External).

- Addressing staff planning and scheduling decisions in isolation of interrelated activities have been found to be ineffective. Thus, it is recommended to consider the mutual dynamic interactions between the different staff types and resources in order to facilitate coordination between various resources.

- In order to avoid sub-optimal staffing and scheduling decisions, it is recommended that integration between staff planning and scheduling at different decision levels (i.e. strategic, tactical, and operational) has to be evident. This alignment between the different levels helps managers to improve their operational performance and avoid burnout results from the situational understaffing.

- In order to reduce the impact of minor injuries patients (triaged category 4 and 5) issue, those patients should not be seen in the ED. They should be seen in a different location, and the main unit should be open for patients in category one, two and three. This requires devising a new pathway for minor injuries patients. In order to implement this scenario, management has to open an offsite minor injuries clinic and to redirect those patients after triage. Management and staff also should focus more on informing patients, GPs, and public that EDs are not equipped for minor injuries. This has worked in UK. In doing so, more rooms will be available to serve critical patients.

- The balance of medical staff workload is a burning issue that has a significant impact on the paradigm of healthcare system internationally. Medical personnel burnout consequences vary from error in diagnosis, operational issues, complexity in scheduling, failure in hospital redesign process and unforeseen patients experience. The study recommends the use of smart scheduling system to plan the staff shifts, workload and that the organisation management has to be careful of the impact of the staff burnout on performance. Demand fluctuation will require better planning, especially with limited capacity and cost reduction policies. The proposed framework help the manager alerts the mangers when the staffing workload exceeds a certain threshold (i.e. staff utilisation does not exceed 60%). It is also recommended that staff burnout should be monitored where the framework help to in its prediction.

- It is recommended that managers utilise the four perspectives of evaluation as an integral part of the decision process. The framework helps management to systematically and consistently identify the adequacy of staffing levels to meet patients' needs and realise the implications of new schedules on staff satisfaction, and quality of services without compromising both efficiency and effectiveness.

- Based on explored experiments from the research, management should utilise flexible shifts in order to develop an effective and efficient staff schedules. Optimal staffing levels are a necessary step that enables hospital managers to align their staff patterns to meet patients' needs, but it is not sufficient. Staff schedules based on fixed shifts do not help management to secure adequate staffing without extra cost (i.e. overstaffing) and results in unfairness regarding unbalanced staff workloads. Variable shift-length and flexible start-time are useful and practical policies and will ensure an improvement in the quality of schedules regarding coverage, operational efficiency, responsiveness, and flexibility. Particularly, adopting the four-shift policy (12H, 10H, 8H and 6H) under Flex2 setting can eliminate the nurse overstaffing.

- For implementing the proposed innovative schedule, it is of utmost importance to create a proper awareness among the staff and increase the engagement level in decision-making process. It is also recommended to apply it gradually on a single staff grade as a pilot (e.g. ANP). Indeed, these will not only help the hospital management to avoid employee resistance to change but will also ensure that future issues in a large scale rollout would be minimised.

- Moving forward, staff working fixed long shifts are more likely to experience burnout and job dissatisfaction than staff is working short shifts. However, long shifts are common and popular in hospital systems. Shorter shifts can be incentivised by highlighting the problems of long shifts to encourage employees to sign up for shorter shifts. Allowing staff to work shorter shifts will not only help employees to have better work-life balance but will also help management to retain their staff. In order to reduce resistance from staff and unions, hospitals should not force their staff to work short shifts. It is recommended to allow staff to sign up for their shift lengths as part of their preferences.

- There was a dearth of data about certain parameters, for example, time providers spend on patients and direct/indirect activities that were not captured by the IT system. This type of required information in this study is the same data that are frequently required to model, track the patient's flow, and accurately estimate the staff workload. Current practices utilise manual data acquisition through traditional data collection instruments such as observations and interviews. This study recommends the need for the integration of the recent wireless data exchange technology (e.g. NFC) and the hospital IT systems in order to capture and track patient related activities automatically.

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Appendix A

Literature Supplements

Classification Tables

Table A.1 Classification of the medical staff planning articles based application area and staff.

Application Area	Nurse		Physician		Multiple Resources		Total
	n		*n*		*n*		*n* (%)
Unit Level	12		4		12		24 (67%)
ED	4	(Linda V Green, Savin, & Savva, 2013; Henneman et al., 2015; Egbert van der Veen et al., 2014; Yankovic & Green, 2011)	3	(Coats, 2001; Cohen, Mandelbaum, & Zychlinski, 2014; Vassilacopoulos, 1985)	10	(Al-Najjar & Ali, 2011; Brenner et al., 2010; Feng et al., 2015; Ganguly et al., 2014; Ghanes et al., 2015; Linda V Green et al., 2006; Oddoye, Yaghoobi, Tamiz, Jones, & Schmidt, 2007; Yom-Tov & Mandelbaum, 2014; Zeinali et al., 2015; Zeltyn et al., 2011)	17 (47%)
• OR/ICU/PACU	4	(DAVIS, MEHROTRA, HOLL, & DASKIN, 2014; Duraiswamy, Welton, & Reisman, 1981; Hashimoto, Bell, & Marshment, 1987; Kortbeek et al., 2015)	1	(Molema et al., 2007)			5 (14%)
• IC	4	(de Vericourt et al., 2011; Harper et al., 2009; L. L. Li & King, 1999; Sarno & Nenni, 2015)					4 (11%)
• OP					2	(Bretthauer et al., 1998; Carlson, Hershey, & Kropp, 1979)	2 (6%)
Multiple Units Level	3	89]-[91]			1	(Gnanlet & Gilland, 2009)	4 (11%)
Hospital	3	(M. Brusco & Showalter, 1993; Lowerre, 1979; Vandankumar M Trivedi, 1981)	1	(Anderson & Gamarnik, 2015)*			4 (11%)
Total	18 (50%)		5 (14%)		13 (36%)		36 (100%)

Note for abbreviations– ED: Emergency Department; OR: Operating Rooms; ICU: Intensive Care Unit; OP: Outpatient; PACU: Post-Anaesthesia Care Unit; IC: Inpatient Care

Table A.2 classification of the articles according to solution methods, stage and study scope.

	Study Orientation/Scope						
Methods/ Stage	Theory		Managerial perspective		Computational Algorithmic		Total
	n	References	*n*	References	*n*	References	
AN	4		13				17
Planning	4	(Anderson & Gamarnik, 2015; Cohen et al., 2014; Mincsovics & Dellaert, 2010; Yom-Tov & Mandelbaum, 2014)	11	(Anderson & Gamarnik, 2015; Cohen et al., 2014; DAVIS et al., 2014; de Vericourt et al., 2011; Ganguly et al., 2014; Gnanlet & Gilland, 2009; Linda V Green et al., 2006, 2013; Lowerre, 1979; Mincsovics & Dellaert, 2010; Yankovic & Green, 2011)			15
Integrated Models			2	(Campbell, 2012; Izady & Worthington, 2012)			2
SIM	1		21				22
Planning			15	(Al-Najjar & Ali, 2011; Brenner et al., 2010; Cabrera et al., 2011; Carlson et al., 1979; Coats, 2001; Duraiswamy et al., 1981; Ghanes et al., 2015; Griffiths et al., 2005; Harper et al., 2009; Hashimoto et al., 1987; Henneman et al., 2015; Molema et al., 2007; Sarno & Nenni, 2015; Zeinali et al., 2015; Zeltyn et al., 2011)			15
Scheduling			4	(Badri & Hollingsworth, 1993; Dittus et al., 1996; EL-Rifai et al., 2014; Yeh & Lin, 2007)			4
Allocation	1	(Siferd & Benton, 1994)	1	(Inman et al., 2005)			2
Assignment			1	(Sundaramoorthi et al., 2010)			1
Integrated Models							
EX/DC	13		63		13		89

Planning			10	(Bretthauer et al., 1998; M. Brusco & Showalter, 1993; Ganguly et al., 2014; L. L. Li & King, 1999; Oddoye et al., 2007; Vandankumar M Trivedi, 1981; Egbert van der Veen et al., 2014; Vassilacopoulos, 1985; Wang et al., 2009; D. M. D. Warner & Prawda, 1972)			10
Scheduling	11	(Blochliger, 2004; Glass & Knight, 2010; Jaumard, Semet, & Vovor, 1998; Maenhout & Vanhoucke, 2009; Martinelly et al., 2014; Millar & Kiragu, 1998; Ronnberg et al., 2010; Smet et al., 2016; S Topaloglu & Ozkarahan, 2004; Vanhoucke & Maenhout, 2009; Yilmaz, 2012)	36	(Arthur & Ravindran, 1981; Azaiez & Al Sharif, 2005; Bagheri, Gholinejad Devin, & Izanloo, 2016; J. Bard & Purnomo, 2005a; Beaulieu, Ferland, Gendron, & Michelon, 2000; Berrada, Ferland, & Michelon, 1996; Bowers, Noon, Wu, & Bass, 2016; Bruni & Detti, 2014; Brunner et al., 2009, 2011; Michael J. Brusco & Jacobs, 1995; Cohn, Root, Kymissis, Esses, & Westmoreland, 2009; De Grano et al., 2009; Elomri, Elthlatiny, & Mohamed, 2015; Ferrand et al., 2011; Fugener, Brunner, & Podtschaske, 2015; Gunawan & Lau, 2013; Huarng, 1999; Irvin & Brown, 1999; Mark W. Isken, 2004; Liao & Kao, 1997; Lin et al., 2014; M'Hallah & Alkhabbaz, 2013; Martinelly et al., 2014; Ovchinnikov & Milner, 2008; OZKARAHAN & BAILEY, 1988; Ronnberg et al., 2010; Savage, Woolford, Weaver, & Wood, 2015; HannahK. K. Smalley & Keskinocak, 2014; Seyda Topaloglu, 2006, 2009; Seyda Topaloglu & Selim, 2010; Van Huele & Vanhoucke, 2014; D. M. Warner, 1976; Weil, Heus, Francois, & Poujade, 1995; D. Wright et al., 2006)	12	(J. F. Bard & Purnomo, 2007; J. Bard & Purnomo, 2005d; Belien & Demeulemeester, 2007; Belien, Demeulemeester, Belien, & Demeulemeester, 2008; E. K. Burke & Curtois, 2014; Dohn & Mason, 2013; Goler et al., 2013; Lim, Mobasher, Bard, & Najjarbashi, 2016; Maenhout & Vanhoucke, 2010; Meyer & Hofe, 2001; Purnomo & Bard, 2007; Stolletz & Brunner, 2012)	59

Allocation			5	(J. Bard & Purnomo, 2005b, 2005c; M J Brusco, 2008; A. Clark & Walker, 2011; V. M. Trivedi & Warner, 1976)			5
Assignment			4	(E. A. Ernst et al., 1973; Liang & Turkcan, 2015; Punnakitikashem et al., 2008; Sir et al., 2015)			4
Integrated Models	2	(Komarudin et al., 2013; Venkataraman & Brusco, 1996)	8	(Abernathy et al., 1973; Chen, Lin, & Peng, 2016; Maenhout & Vanhoucke, 2013b, 2013c; Punnakitikashem et al., 2013; Venkataraman & Brusco, 1996; P. D. Wright et al., 2010; P. D. Wright & Mahar, 2013)	1	(Kim & Mehrotra, 2015)	11
HU/MH	8		13		41		62
Planning			1	(Maass et al., 2015)	1	(Feng et al., 2015)	2

Scheduling	6	(Brucker et al., 2011; Carrasco, 2010; Carter & Lapierre, 2001; De Causmaecker & Vanden Berghe, 2003; Eiselt & Laporte, 1987; Sherali et al., 2002)	6	(Bellanti et al., 2004; M. Guo et al., 2014; OZKARAHAN & BAILEY, 1988; Pierskalla & Rath, 1976; Puente et al., 2009; T. C. Wong et al., 2014)	38	(Uwe Aickelin & Burke, 2009; Uwe Aickelin et al., 2007; Uwe Aickelin & Dowsland, 2000, 2004; Uwe Aickelin & White, 2004; Altamirano et al., 2012; Burak Bilgin et al., 2012; Brucker et al., 2008; E. K. Burke, Causmaecker, & Berghe, 2004; E. K. Burke, Causmaecker, Petrovic, et al., 2004; E. K. Burke et al., 2006, 2013, 2012; E. K. Burke, Curtois, van Draat, et al., 2010; Buyukozkan & Sarucan, 2014; Constantino et al., 2014; K. A. Dowsland & Thompson, 2000; Ferland et al., 2001; Franz & Miller, 1993; Gascon et al., 2000; Goodman et al., 2007; Hadwan et al., 2013; Ikegami & Niwa, 2003; Legrain et al., 2015; J Li et al., 2009; Jingpeng Li et al., 2012; Lu et al., 2012; Maenhout & Vanhoucke, 2008; Martin, Ouelhadj, Smet, Vanden Berghe, & Ozcanc, 2013; Nonobe & Ibaraki, 1998; Ohki et al., 2010; Parr & Thompson, 2007; Hannah K. Smalley et al., 2015; Tassopoulos et al., 2015; Tsai & Li, 2009; Christos Valouxis et al., 2012; Wu et al., 2015; P. Y. Yin et al., 2011)	50

Allocation	2	(Campbell, 1999; Alistair Clark et al., 2015)	3	(Campbell, 1999; Maenhout & Vanhoucke, 2011, 2013d)	2	(Maenhout & Vanhoucke, 2013a; Pato & Moz, 2008)	7
Assignment			1	(Mullinax & Lawley, 2002)			1
Integrated Models			2	(Sinreich & Jabali, 2007)(Sinreich et al., 2012)			2
AI/MAS	3		1		4		8
Scheduling	3	(Chiaramonte & Chiaramonte, 2008; Scott & Simpson, 1998; Winstanley, 2004)	1	(Okada & Okada, 1988)	4	(Costa, Rocha, Costa, & Pereira, 2012; J. P. Li & Aickelin, 2004; Jingpeng Li et al., 2010; G. Y. C. Wong & Chun, 2004)	8
Assignment							
Integrated Models							
HY/HH	2				25		27

Scheduling	2	(Michael, Jeffery, & David, 2015; Petrovic, Berghe, Vanden Berghe, & Berghe, 2010)			24	(Baeklund, 2014; R. B. R. Bai et al., 2010; R. Bai, Blazewicz, Burke, Kendall, & McCollum, 2012; G. R. Beddoe & Petrovic, 2006; Gareth Beddoe et al., 2008; B Bilgin, Demeester, Misir, Vancroonenburg, & Vanden Berghe, 2012; E. K. Burke, Cowling, Causmaecker, & Berghe, 2001; E. K. Burke, De Causmaecker, & Vanden Berghe, 1999; E. K. Burke, Curtois, Post, Qu, & Veltman, 2008; E. K. Burke, Curtois, Qu, et al., 2010; E. K. Burke, Kendall, et al., 2004; E. K. Burke, Li, et al., 2010; Cipriano, Gaspero, & Dovier, 2006; Cowling, Kendall, & Soubeiga, 2002; K. a. Dowsland, 1998; J. Guo, Morrison, Jacobson, & Jokela, 2014; He & Qu, 2012; Inoue, Furuhashi, Maeda, & Takaba, 2003; Moz & Pato, 2003; E. Ozcan & Ozcan, 2005; Qu & He, 2009; Rousseau et al., 2002; Smet, Bilgin, De Causmaecker, & Vanden Berghe, 2014; Seyda Topaloglu & Ozkarahan, 2011; C Valouxis & Housos, 2000)	26
Allocation					1	(Moz & Pato, 2003)	1
Grand Total	31		111		83		225

Table A.3 Classification of articles according to stochastic elements (Stages).

	Stage									
Stochastic Parameter	Planning		Scheduling		Allocation		Assignment		Integrated Models	
	n		*n*		*n*	*n*	*n*			
Demand Arrival	22	(Al-Najjar & Ali, 2011; Anderson & Gamarnik, 2015; Bretthauer et al., 1998; Coats, 2001; Cohen et al., 2014; DAVIS et al., 2014; de Vericourt et al., 2011; Duraiswamy et al., 1981; Feng et al., 2015; Ganguly et al., 2014; Ghanes et al., 2015; Gnanlet & Gilland, 2009, 2014; Linda V Green et al., 2006; Harper et al., 2009; Henneman et al., 2015; Mincsovics & Dellaert, 2010; Sarno & Nenni, 2015; Yankovic & Green, 2011; Yom-Tov & Mandelbaum, 2014; Zeinali et al., 2015; Zeltyn et al., 2011)	5	(Badri & Hollingsworth, 1993; Bagheri et al., 2016; Dittus et al., 1996; EL-Rifai et al., 2014; Yeh & Lin, 2007)					6	(Abernathy et al., 1973; Campbell, 2012; Chen et al., 2016; Sinreich & Jabali, 2007; Sinreich et al., 2012; P. D. Wright & Mahar, 2013)
Service Time	14	(Al-Najjar & Ali, 2011; Bretthauer et al., 1998; Coats, 2001; Cohen et al., 2014; de Vericourt et al., 2011; Feng et al., 2015; Ghanes et al., 2015; Linda V Green et al., 2006; Henneman et al., 2015; Sarno & Nenni, 2015; Yankovic & Green, 2011; Yom-Tov & Mandelbaum, 2014; Zeinali et al., 2015; Zeltyn et al., 2011)	3	(Badri & Hollingsworth, 1993; EL-Rifai et al., 2014; Yeh & Lin, 2007)					2	(Sinreich & Jabali, 2007; P. D. Wright & Mahar, 2013)

Routing Probabilities	11	(Al-Najjar & Ali, 2011; Coats, 2001; Duraiswamy et al., 1981; Feng et al., 2015; Ghanes et al., 2015; Harper et al., 2009; Hashimoto et al., 1987; Henneman et al., 2015; Sarno & Nenni, 2015; Zeinali et al., 2015; Zeltyn et al., 2011)	4	(Badri & Hollingsworth, 1993; Dittus et al., 1996; EL-Rifai et al., 2014; Yeh & Lin, 2007)	1	(Inman et al., 2005)	1	(Sundaramoorthi et al., 2010)		
Acuity/ workload/ Census	3	(Ganguly et al., 2014; Hashimoto et al., 1987; Sarno & Nenni, 2015)	1	(Seyda Topaloglu & Selim, 2010)	2	(Inman et al., 2005; Siferd & Benton, 1994)	1	(Punnakitikashem2 et al., 2008)		(Kim & Mehrotra, 2015; Punnakitikashem et al., 2013)
Absenteeism Rate	3	(Duraiswamy et al., 1981; Linda V Green et al., 2006, 2013)			1	(Inman et al., 2005)				

Table A.4 Classification of articles according to stochastic elements (Solutions).

	Solution Method							
Stochastic Parameter	AN		EX/DC		HU		SIM	
	n		*n*		*n*		*n*	
Demand Arrival	11	(Anderson & Gamarnik, 2015; Campbell, 2012; Cohen et al., 2014; DAVIS et al., 2014; de Vericourt et al., 2011; Ganguly et al., 2014; Gnanlet & Gilland, 2009; Linda V Green et al., 2006; Mincsovics & Dellaert, 2010; Yankovic & Green, 2011; Yom-Tov & Mandelbaum, 2014)	6	(Abernathy et al., 1973; Bagheri et al., 2016; Bretthauer et al., 1998; Chen et al., 2016; Gnanlet & Gilland, 2014; P. D. Wright & Mahar, 2013)	2	(Sinreich & Jabali, 2007; Sinreich et al., 2012)	14	(Al-Najjar & Ali, 2011; Badri & Hollingsworth, 1993; Coats, 2001; Dittus et al., 1996; Duraiswamy et al., 1981; EL-Rifai et al., 2014; Feng et al., 2015; Ghanes et al., 2015; Harper et al., 2009; Henneman et al., 2015; Sarno & Nenni, 2015; Yeh & Lin, 2007; Zeinali et al., 2015; Zeltyn et al., 2011)
Service Time	5	(Cohen et al., 2014; de Vericourt et al., 2011; Linda V Green et al., 2006; Yankovic & Green, 2011; Yom-Tov & Mandelbaum, 2014)	2	(Bretthauer et al., 1998; P. D. Wright & Mahar, 2013)	2	(Sinreich & Jabali, 2007; Sinreich et al., 2012)	11	(Al-Najjar & Ali, 2011; Badri & Hollingsworth, 1993; Coats, 2001; EL-Rifai et al., 2014; Feng et al., 2015; Ghanes et al., 2015; Henneman et al., 2015; Sarno & Nenni, 2015; Yeh & Lin, 2007; Zeinali et al., 2015; Zeltyn et al., 2011)

Routing Probabilities							17	(Al-Najjar & Ali, 2011; Badri & Hollingsworth, 1993; Coats, 2001; Dittus et al., 1996; Duraiswamy et al., 1981; EL-Rifai et al., 2014; Feng et al., 2015; Ghanes et al., 2015; Harper et al., 2009; Hashimoto et al., 1987; Henneman et al., 2015; Inman et al., 2005; Sarno & Nenni, 2015; Sundaramoorthi et al., 2010; Yeh & Lin, 2007; Zeinali et al., 2015; Zeltyn et al., 2011)
Acuity/workload/Census	1	(Ganguly et al., 2014)	4	(Kim & Mehrotra, 2015; Punnakitikashem et al., 2013, 2008; Seyda Topaloglu & Selim, 2010)			4	(Hashimoto et al., 1987; Inman et al., 2005; Sarno & Nenni, 2015; Siferd & Benton, 1994)
Absenteeism Rate	2	(Linda V Green et al., 2006, 2013)					2	(Duraiswamy et al., 1981; Inman et al., 2005)

Table A.5 Classification of articles by performance criteria.

	Staffing and Scheduling Stage									
Performance Criteria	Planning		Scheduling		Allocation		Assignment		Integrated Models	
	n		*n*		*n*		*n*		*n*	
Efficiency										
Required staff	1	(L. L. Li & King, 1999)	2	(Arthur & Ravindran, 1981; Belien et al., 2008)	3	(Inman et al., 2005; Siferd & Benton, 1994; V. M. Trivedi & Warner, 1976)				
Staffing Cost	17	(M. Brusco & Showalter, 1993; Carlson et al., 1979; DAVIS et al., 2014; Duraiswamy et al., 1981; Ganguly et al., 2014; Gnanlet & Gilland, 2009, 2014; Linda V Green et al., 2013; Harper et al., 2009; Hashimoto et al., 1987; Kortbeek et al., 2015; L. L. Li & King, 1999; Maass et al., 2015; Egbert van der Veen et al., 2014; Wang et al., 2009; D. M. D. Warner & Prawda, 1972; Yom-Tov & Mandelbaum, 2014)	22	(Uwe Aickelin et al., 2007; Azaiez & Al Sharif, 2005; Baeklund, 2014; Bagheri et al., 2016; J. F. Bard & Purnomo, 2007; J. Bard & Purnomo, 2005a, 2005d; Brucker et al., 2011; Brunner et al., 2009, 2011; Michael J. Brusco & Jacobs, 1995; Dohn & Mason, 2013; Mark W. Isken, 2004; M W Isken & Hancock, 1998; Jaumard et al., 1998; Martinelly et al., 2014; Millar & Kiragu, 1998; OZKARAHAN & BAILEY, 1988; Pierskalla & Rath, 1976; Sherali et al., 2002; Smet et al., 2016; C Valouxis & Housos, 2000)	2	(J. Bard & Purnomo, 2005b, 2005c)	1	(E. A. Ernst et al., 1973)	8	(Abernathy et al., 1973; Campbell, 2012; Kim & Mehrotra, 2015; Maenhout & Vanhoucke, 2013b, 2013c; Punnakitikashem et al., 2013; P. D. Wright et al., 2010; P. D. Wright & Mahar, 2013)

Penalty Cost	1	(Mincsovics & Dellaert, 2010)(Vassilacopoulos, 1985)	43	(Uwe Aickelin & Dowsland, 2000, 2004; R. B. R. Bai et al., 2010; J. Bard & Purnomo, 2005d; Gareth Beddoe et al., 2008; Belien & Demeulemeester, 2007; Brucker et al., 2008; Brunner et al., 2009; E. K. Burke, Causmaecker, & Berghe, 2004; E. K. Burke et al., 1999, 2012; E. K. Burke, Causmaecker, Petrovic, et al., 2004; E. K. Burke et al., 2006, 2013; E. K. Burke, Curtois, Post, et al., 2008; E. K. Burke, Curtois, Qu, et al., 2010; E. K. Burke, Curtois, van Draat, et al., 2010; E. K. Burke, Kendall, et al., 2004; E. K. Burke, Li, et al., 2010; Cipriano et al., 2006; Cowling et al., 2002; De Causmaecker & Vanden Berghe, 2003; Dohn & Mason, 2013; K. a. Dowsland, 1998; K. A. Dowsland & Thompson, 2000; J. Guo et al., 2014; Hadwan et al., 2013; He & Qu, 2012; Inoue et al., 2003; Jingpeng Li et al., 2012, 2010; Liao & Kao, 1997; Lu et al., 2012; Maenhout & Vanhoucke, 2008; Nonobe & Ibaraki, 1998; Ohki et al., 2010; E. Ozcan & Ozcan, 2005; Parr & Thompson, 2007; Puente et al., 2009; Rousseau et al., 2002; Smet et al., 2014; Tsai & Li, 2009; Christos Valouxis et al., 2012)	3	(J. Bard & Purnomo, 2005b; Alistair Clark et al., 2015; Maenhout & Vanhoucke, 2011)			4	(Abernathy et al., 1973; Komarudin et al., 2013; Maenhout & Vanhoucke, 2013b; Sinreich & Jabali, 2007)
Float Cost	7	(Gnanlet & Gilland, 2009, 2014; Harper et al., 2009; Kortbeek et al., 2015; L. L. Li & King, 1999; Maass et al., 2015; Oddoye et al., 2007)	10	(J. F. Bard & Purnomo, 2007; J. Bard & Purnomo, 2005a, 2005d; Jaumard et al., 1998; Legrain et al., 2015; Ronnberg et al., 2010; Smet et al., 2016; Stolletz & Brunner, 2012; Winstanley, 2004)	5	(J. Bard & Purnomo, 2005b, 2005c; Campbell, 1999; Inman et al., 2005; V. M. Trivedi & Warner, 1976)			6	(Abernathy et al., 1973; Maenhout & Vanhoucke, 2013b, 2013c; Punnakitikashem et al., 2013; P. D. Wright et al., 2010; P. D. Wright & Mahar, 2013)

Part-time Cost	4	(Hashimoto et al., 1987; Molema et al., 2007; Vandankumar M Trivedi, 1981; Egbert van der Veen et al., 2014)	24	(Uwe Aickelin & Burke, 2009; Uwe Aickelin et al., 2007; Uwe Aickelin & Dowsland, 2000, 2004; Uwe Aickelin & White, 2004; R. B. R. Bai et al., 2010; R. Bai et al., 2012; Michael J. Brusco & Jacobs, 1995; E. K. Burke, Causmaecker, & Berghe, 2004; E. K. Burke et al., 2006, 2001; E. K. Burke, Causmaecker, Petrovic, et al., 2004; E. K. Burke, Curtois, Post, et al., 2008; E. K. Burke, Curtois, Qu, et al., 2010; E. K. Burke, Kendall, et al., 2004; De Grano et al., 2009; K. a. Dowsland, 1998; K. A. Dowsland & Thompson, 2000; Goodman et al., 2007; Irvin & Brown, 1999; Mark W. Isken, 2004; J. P. Li & Aickelin, 2004; J Li et al., 2009; Jingpeng Li et al., 2012)	2	(J. Bard & Purnomo, 2005b, 2005c)			2	(Maenhout & Vanhoucke, 2013c; Venkataraman & Brusco, 1996)
Outsourcing Cost	5	(M. Brusco & Showalter, 1993; Gnanlet & Gilland, 2009; Harper et al., 2009; Hashimoto et al., 1987; Egbert van der Veen et al., 2014)	7	(J. Bard & Purnomo, 2005a, 2005d, Brunner et al., 2009, 2011; De Grano et al., 2009; M'Hallah & Alkhabbaz, 2013; Purnomo & Bard, 2007)	3	(J. Bard & Purnomo, 2005b, 2005c; Inman et al., 2005)			3	(Campbell, 2012; Punnakitikashem et al., 2013; P. D. Wright et al., 2010)
Overtime Cost	5	(M. Brusco & Showalter, 1993; DAVIS et al., 2014; Hashimoto et al., 1987; L. L. Li & King, 1999; Vandankumar M Trivedi, 1981)	9	(Azaiez & Al Sharif, 2005; Bagheri et al., 2016; Brunner et al., 2009, 2011; E. K. Burke, Curtois, Post, et al., 2008; Lim et al., 2016; Martinelly et al., 2014; Stolletz & Brunner, 2012; Van Huele & Vanhoucke, 2014)	2	(J. Bard & Purnomo, 2005c; Maenhout & Vanhoucke, 2013d)	1	(Liang & Turkcan, 2015)	7	(Campbell, 2012; Maenhout & Vanhoucke, 2013b, 2013c; Punnakitikashem et al., 2013; Venkataraman & Brusco, 1996; P. D. Wright et al., 2010; P. D. Wright & Mahar, 2013)

Overstaffing	3	(DAVIS et al., 2014; Hashimoto et al., 1987; Oddoye et al., 2007)	6	(Gascon et al., 2000; Ovchinnikov & Milner, 2008; Winstanley, 2004)	1	(Maenhout & Vanhoucke, 2011)			5	(Izady & Worthington, 2012; Kim & Mehrotra, 2015; Maenhout & Vanhoucke, 2013b, 2013c; Sinreich & Jabali, 2007)
Effectiveness										
Understaffing	6	(DAVIS et al., 2014; Hashimoto et al., 1987; L. L. Li & King, 1999; Mincsovics & Dellaert, 2010; Vandankumar M Trivedi, 1981; D. M. D. Warner & Prawda, 1972)	8	(Baeklund, 2014; Bellanti et al., 2004; Dohn & Mason, 2013; Jaumard et al., 1998; Lim et al., 2016; OZKARAHAN & BAILEY, 1988; Savage et al., 2015; S Topaloglu & Ozkarahan, 2004)	2	(Maenhout & Vanhoucke, 2011, 2013d)			5	(Izady & Worthington, 2012; Kim & Mehrotra, 2015; Maenhout & Vanhoucke, 2013b, 2013c; Sinreich & Jabali, 2007)
Schedule Disruption					5	(J. Bard & Purnomo, 2005b; Alistair Clark et al., 2015; Maenhout & Vanhoucke, 2013d; Moz & Pato, 2003; Pato & Moz, 2008)				
Schedule Robustness			3	(EL-Rifai et al., 2014; Jingpeng Li et al., 2012; T. C. Wong et al., 2014)						
Utilisation	2	(Badri & Hollingsworth, 1993; Brenner et al., 2010; Feng et al., 2015)	2	(Badri & Hollingsworth, 1993; M. Guo et al., 2014)	1	(Campbell, 1999)				
Staff Satisfaction										

Preferences			60	(Uwe Aickelin & Burke, 2009; Uwe Aickelin et al., 2007; Uwe Aickelin & Dowsland, 2000, 2004; Uwe Aickelin & White, 2004; Arthur & Ravindran, 1981; Azaiez & Al Sharif, 2005; R. B. R. Bai et al., 2010; R. Bai et al., 2012; J. F. Bard & Purnomo, 2007; J. Bard & Purnomo, 2005d; Burak Bilgin et al., 2012; Bowers et al., 2016; Brucker et al., 2008; E. K. Burke, Causmaecker, & Berghe, 2004; E. K. Burke et al., 2001, 2013, 1999, 2012; E. K. Burke, Causmaecker, Petrovic, et al., 2004; E. K. Burke et al., 2006; E. K. Burke & Curtois, 2014; E. K. Burke, Curtois, Post, et al., 2008; E. K. Burke, Curtois, Qu, et al., 2010; E. K. Burke, Curtois, van Draat, et al., 2010; E. K. Burke, Kendall, et al., 2004; E. K. Burke, Li, et al., 2010; Constantino et al., 2014; De Grano et al., 2009; K. a. Dowsland, 1998; K. A. Dowsland & Thompson, 2000; Ferrand et al., 2011; Franz & Miller, 1993; Goodman et al., 2007; Gray, McIntire, & Doller, 1993; Gunawan & Lau, 2013; Huarng, 1999; Ikegami & Niwa, 2003; Irvin & Brown, 1999; Jaumard et al., 1998; Legrain et al., 2015; H. Li et al., 2003; J. P. Li & Aickelin, 2004; J Li et al., 2009; Jingpeng Li et al., 2012; Lin et al., 2014; Maenhout & Vanhoucke, 2008, 2010; Michael et al., 2015; Pierskalla & Rath, 1976; Puente et al., 2009; Purnomo & Bard, 2007; Sherali et al., 2002; Hannah K. Smalley et al., 2015; Stolletz & Brunner, 2012; Ş Topaloglu & Ozkarahan, 2004; D. M. Warner, 1976; Weil et al., 1995; P. Y. Yin et al., 2011)	1	(Maenhout & Vanhoucke, 2011)			5	(Chen et al., 2016; Maenhout & Vanhoucke, 2013b, 2013c; P. D. Wright et al., 2010; P. D. Wright & Mahar, 2013)
Fairness :similarity among staff			14	(Altamirano et al., 2012; Bowers et al., 2016; K. a. Dowsland, 1998; Elomri et al., 2015; Fugener et al., 2015; Huarng, 1999; Legrain et al., 2015; Martin et al., 2013; Ohki et al., 2010; Ronnberg et al., 2010; Stolletz & Brunner, 2012; Seyda Topaloglu, 2006; C Valouxis & Housos, 2000; Wu et al., 2015)	2	(Maenhout & Vanhoucke, 2011, 2013d)	1	(Mullinax & Lawley, 2002)	2	(Maenhout & Vanhoucke, 2013b, 2013c)

Fairness: Workload Balance			6	(Bowers et al., 2016; Bruni & Detti, 2014; Cipriano et al., 2006; Elomri et al., 2015; Ikegami & Niwa, 2003; HannahK. K. Smalley & Keskinocak, 2014)			5	(Liang & Turkcan, 2015; Mullinax & Lawley, 2002; Punnakitikashem et al., 2008; Sir et al., 2015; Sundaramoorthi et al., 2010)	1	(Punnakitikashem et al., 2013)
Patient Experience										
Waiting Time	9	(Badri & Hollingsworth, 1993; Bretthauer et al., 1998; Carlson et al., 1979; Coats, 2001; de Vericourt et al., 2011; EL-Rifai et al., 2014; Linda V Green et al., 2006; Oddoye et al., 2007; Yankovic & Green, 2011; Zeinali et al., 2015; Zeltyn et al., 2011)	2	(Yeh & Lin, 2007; Yilmaz, 2012)						
Length of Stay	3	(Feng et al., 2015; Ghanes et al., 2015; Henneman et al., 2015)							2	(Sinreich & Jabali, 2007; Sinreich et al., 2012)
Continuity of Care			3	(Huarng, 1999; Maenhout & Vanhoucke, 2010; Hannah K. Smalley et al., 2015)	1	(Alistair Clark et al., 2015)	2	(Liang & Turkcan, 2015; Punnakitikashem et al., 2008)	2	(Maenhout & Vanhoucke, 2013b, 2013c)

IP Formulation

One of the earliest applications of integer programming (IP) of the personnel scheduling problem was the set covering formulation for employees scheduling at toll booths to reduce delays Dantzig (1954). Set covering determines the minimum number of staff at various levels to satisfy the period requirements (e.g. hourly) of different functions, taking into account the upper limit on consecutive work periods. Based on the definition of decision variables and the constraints, the set covering formalisation is a convenient representation of the shift, days off, and tour scheduling (Morris & Showalter, 1983). A general explicit set covering formalisation is presented in the problem (P1) as described by (Aickelin & Dowsland, 2000). The IP formulation can be represented as following:

$$\text{(P)}\quad \begin{aligned} &\min \sum_{j\in J} c_j x_j \\ &\text{s.t.} \quad \sum_{j\in J} a_{ikj} x_j \geq b_{ik} && \forall i \in I and k \in K && \text{(A.1)} \\ &\qquad x_j \geq 0 and Integer && \forall j \in J && \text{(A.2)} \end{aligned}$$

Table A.6 The difference between shift, days off, and tour scheduling problems.

Scheduling Problem	Notations					
	Decision Variables x_j	Staff Requirements b_{ik}	J	I	K	a_{ikj}
Cyclic Shift scheduling	the number of staff to be allocated to day shift pattern j.	The number of full-time-equivalent staff required to satisfy the fluctuated demand in period i of day k.	Set of possible daily shift types.	Set of possible time periods to be considered over a single day.	Set of planning days.	$a_{ikj} = 1$, if period i of day k is a work period in shift j and $a_{ikj} = 0$, otherwise

Cyclic Days-off scheduling	The number of staff to be allocated to days-off pattern j.	The number of full-time-equivalent staff required to satisfy the fluctuated demand at day i of week k.	Set of daily possible days-off patterns types.	Set of days per week.	Set of planning weeks.	$a_{ikj} = 1$, if day i of week k is a work day in days-off pattern j and $a_{ikj} = 0$, otherwise
Cyclic Tour scheduling (integrative staff (shift + days-off)	The number of employees to be allocated to tour j.	The number of full-time-equivalent staff required to satisfy the fluctuated demand in a period i of day k.	Set of possible daily tour types.	Set of possible time periods to be allocated over a week.	Set of planning days.	$a_{ikj} = 1$, if period i of day k is a work period in tour j and $a_{ikj} = 0$, otherwise

The differences between the three types of cyclic staff scheduling are depicted in Table A.6. The value of $c_j$is the cost associated with allocating a medical staff to a pattern (tour) j which reflect differential wage-and-benefits rates for various patterns or even their relative desirability (Baker, 1976). The objective is to minimise the cost of assigning full-time equivalent staff to satisfy the fluctuated demand. If the objective is to minimise the staff size, then the value of $c_j = 1$. Staff requirements (bi) for each interval (staffing problem) is a crucial step in the solution of staff scheduling problem which mainly depends on external demand. All of these formulation does not assign the employees to shifts or days off and assumes all employees are homogeneous (Jackson, Havens, Va, & Dollard, 1997).

The modelling of the scheduling problem requirements varies with the different work environments which imply staff scheduling problem with distinct features. The main differentiating dimensions addressed in the literature include:

- Continuous operations (24-hours) vs. discontinuous operation (less than 24-hours);

- The planning horizon employed which ranges from few days to few weeks or user-defined;
- The planning periods per day, e.g. 4-hours, 2-hours, 1-hours, or 30-min.
- Characteristics of the staff which includes contract types (full-/part-time), various skills, different productivities, substitutability rules, and individual preferences.
- Flexible shift vs. fixed shift. Flexibility varies regarding shift stating-tie, the length of breaks duration and shift overlap.
- Coverage constraints: Minimum/maximum of staff required/allowed to be allocated to a specific shift for a particular day in a planning horizon.
- Fairness/workload balance: uniform distribution of the weekends, days off, and shift types among all staff.
- Weekends: Periodicity of weekends off, long weekends, and compensation for weekends assignment.
- A consecutive sequence of shifts regarding minimum/maximum number of consecutive working/rest days, days off after a night shift, and mandatory patterns of working shifts.

These constraints are modelled either as a hard constraint if their satisfaction is a must or as soft constraints otherwise. The unsatisfied soft constraints are often penalised in the objective function to minimise the total sum of deviations.

Appendix B

Methodology Supplements

Philosophical assumptions of OR/MS

In the debate about the justification of science, Nola and Sankey (Nola & Sankey, 2007) introduced a three-level framework consider all proposal in this regard. *Scientific theories*, Level 1, is the outcome of scientific activities, aiming to provide a better understanding of nature (e.g. theories of motion). *Scientific methodologies*, level 2, depicts the logic, values and rules of the scientific method that guides and describe the activities of science at level 1. *Metamethodologies of science*, level 3, guides and justifies the choices scientific methodologies at level 2. Ormerod (R. J. Ormerod, 2010) has applied Nola and Sankey's framework to OR/MS academic research (B.1). Ormerod distinguishes between OR/MS academic and practice to provide some clarity to the analysis and insights into the gap between them which is sometimes difficult to bridge. Level 1, the outcomes of OR/MS academic research, represents the models, methods, and methodologies which are equivalent to theories of science. The research in OR/MS is often administered from the ethos of mathematics. Furthermore, the practice of OR/MS can be the research subject that involves social science perspective. At level 2, the researchers can adopt methods from mathematics, science, or social sciences as the question of the research dictates. Level 3 represent the justification of the three domains of mathematics, science, and social science.

Table B.1 OR/MS AcademicOR/MS Practice.

Level 3 Metamethodologies (justification) **Mathematics: Foundations and axioms of mathematics and statistics.Science: A priori, Empirical, Conventionalist, decision theoretical…Social science: Positivism, Interpretivist (phenomenology), Pragmatism**	**Level 3 Metamethodologies (justification) Pragmatism**
Level 2 Research methodologies (values and rules) 1. Methods of mathematics and statistics2. Methods of science **Aristotle's Organon; ... ; Bacon's Novum Organon; Descartes's Rules for the Direction of the Mind; ... ; Newton's 'Rules of Reasoning in Philosophy'; ... ; Duhem's aims and rules; Popper's critical rationalism; Lakatos's scientific research Programmes; Kuhn's weighted values; Feyerabend's methodological pluralism; Bayesianism; decision-theoretic methods.**3. Methods of social science **Economics (classical, Marxist, Instructional, etc.), sociology (functionalism, phenomenology, rational choice, conflict, etc.), political sciences, etc.research methods: comparative research, archival research, content analysis, performance analysis, experimental research, survey research, life history, longitudinal case studies, observation, statistical analysis, quantitative modelling, simulation, field studies, action research, and so**	**Level 2 OR Values and methodologiesValues**: pragmatism, common sense, professional ethics **Ethos**: science, consultancy, social science **Relevant disciplines**: science (method); mathematics (pure, applied); social science (economics, psychology, behavioural science) **Methodologies**: traditional OR approach, articulate intervention, soft systems methodology, inquiring systems, interactive planning, strategic choice analysis, drama theory, critical systems heuristics, total systems intervention, pragmatic pluralism, transformation competence perspective, critical pragmatism, others.

Level 1 Research into OR methods and practice Methods (theories) **Queuing; stochastic processes; simulation; systems dynamics; etc.2. Mathematical functions; mathematical optimisation; scheduling; allocation; search; critical path analysis; etc. 3. Statistical inference; forecasting; stock control; etc.4. What ... if modelling; financial modelling; spreadsheets; etc.5. Decision analysis; scenario development; decision trees; robustness analysis; multi-criteria decision analysis; strategic choice analysis; strategic options development and analysis; etc. 6. Games; meta-games; hyper-games; drama theory; etc. 7. Facilitation; Delphi; nominal group technique; cognitive mapping; etc.8. Systems theory; viable systems model; soft systems methodology; critical systems theory; etc. 9. Others** Practice(habits)**1. The process of OR: case studies, etc. 2. Use of methods: questionnaires, etc. 3. Competencies of OR: content analysis, etc. 4. Management and structure of O**	**Level 1 Analysis of theories, actions, proposals, and consequences** **Activities** (i) Understanding context: based on common sense and experience (ii) Designing and managing intervention processes: using craft skills, informal methodologies and public methodologies from Level 2 above (iii) Conducting analysis: using methods listed in Table 3, applying common sense and drawing on experience and craft skills. **Outputs The immediate output of interventions**: structured problems, data, algorithms, models, operational rules, forecasts, advice, explanation, insight, learning, commitment, options, policies, structure, plans, strategies, tactics, evaluations, decision support, etc.
	Level 0 Organisational the worldResulting changes in human activity systems implemented mainly by others: new or changes to:- factories, distribution depots, mines, machinery, layouts, scheduling, vehicles, ships, aircraft, drilling rigs, offices, computer systems, communication networks, call centres, weapons, shops, pubs, branches, products, services, laws, rules policies, procedures, organization, etc.

Source: adapted from (Ormerod, 2010)

Deductive vs Inductive Approach

Table B.2 Research approach: deductive vs inductive research

Criteria	Deduction	Induction
Logic	In a deductive inference, when the premises are true, the conclusion must also be true.	In an inductive inference, known premises are used to generate untested conclusions
Generalisation	Generalising from the general to the specific.	Generalising from the specific to the general.
Data	**Quantitative**. Data collection is used to evaluate propositions or hypotheses related to an existing theory.	**Qualitative**. Data collection is used to explore a phenomenon, identify themes and patterns and create a conceptual framework.
Approach	Structured	Flexible
Purpose	**Explanatory**; Explanation of causal relationships between variables	**Exploratory**; Gaining an understanding of the phenomena.
Paradigm	Positivist	Interpretivist
Process of investigation	Theory Hypothesis Observation Confirmation.	Observation Patterns Hypothesis Theory.
Research Orientation	Theory-testing research (Theory falsification or verification).	Theory-building research (Theory generation and building)

Source: adapted from (Saunders et al., 2016)

Interviews Participation Letter

Dear [title].[name],

Acknowledging the fact that hospital staffing and its planning activities are one of the hurdles that can impede service quality and productivity, 3S Group - College of Business at Dublin Institute of Technology (DIT) is conducting a research study with an ultimate objective of developing a medical staffing OPTIMISER. As part of the study, a thorough understanding of the staffing process will be achieved by interviews. 3S Group is currently working with leading university hospitals in Ireland (e.g. Beaumont Hospital, Tallaght Hospital, Sligo Regional Hospital, Cork University Hospital, St. Luke's General Hospital, Mater Hospital and Letterkenny Hospital) to complete this phase. It is agreed with the hospital partners that the pilot study will address the hospital medical staffing.

This research aims to combine qualitative and quantitative research in the process of developing this comprehensive staffing analytical tool that will incorporate; demand fluctuations, workload balance, staff preferences, burnout threshold, operational structure, and more.

Your input is highly appreciated, and we would be grateful if you can contribute in the interview phase by sparing 20 minutes for a brief interview regarding your insights on the staffing process and scheduling decisions. Your participation in the study will add significant value to the research findings which we will happily share with you.

We acknowledge your experience. Therefore, a non-confidentiality protocol of DIT will be applied as part of the research ethics. That means neither your profile nor your hospital will be declared without your consent. The information you provide will feed directly into the development of this analytical tool without prejudice.

Looking forward to hearing from you.

Best Regards,

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Preliminary Questionnaire

1. **In the following questions, try to describe the scheduling process:**

Questions	Answers
What is the frequency of the rota?	• Weekly • Bi-weekly • Monthly • Other
Is the staff rota done locally by your unit?	• Yes • NO
Do you use a rotating rota (predetermined /fixed rota)?	• Yes • NO
How long does it take to prepare a rota?	____________________

From the initial Rota to the day of the service, how can you describe the updates that can occur because of the new information available regarding to the staff and demand? **In other words, how frequently is it modified?**	• 5= Very Frequently, • 4= Frequently, • 3= Occasionally, • 2=Rarely, • 1=Very Rarely
To what extent do you allow flexible shifts (start/end times) to increase staff satisfaction?	• 5= Very important, • 4= Somewhat, • 3= Undecided, • 2= Not really, • 1= Not important at all

In your opinion, what are the criteria of high-quality rota in your department? (Select all applied)	• Cost reduction and not exceeding budget • Meeting the demand requirement, • Eliminating both under/over-staffing, • Staff fairness • Meeting staff preferences, • Staff satisfaction • Patient experience, • Work-life balance • Other: ______________________
The manager's view of how rota is managed is different to how the staff view it. In your opinion, how important is it to consider staff's view?	• 5= Very important, • 4= Somewhat, • 3= Undecided, • 2= Not really, • 1= Not important at all

In your opinion, staff preferences (for shift/days off) should be considered.	• 5=totally agree • 4= agree, • 3= not sure, • 2= disagree, • 1= totally disagree

2. **In your opinion, to what extent do you see the importance of the following variables when you staff your department?**

These variables are very important When staffing my department,	**5**	**4**	**3**	**2**	**1**
The structural layout of the unit.					
Patient Pathways/ clinical processes of care.					
Considering access to diagnostic services.					
End-point services such as availability of ICU/HDU/ or ward admission.					
Admin work and personal time.					
Number of boarded patients.					

5= Very important, 4= Somewhat Important, 3= Undecided, 2= Not Important and 1= Not important at all

3. **To what extent do you agree that the following practices may cause your staff dissatisfaction and burnout?**

Practices	**5**	**4**	**3**	**2**	**1**
Working understaffed shifts.					
Mandatory overtime/leave late.					
Add a new shift.					
Forced floating (redeployment).					
Undesirable shifts or rotation.					
Cancell/change breaks.					
Continuous changes in the rota.					
Inappropriate skill-mix.					

5= Totally Agree, 4= Agree, 3= Not Sure, 2= Disagree and 1= Totally Disagree.

In-depth Interviews

A. General

- Your years of experience in healthcare, years of experience as a manager, unit capacity (beds, staff type, and skill-mix), Types of shifts.

B. Workload_Analysis

One of the key components for setting the staffing and scheduling is to assess the workload (demand for care). In this context, several factors may affect the assessment,

B1. What factors do you consider in your workload analysis?

B2. How does the demand fluctuation affect your staff scheduling?

- What are the practices that can help you to mitigate their effects?
- Does your unit/hospital adopt any staffing strategies to meet such unexpected demand? Can you explain?

C. Staffing

C1. How do you determine the staffing number/hours per shift?

C2. Do you think there are differences between regular staff and e.g. agency/locum?

- If yes, do you consider the productivity element when staffing your unit?

D. Scheduling and Rostering

D1. Can you explain your process in setting the rota?

D2. Is the medical staffing and scheduling challenging?

- If yes, in your opinion what are the main challenges?

D3. What short-term strategies/tactics do you use to overcome scheduling and staffing problems?

E. Control

E1. What are the biggest frustrations in your daily scheduling routine?

E2. Is your unit/hospital currently understaffed?

- If yes, in your opinion what are the main reasons for this shortage?
- What are the short-term backup strategies/practices that your unit/hospital adopt to respond to understaffing?

E3. What happens if these backup strategies could not be implemented (limited access to agency/locum)?

- If they continue with understaffing, does that affect the patient safety and liability?

G. Management responsibility and Concerns

G1. Are you aware of any long-term plans/solutions by your hospital to resolve the persistent scheduling and staffing challenges? If yes, please elaborate.

H. Work Environment (Motivation)

Some recent literature highlighted that staffing and scheduling problems are among the causes of staff dissatisfaction and stress/burnout.

H1. In your opinion, what are situations could contribute to staff stress in today's environment?

H2. why healthcare facilities are having increasing staffing problems? Elaborate.

H3. What coping strategies as a unit manager do you utilise to deal with stressed/burnout staff?

I. IT systems

I1. Do you use any IT solution to help in demand prediction, staffing, scheduling?

- If yes, what system do you use?

I2. In your opinion, what are the most important features you need in an IT system that would help you plan and schedule your staff efficiently? I3. Do you think predictive analytics can help to improve staffing and scheduling decisions?

Appendix C

Case Study Supplements

Conceptual model for DES

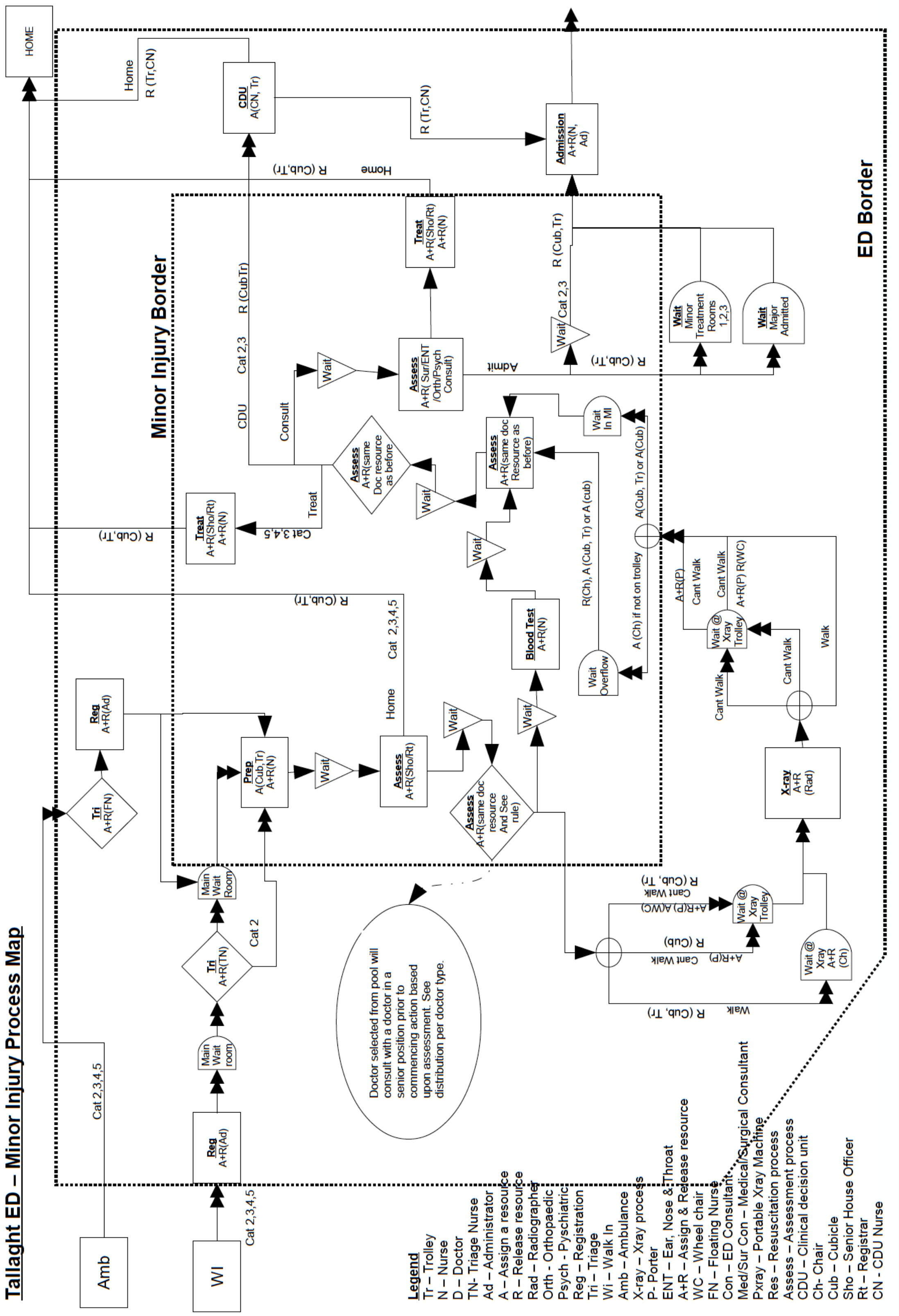
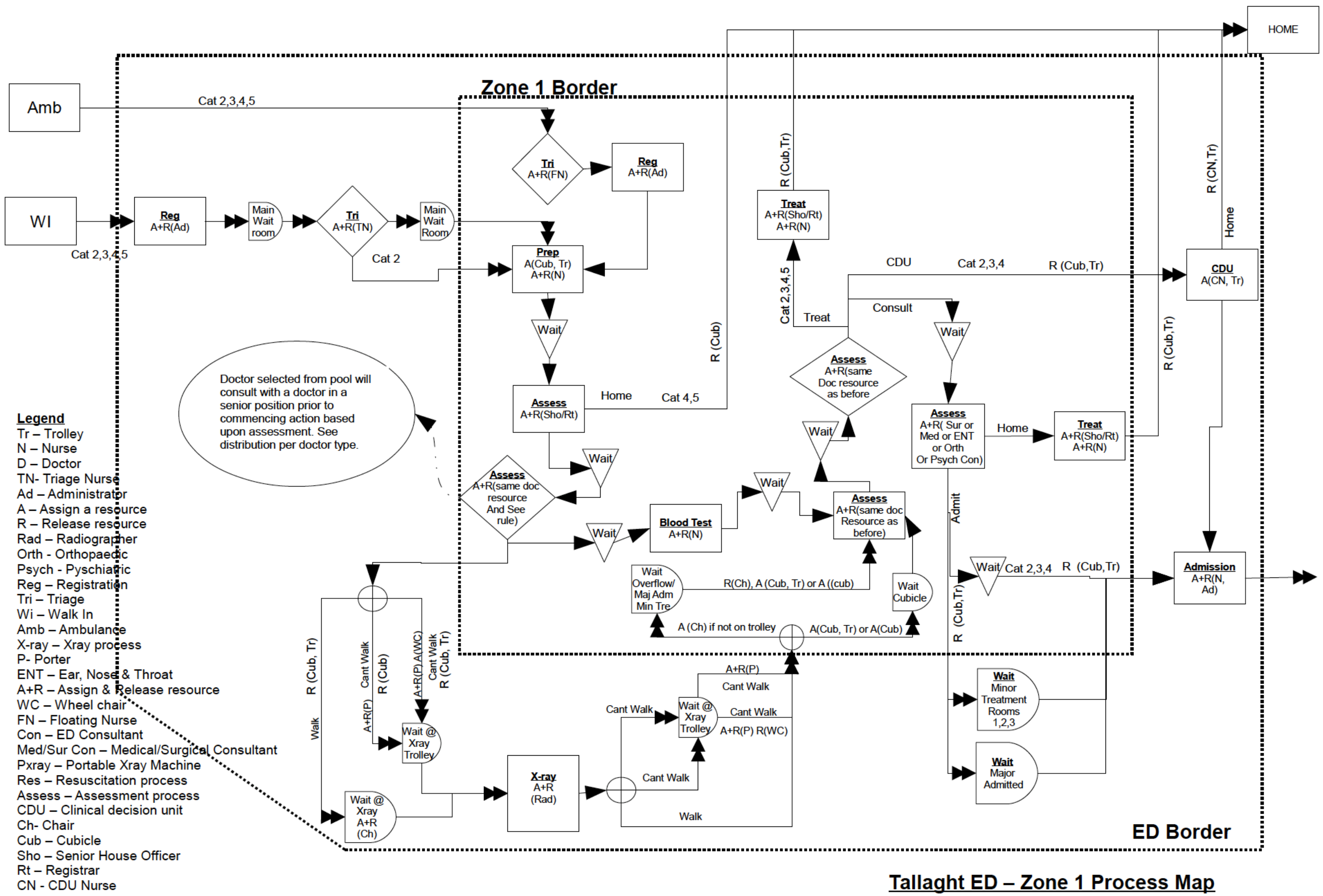


Fig. C.1 Minor Injury Map



Legend
Tr – Trolley
N – Nurse
D – Doctor
TN- Triage Nurse
Ad – Administrator
A – Assign a resource
R – Release resource
Rad – Radiographer
Orth - Orthopaedic
Psych - Pyschiatric
Reg – Registration
Tri – Triage
Wi – Walk In
Amb – Ambulance
X-ray – Xray process
P- Porter
ENT – Ear, Nose & Throat
A+R – Assign & Release resource
WC – Wheel chair
FN – Floating Nurse
Con – ED Consultant
Med/Sur Con – Medical/Surgical Consultant
Pxray – Portable Xray Machine
Res – Resuscitation process
Assess – Assessment process
CDU – Clinical decision unit
Ch- Chair
Cub – Cubicle
Sho – Senior House Officer
Rt – Registrar
CN - CDU Nurse

Fig. C.2 Major Injury Map

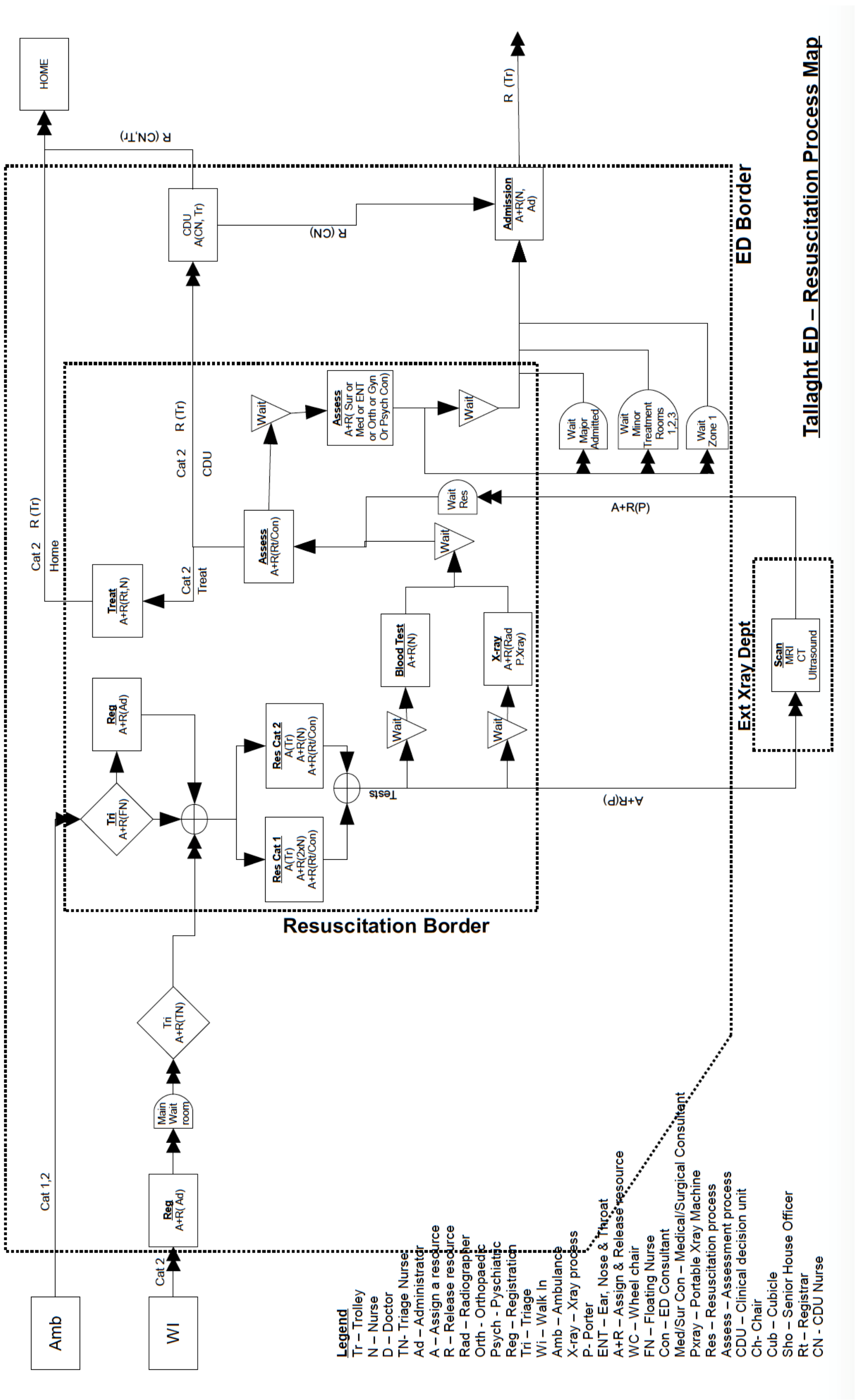


Fig. C.3 Resus Map

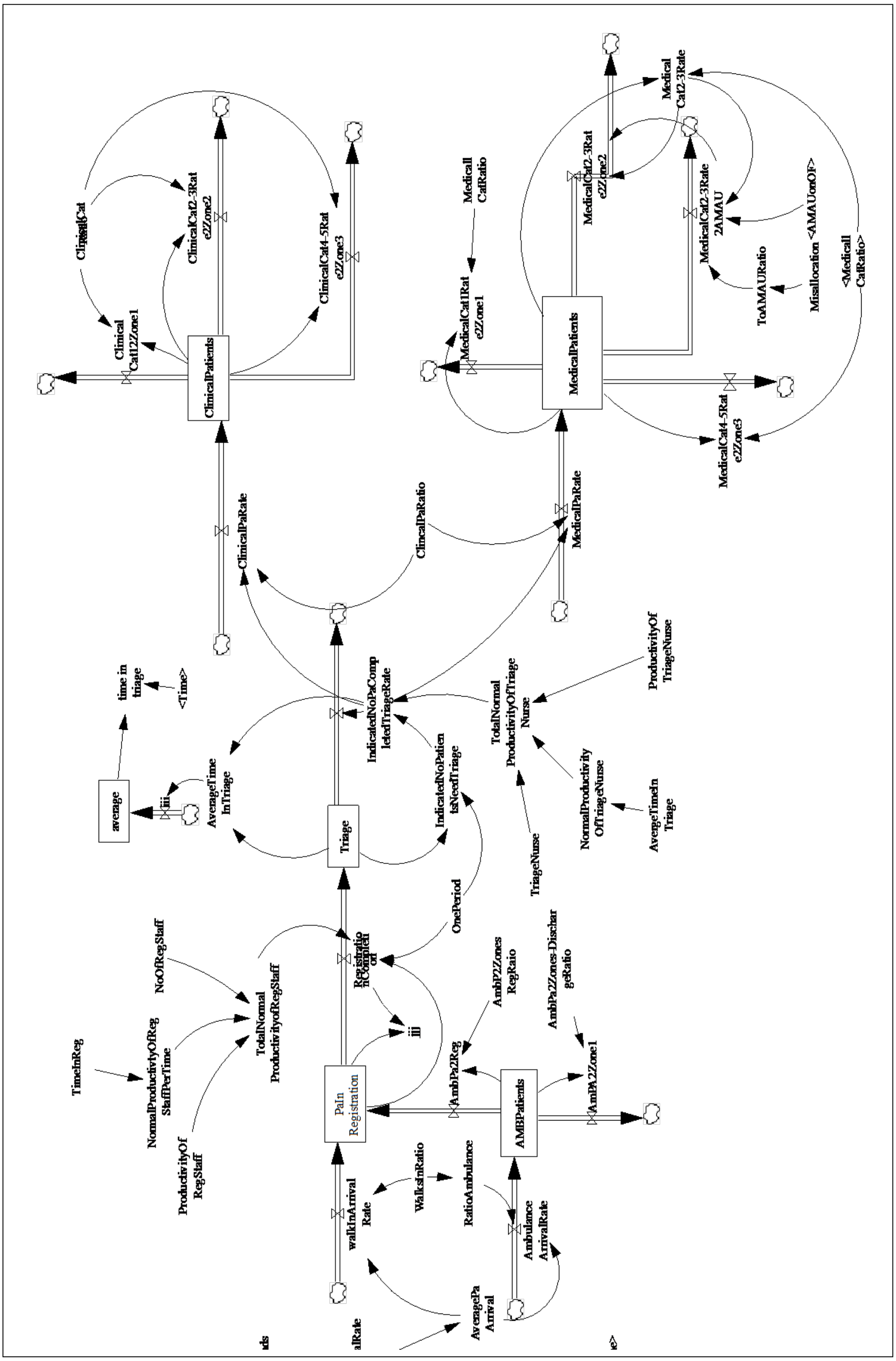


Fig. C.4 Stock and flow Map1

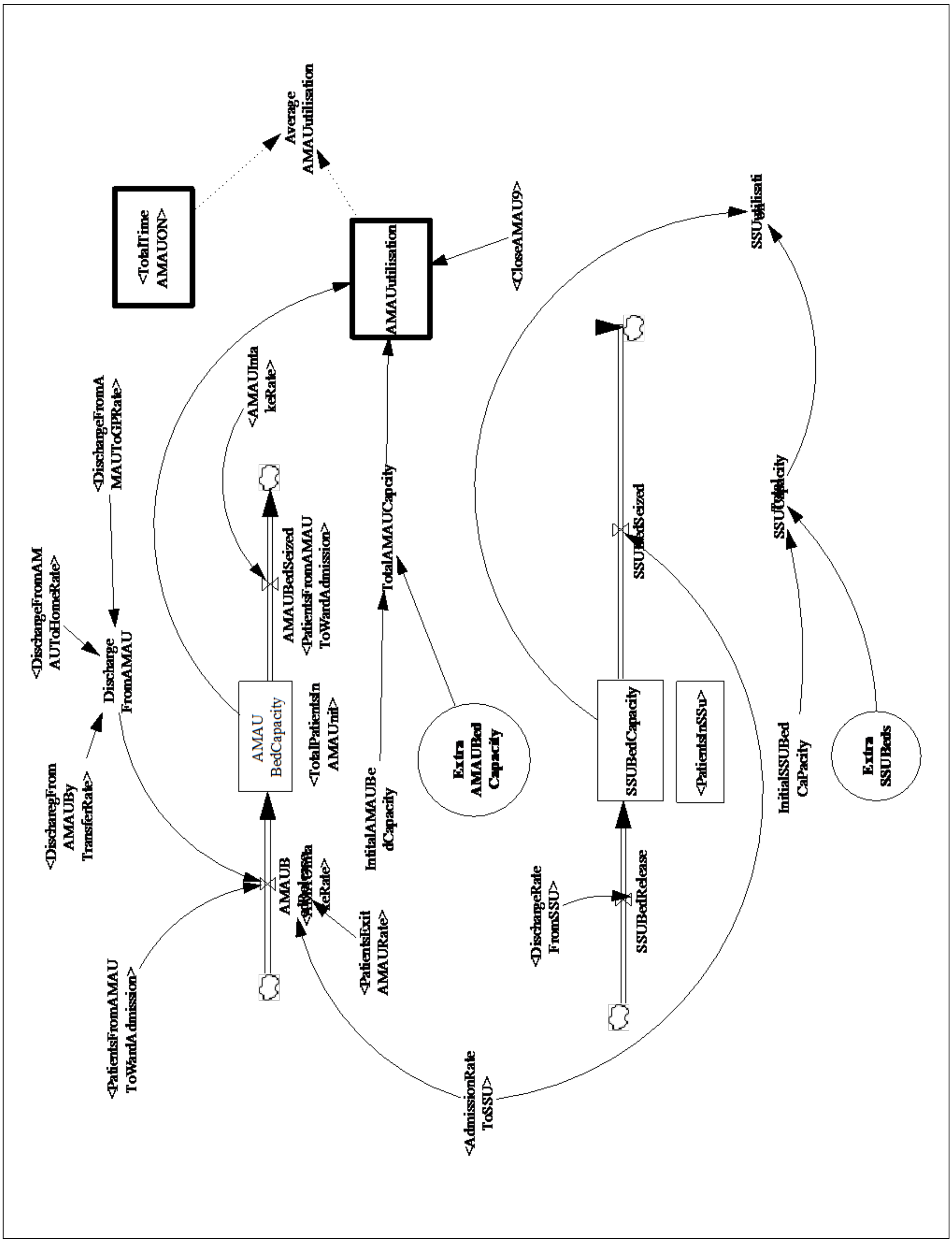


Fig. C.5 Stock and flow Map2

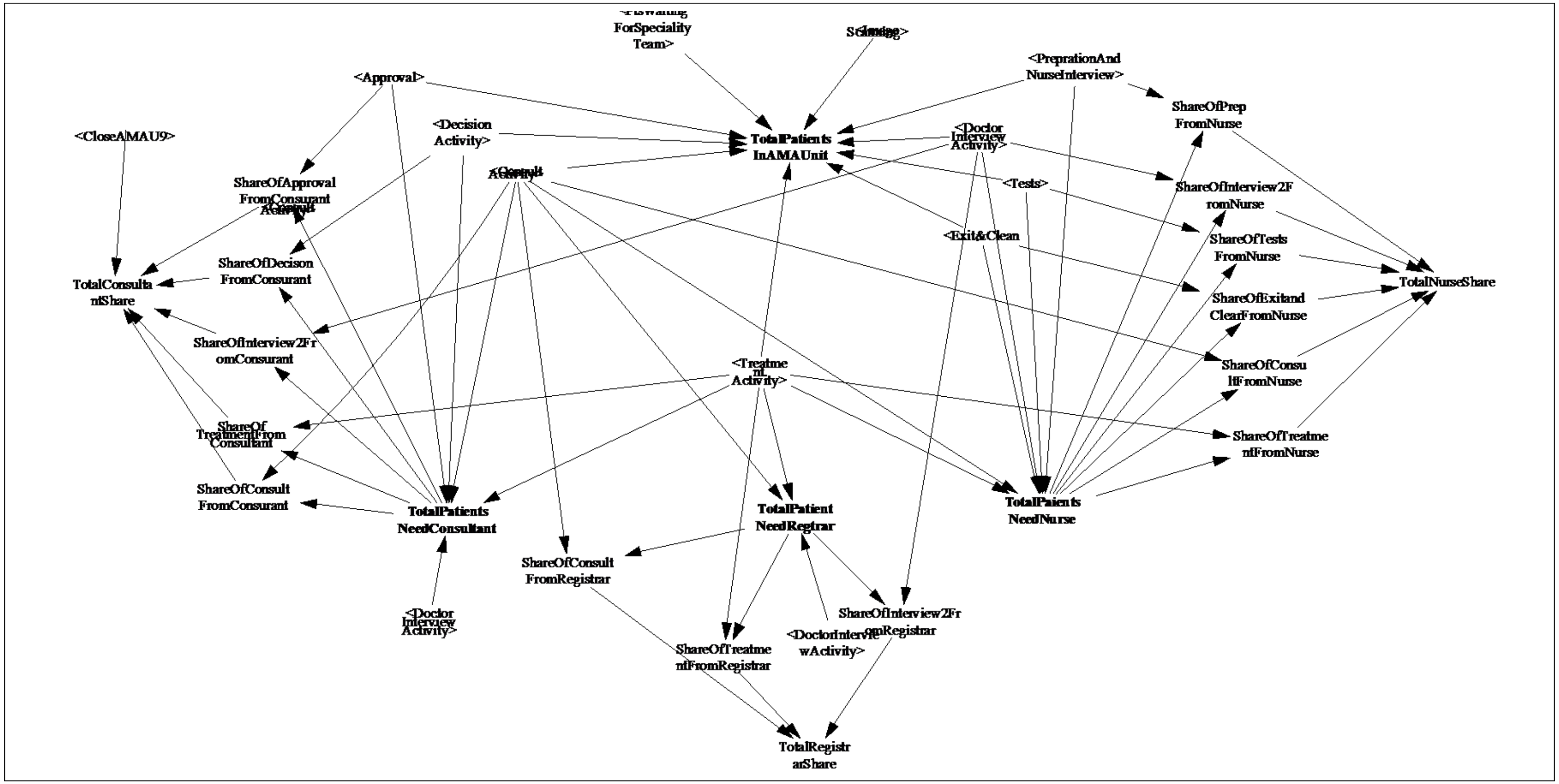


Fig. C.6 Stock and flow Map3

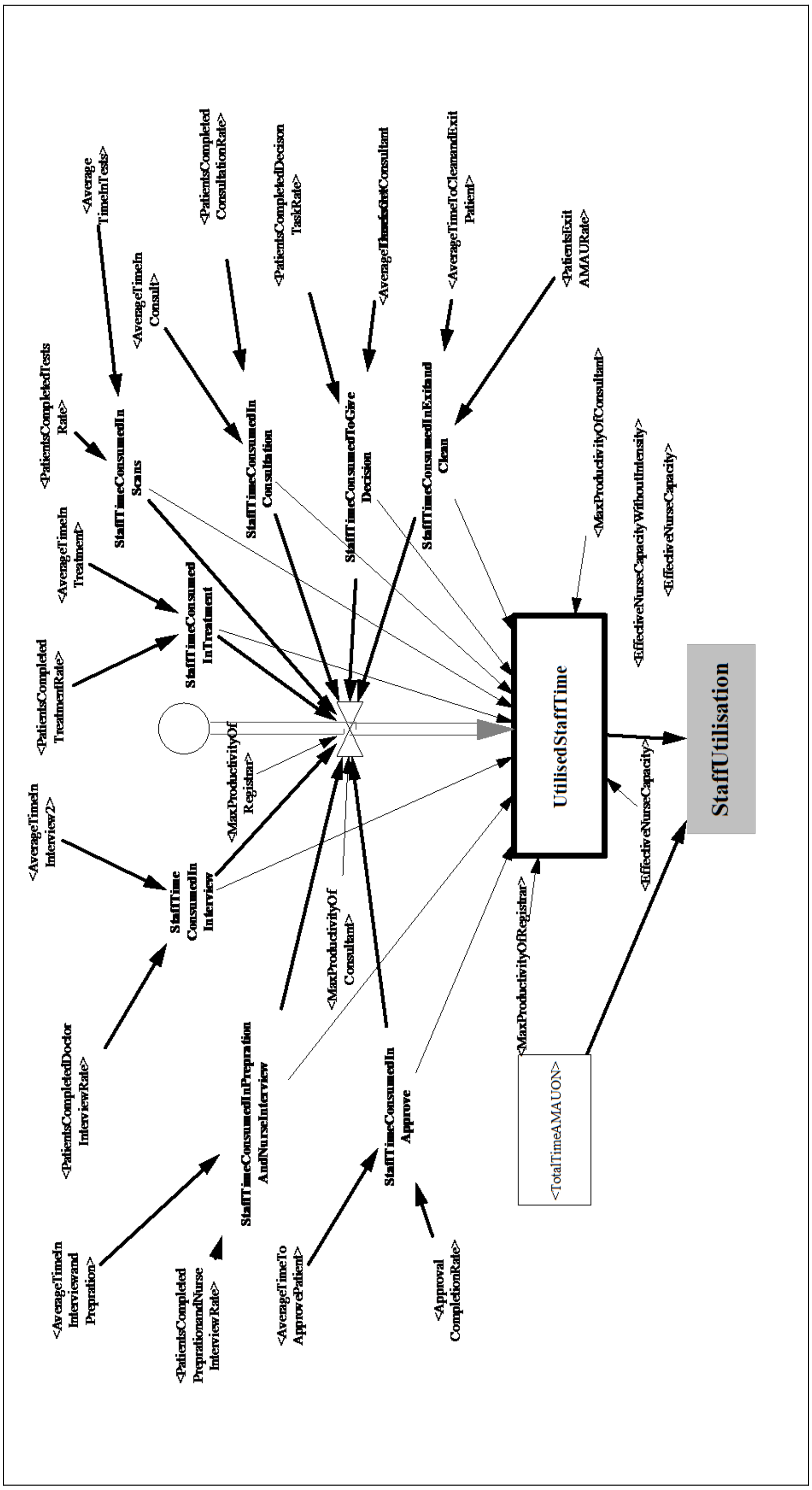


Fig. C.7 Stock and flow Map4

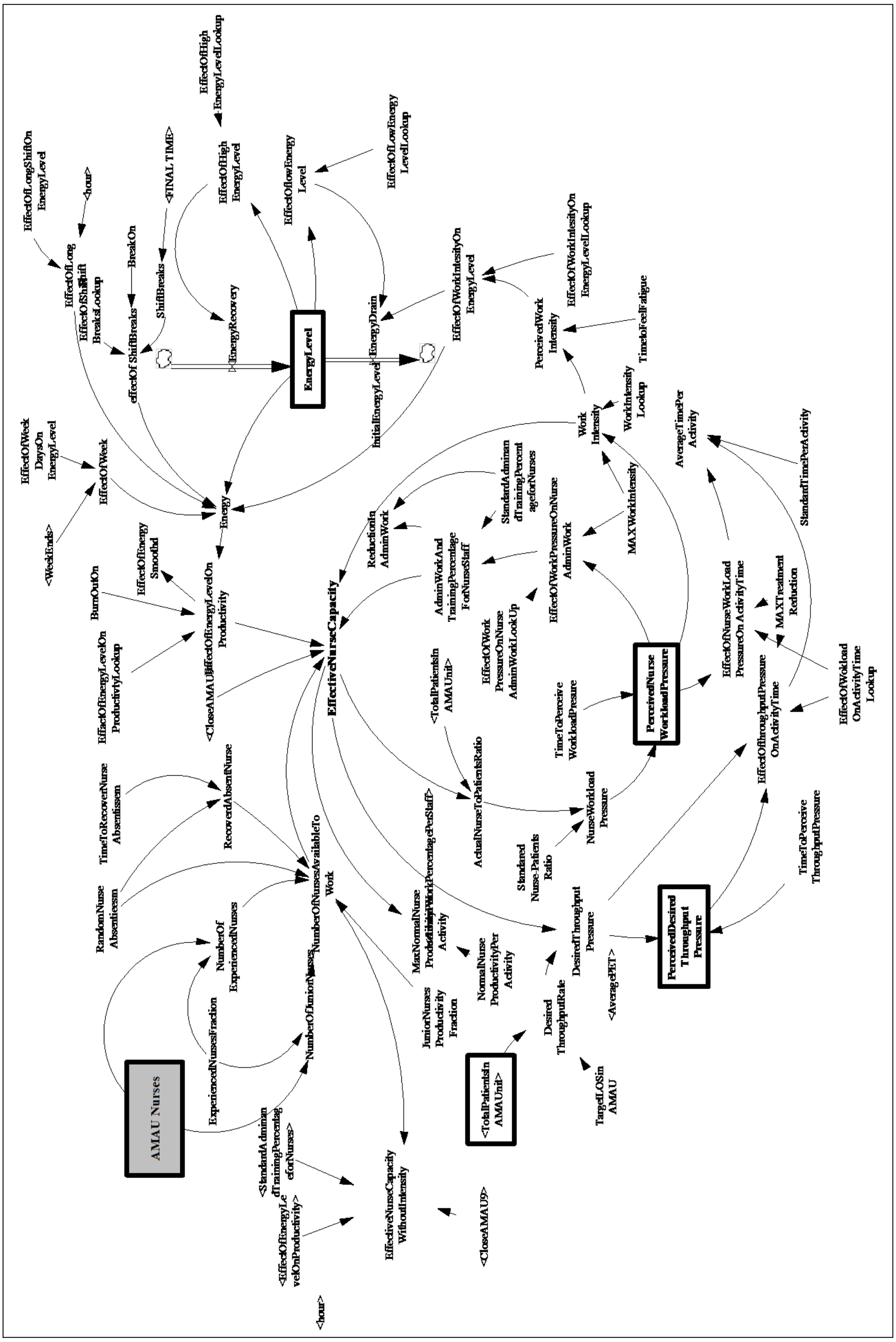


Fig. C.8 Stock and flow Map5

Sample of Input Data

Table C.1 Resources capacity.

Resource	Capacity	Unit
Porters	4	ED
Cleaners	4	ED
Wheelchair	25	ED
Portable X-ray	10	ED
Cubicle	23	ED
MRI	10	Radiology
CT	10	Radiology
CDU	100	ED
ECG	5	ED
Radiography (x-ray)	10	ED
Major Admitted & Treatment Rooms	7	ED
US	10	Radiology
Resus Trolley	5	ED
Major Trolley	18	ED
Minor Trolley	8	ED
AMAU Trolley	11	AMAU
Cleaners	2	AMAU
Portable X-ray	0	AMAU
ECG	0	AMAU

Table C.2 Scans Probabilities.

Station	Scan/Test	Scans Probabilities
Resus	Blood Test	0.91
Resus	ECG	0.92
Resus	X-ray	0.63
Resus	MRI	0.003
Resus	CT	0.031
Resus	US	0.021
Major	X-ray	0.442
Major	Blood Test	0.84
Major	ECG	0.71
Major	MRI	0.01
Major	CT	0.03
Major	US	0.017
Ambulatory Care	X-ray	0.59
Ambulatory Care	Blood Test	0.61
Ambulatory Care	ECG	0.18
Ambulatory Care	MRI	2.00E-04
Ambulatory Care	CT	0.002
Ambulatory Care	US	0.001
AMAU	X-ray	0
AMAU	Blood Test	0
AMAU	ECG	0
AMAU	MRI	0.01
AMAU	CT	0.2
AMAU	US	0.05

Table C.3 Processing Time (min).

Station	Activity	Min	Most likely	Max
Resus	Patient pass	1	2	2
Resus	Preparation	1	5	7
Resus	Diagnose	60	90	120
Resus	Resus	60	90	120
Resus	Consult Decision	2	5	10
Resus	Treat	5	10	15
Resus	Exit	2	5	7
Resus	Clean	5	5	10
Major	Patient pass	1	5	7
Major	Preparation	1	5	7
Major	Interview	10	20	30
Major	Speciality team	90	225	300
Major	Consult Decision	5	10	15
Major	Treat	5	10	15
Major	Exit	1	5	7
Major	Clean	1	5	7
Minor	Patient pass	1	5	7
Minor	Preparation	1	5	7
Minor	Consult Decision	1	5	7
Minor	Treat	5	10	15
Minor	Exit	1	5	7
Minor	Clean	1	5	7
AMAU	Patient pass	1	5	7
AMAU	Preparation	15	20	30
AMAU	Interview	20	30	50
AMAU	Discussion	5	10	15
AMAU	Consult	10	15	20
AMAU	Consult Decision	5	10	15
AMAU	Exit	1	5	7
AMAU	Clean	1	5	7
AMAU	Speciality team	90	180	300

ED	Registration	2	5	7
ED	Triage	2	10	15
Radiology	X-ray	30	40	60
Lab	Blood Test	5	10	20
Radiology	ECG	5	10	20
Radiology	MRI	10	30	40
Radiology	CT	10	30	40
Radiology	US	10	30	40
AMAU	Transfer patient	3	5	10
Resus	Speciality team	90	225	300
Minor	Interview	10	15	20
Minor	Speciality team	60	90	160

Table C.4 Other Processing times (minutes).

Department	Service	Min	Most likely	Max
ED	Registration	2	5	7
ED	Triage	2	10	15
ED	X-ray	10	20	30
ED	Blood Test	5	10	20
ED	ECG	5	10	20
ED	MRI	10	30	40
ED	CT	10	30	40
ED	US	10	30	40

Table C.6 Routing Probabilities.

Station	Route	Process	Process Label	Likelihood
Major	Route1	A	Treatment	0.4
Major	Route1	B	Normal	0.58
Major	Route1	C	Speciality Team	0.02
Major	Route1	D	Discharge	0
Major	Route1	E	null	0
Major	Route2	A	Treatment	0.517
Major	Route2	B	Speciality Team	0.483
Major	Route2	C	null	0
Major	Route2	D	null	0
Major	Route2	E	null	0
Major	Route3	A	Minor	0.01
Major	Route3	B	Discharge	0.61
Major	Route3	C	Admission	0.38
Major	Route3	D	null	0
Major	Route3	E	null	0
Resus	Route1	A	Diagnostic	0.956
Resus	Route1	B	Resus	0.044
Resus	Route1	C	null	0
Resus	Route1	D	null	0
Resus	Route1	E	null	0
Resus	Route2	A	Major	0.119

Resus	Route2	B	Minor	0.041
Resus	Route2	C	Normal	0.84
Resus	Route2	D	null	0
Resus	Route2	E	null	0
Resus	Route3	A	Major	0.75
Resus	Route3	B	Minor	0
Resus	Route3	C	Discharge	0.25
Resus	Route3	D	null	0
Resus	Route3	E	null	0
Minor	Route1	A	Treatment	0.06
Minor	Route1	B	Normal	0.94
Minor	Route1	C	null	0
Minor	Route1	D	Major	0
Minor	Route1	E	null	0
Minor	Route2	A	Exit	1
Minor	Route2	B	null	0
Minor	Route2	C	null	0
Minor	Route2	D	null	0
Minor	Route2	E	null	0
Minor	Route3	A	Major	0.05
Minor	Route3	B	Discharge	0.95
Minor	Route3	C	null	0
Minor	Route3	D	null	0
Minor	Route3	E	null	0
AMAU	Route1	A	null	1
AMAU	Route2	A	null	1
AMAU	Route3	A	null	1

Table C.5 Arrival mode, clinical group and triage category.

Ambulance	Clinical Group	Triage1	Triage2	Triage3	Triage4	Triage5
1	Assault	0.019	0.243	0.583	0.155	0
1	Dental	0	0	0.5	0	0.5
1	Dermatological	0	0.333	0.333	0.333	0
1	ENT	0	0.178	0.6	0.2	0.022
1	Medical	0.045	0.393	0.5	0.056	0.006
1	Obs/Gynae	0	0.357	0.5	0.119	0.024
1	Ophthalmological	0	0.333	0.333	0.333	0
1	Orthopaedics	0.004	0.185	0.594	0.194	0.022
1	Other	0.032	0.202	0.532	0.197	0.037
1	Psychiatric	0	0.493	0.448	0.049	0.01
1	RTA	0.028	0.5	0.404	0.067	0
1	Sports Injury	0	0.375	0.438	0.188	0
1	Surgery	0.007	0.243	0.625	0.112	0.013
1	Trauma	0.067	0.294	0.491	0.142	0.005
1	Urology	0	0.25	0.662	0.074	0.015
1	Vascular	0	0.353	0.235	0.412	0
0	Assault	0	0.044	0.518	0.412	0.027
0	Dental	0	0	0.579	0.316	0.105
0	Dermatological	0	0.011	0.318	0.477	0.193
0	ENT	0.002	0.112	0.596	0.266	0.024
0	Medical	0.002	0.201	0.578	0.192	0.027
0	Obs/Gynae	0	0.088	0.616	0.277	0.019
0	Ophthalmological	0.015	0.215	0.538	0.169	0.062
0	Orthopaedics	0	0.052	0.367	0.506	0.075
0	Other	0	0.041	0.326	0.466	0.167
0	Psychiatric	0	0.481	0.472	0.026	0.022
0	RTA	0	0.04	0.56	0.383	0.017
0	Sports Injury	0	0.045	0.44	0.481	0.034
0	Surgery	0.001	0.08	0.572	0.322	0.026
0	Trauma	0.001	0.06	0.404	0.505	0.03
0	Urology	0	0.179	0.571	0.238	0.012
0	Vascular	0	0.08	0.44	0.28	0.2

Table C.7 The simulation results of the different scenarios.

KPIS	Base	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12
ED PET ALL	548.102	516.13	570.24	524.25	503.93	508.36	465.99	487.56	471.73	537.14	501.27	495.95	650.38
ED PET Admitted	790.425	729.44	800.16	772.07	633.23	709.93	614.74	692.75	617.03	790.52	707.56	636.66	917.77
ED PET Discharged	372.922	363.17	404.14	347.74	411.57	365.89	358.31	343.78	368.48	360.18	351.35	396.55	549.51
ED Proportion of Admission	0.237	0.24	0.24	0.23	0.23	0.23	0.24	0.23	0.23	0.23	0.24	0.23	0.24
% Pts<6hrs	0.488	0.50	0.47	0.50	0.49	0.50	0.52	0.52	0.52	0.50	0.50	0.50	0.40
% pts<9hrs	0.655	0.68	0.64	0.67	0.69	0.68	0.72	0.70	0.71	0.67	0.68	0.69	0.55
ED SHO Util.	0.726	0.72	0.73	0.72	0.73	0.72	0.72	0.72	0.72	0.73	0.72	0.73	0.73
ED Reg. Util.	0.708	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.70	0.71	0.70
ED Nurse Util.	0.723	0.77	0.69	0.64	0.72	0.68	0.65	0.65	0.67	0.66	0.65	0.65	0.80
Tri.Nurse Util.	0.396	0.39	0.40	0.39	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.39
ED ANP Util.	0.614	0.66	0.55	0.51	0.59	0.56	0.52	0.51	0.55	0.51	0.51	0.53	0.67
ED Consult. Util.	0.280	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.27	0.27
AMAU Access	3100.20	2966.40	3096.00	3021.60	3069.60	3142.80	3340.80	3266.40	3128.40	3066.00	3147.60	3091.20	3044.00
AMAU Admission Rate	0.546	0.54	0.55	0.55	0.56	0.56	0.55	0.54	0.54	0.56	0.55	0.56	0.55
AMAU PET	251.018	275.58	246.28	243.50	276.67	243.27	218.62	229.88	231.50	236.60	236.85	229.94	269.17
AMAU SHO Util	0.167	0.14	0.19	0.19	0.14	0.18	0.22	0.21	0.18	0.19	0.20	0.20	0.15
AMAU Reg Util	0.484	0.47	0.47	0.46	0.48	0.48	0.50	0.49	0.48	0.47	0.48	0.47	0.47

AMAU Nurse Util	0.633	0.84	0.50	0.35	0.83	0.51	0.39	0.38	0.50	0.36	0.36	0.36	0.79
AMAU Consult Util.	0.451	0.43	0.43	0.43	0.45	0.48	0.47	0.47	0.48	0.42	0.43	0.44	0.44
WT Disch. in ED	182	186.42	201.20	178.80	198.75	182.45	178.38	170.29	181.78	181.94	181.29	190.20	245.25
WT Disch. in AMAU	106.2	150.31	102.23	96.88	158.63	110.47	84.42	91.65	97.75	89.47	98.73	93.53	166.95