Modelling and Analysis of Heterogeneous Data to Improve Process Flow in the Emergency Department

by

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Table of Abbreviations

Acronyms or abbreviations	**Meaning**
ABS	Agent-Based Simulation
ACP	advanced care practitioner
ACS	Acute Coronary Syndromes
AMU	Acute Medical Unit
ATS	Australian Triage Scale
CAS	Casualty Card
CDU	Clinical Decisions Unit
COVID	Coronavirus Disease
CQI	Continuous Quality Improvement
CT	Computer Tomography
CTAS	Canadian Triage and Acuity Scale
DES	Discrete Event Simulation
DH	Department of Health
ECG	Electrocardiogram
ECT	Emergency Care Technicians
ED	Emergency Department
EDC	Emergency Department Coordinator
EM-HRG	Emergency Medicine Healthcare Resource Groups
EMS	Emergency Medical Services
ENP	Emergency Nurse Practitioner
EPV	Event Per Variable
ESI	Emergency Severity Index
EWS	Early Warning Score
FCE-HRG	Finished Consultant Episodes Healthcare Resource Groups
GLM	Generalized Linear Model
GP	General Practitioner
HCA	Healthcare Assistant

HES	Hospital Episode Statistics
IBM	International Business Machines
IT	Information Technology
LDA	Loop Disintegration Approach
LOS	Length Of Stay
LWBS	Left Without Being Seen
MRI	Magnetic Resonance Imaging
MSitAE	A&E Attendances and Emergency Admissions Monthly Trust Situation Reports
MTS	Manchester Triage System
NEWS	National Early Warning Score
NHS	National Health Service
NICE	National Institute for Health and Clinical Excellence
OPAL	Old Persons Assessment and Liaison team
OR	Operational Research
POCT	Point Of Care Test
PRF	Patient Report Form
QI	Quality Indicator
QQ	Quantile-quantile
QUEST	Quick, Unbiased, Efficient Statistical Tree
RAD	Role Activity Diagram
SATS	South African Triage Scale
SAU	Surgical Assessment Unit
SD	System Dynamics
SE	Standard Error
SEWS	Standardised Early Warning Score
SOP	Standard Operating Procedure
SPO	Structure-Process-Outcome
TTO	To Take Out
VIF	Variance Inflation Factor
VSM	Value Stream Mapping

Dedication

To my dear husband for his endless love and support, to my children for being so understanding and to my parents and sisters for their encouragement.

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I thank the Almighty God for the opportunity, grace and strength to start this study and complete it despite all the challenges along the way. I am extremely thankful to my supervisors, my previous first supervisor; Apostle Professor Kwabena Agyapong-Kodua, who believed in me and encouraged me to start this journey. To my current first supervisor, Dr Sudakshina (Sudi) Lahiri, I am immensely grateful for your patience, dedication, support and guidance through the years; you were always there when I returned from a temporary withdrawal and kept me focused throughout. I am grateful to Professor Robert Harrison, my second supervisor for his words of wisdom. My extreme gratitude also goes to Professor Dariusz (Derek) Ceglarek for his leadership and support and to all members of the Digital Lifecycle Management (DLM) group of Warwick Manufacturing Group (WMG), University of Warwick, with whom I interacted through the years. My appreciation also goes to my line manager at work, who has supported me throughout my studies, and my team members and work colleague. Thank you to my family and friends who have cheered me on and supported me in diverse ways especially with childcare to make this dream a reality.

Declaration

This thesis is presented in accordance with the regulations for the degree of Doctor of Philosophy. It has been written and compiled by myself and has not been submitted anywhere else. The work in this thesis has been undertaken by me except where otherwise stated.

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Abstract

Emergency Departments (EDs) must treat growing numbers of patients quickly and efficiently. However, there are bottlenecks caused by many reasons including the lack of information to process patients timely, the lack of decision-makers and the lack of timely decision-making that is affecting the smooth flow of processes. Techniques used to address bottlenecks have yielded limited sustainability due to reliance on simplistic models as inputs which do not account for the complexities and variations in the real system. This study aimed to address bottlenecks by developing a systematic model-driven approach, for assessing ED processes for improving waiting time as measured by the 4-hour quality indicator (4HQI).

Using an exploratory framework, this study employed a mixed-method approach in examining heterogeneous data to realise its aim. Semi-structured interviews with 21 ED clinicians were conducted in a level-1 ED of an Acute Trust in the UK. Interview transcripts embedded with systems knowledge were extracted to develop role activity diagrams (RAD) to capture granularity of care processes and identify bottlenecks through process mapping. Additionally, service utilisation data were analysed using logistic regression, generalized linear model and decision tree. The impact of changes on waiting time was assessed using Discrete Event Simulation (DES).

Process mapping revealed Majors, the unit that treats complex patients to be the most problematic in the ED and also identified five bottlenecks in the unit: awaiting specialty input, test outside the ED, awaiting transportation, bed search and inpatient handover. The process maps further revealed that information available to the ED at the pre-hospital phase and before entry into Majors can be better utilised to address bottlenecks, especially those related to awaiting specialty input, test outside the ED and awaiting transportation. This led to exploring improvement suggestions that included: (1) introducing an advanced nurse practitioner at triage, (2) utilising pre-hospital information to reduce repeat testing and (3) operating a discharge lounge. Results from the qualitative and quantitative analysis were integrated into a discrete event simulation (DES) model to evaluate the–improvement suggestions, leading to reductions in the length of stay (LOS) for given scenarios. Several statistical models for predicting LOS and breach of the 4HQI were also developed.

The methodology developed entailed (1) qualitative process modelling to derive the systems model, (2) quantitative analysis of audit-level patient data to understand decision-making and patient flow (3) integration of qualitative and quantitative analysis results to derive improvement suggestions and (4) simulation to analyse suggestions. RADs served as a granular process mapping technique for bottleneck identification and solution derivation in analysing complex systems. Its application helped to derive realistic models of the system This is the first study to model Majors, unit. Furthermore, a methodology for indirect mapping of RAD to DES was developed to bridge the gap between the two methods where RAD provides granular input to complement DES models. Monitoring patients' length of stay as three-time blocks, was recommended in addition to a model-based, data-informed alert system to support decision-making and patient flow.

This study sheds light on the development of quality indicators scientifically and operationally. The Majors unit identified as the most crowded unit underscores to ED managers and policymakers as an area of focus for improvement initiatives considering limited resources. This study modelled and analysed heterogeneous data to improve process flow in the ED. Implementing the recommendations made would enhance patient flow and bottlenecks, thereby improving waiting times.

Chapter 1

Introduction and Background

This chapter provides an introduction and background to this research. It begins with shedding light on the current state of the healthcare system and the need for improvement. The key focus of this research is presented with information about the research challenges, aim and objectives. A brief description of the thesis structure and an overview of the chapters are presented.

1.1 Current State of the Healthcare System

The delivery of health care is a complex resource-intensive process (Virtue et al., 2011, Ordu et al., 2021). Of particular concern is the Accident & Emergency (A&E) also referred to as the Emergency Department (ED) which is under constant pressure due to the ongoing increase in the number of patients seeking care in the departments (Schull et al., 2001, Duguay and Chetouane, 2007, Hoot et al., 2008, Letham et al., 2012, Sun et al., 2013, Verelst et al., 2015, Zeinali et al., 2015, Elder et al., 2016, Higginson and Boyle, 2018, Uthman et al., 2018, Boyle, 2023). Service utilisation in the ED is primarily linked to the population characteristics of the community within which a hospital is located and equally important, care is closely dependent on the availability of out-of-hospital care (Purdy, 2010, Higginson and Boyle, 2018). To that end, factors such as patient choice and expectation, changes in the population characteristics and lack of sufficient alternatives for out-of-hours care provision are impacting this rise in demand (Coleman et al., 2001, Schneider et al., 2012, Morgan et al., 2015, Wallingford et al., 2018, Çinar et al., 2019).

Emergency Departments are one of the few departments in the hospital that have the potential to influence the efficiency and effectiveness of care delivery in other departments and thereby inform overall performance across the hospital (Eitel et al., 2010, McClelland et al., 2011, Ortiz-Barrios and Alfaro-Saiz, 2020). They are complex environments characterised by limited resources, competing priorities and a broad range of patient acuity levels resulting in a problem commonly known as crowding (Hurwitz et al., 2014, Jarvis, 2016, Oueida et al., 2018). Additionally, EDs face long length of stay (LOS), excessive patient flow time, prolonged waiting time, and rising left without seen rates (Ortiz-Barrios and Alfaro-Saiz, 2020). These problems are interlinked as one impacts the other. Crowding causes extended length of stay leading to excessive patient flow time and in turn, leads to a high left without seen rate.

Crowding is a complex phenomenon in terms of potential causes and effects. Effectively solving it will require addressing factors that operate both within and outside the ED including the wider healthcare system. As the demand changes, its case mix is also changing and EDs are seeing not only critically ill patients, but are also receiving referrals from primary care due to the lack of diagnostic facilities in the communities (Giesen et al., 2006, Proudlove et al., 2007); increase in chronic illnesses (Mallitt et al., 2017); the increased proportion of patients with non-urgent symptoms (Durand et al., 2012); and those with complex medical presentations (Hwang et al., 2013), which are all putting additional pressures on ED resources and clinician time.

The rise in demand is also impacting the ED at an operational level by resulting in longer waiting times, bottlenecks, inefficiencies and unnecessary variations in care (Duguay and Chetouane, 2007, Zhao and Bai, 2010, Weber et al., 2011, Letham et al., 2012, Zhao et al., 2015). These factors are also associated with crowding which is harmful to patients (Hoot and Aronsky, 2008, Boyle et al., 2012, Boyle et al., 2014, Pines and Bernstein, 2015, Oueida et al., 2018, Salmon et al., 2018, Valipoor et al., 2018) and a problem which has received international attention (Derlet and Richards, 2000, Schull et al., 2001, Asplin et al., 2003, Asaro et al., 2007, Bowers et al., 2009, Finamore and Turris, 2009, Martin et al., 2011, Pines et al., 2011b, Boyle et al., 2012, Boyle et al., 2014, Swancutt et al., 2017). Despite the rising demand, EDs are expected to combine the provision of quality care with efficiency (Burke et al., 2017). Quality improvements in the healthcare system as a way of addressing these problems by reducing delays and eliminating inefficiencies in the system have become necessary. A starting point is gaining a better understanding of the overall system performance by undertaking patient flow analysis to investigate care-related processes and resource utilisation (Jun et al., 1999, Harper, 2002, Brailsford et al., 2004, Eldabi et al., 2007, Katsaliaki and Mustafee, 2011).

1.2 The Need for Improvement

The need for improvement is evident and multiple strategies have been recommended in literature as solutions to enhance patient flow and address process inefficiencies (Oueida et al., 2018, Moskop et al., 2019, Peng et al., 2020). As such, a time-related quality indicator

(QI) is to be viewed as a useful measure of ED performance (Gul and Celik, 2020) therefore, making timely care an important QI in EDs worldwide (Schoen et al., 2004, PHCC, 2006, Pines et al., 2011b, Boyle et al., 2012, Letham et al., 2012, Mason et al., 2012, Blunt et al., 2015, Higginson et al., 2015, Sullivan et al., 2016, Campbell et al., 2017). Until recently, EDs in the UK were mandated contractually (DH, 2000, Day and Oldroyd, 2012), to treat and discharge 95% of patients within four hours (DH, 2003, ICF, 2015). However, meeting the QI has been difficult in recent years (Goodacre and Webster, 2005, Blunt et al., 2015, Campbell et al., 2017, Murray et al., 2017, Higginson and Boyle, 2018, Gaughan et al., 2020, O'Dowd, 2022). Elsewhere, EDs are also struggling to meet waiting time expectations (Hoot and Aronsky, 2008, Di Somma et al., 2015, Yarmohammadian et al., 2017, Morley et al., 2018). EDs have tried several ways to meet waiting time requirements by undertaking improvement initiatives, as will be discussed in subsequent sections of this chapter and other chapters, the results of which have led to looking at understanding ED process flows (Proudlove et al., 2007, Eatock et al., 2011, Weber et al., 2011, Mason et al., 2012, Gaughan et al., 2022). Discussions on alternative measures of quality of care are currently underway with proposals for a new bundle of measures to replace the current standards (NHS, 2021).

1.3 Key Focus of the Research

The causes of crowding are multifactorial and vary by hospital hence solutions are complicated, time-consuming, and involve considerable staff time, effort, and investment (Pines and Bernstein, 2015, Chang et al., 2018, Doupe et al., 2018, Wallingford et al., 2018). Solutions may include the whole hospital or focus specifically on the ED (Wallingford et al., 2018).

Approaches utilised to address the problems include operational research (OR) methods (integer programming, optimisation, simulation and queuing theory), statistical methods (regression analysis) and quality improvement methods (continuous quality improvement (CQI), lean manufacturing) (Morgan et al., 2011, Wiler et al., 2011, Kaushal et al., 2015, Saghafian et al., 2015, Zhao et al., 2015, Mielczarek, 2016, Landa et al., 2017, Mohiuddin et al., 2017, Ortiz-Barrios and Alfaro-Saiz, 2020, Peng et al., 2020, Castanheira-Pinto et al., 2021, Palmer and Tian, 2021). Clinical interventions such as rapid assessment, fast track, streaming, Point of Care Testing (POCT) and a co-located primary care clinician in the ED have also been used (Jarvis, 2016, Morley et al., 2018, O'Neill et al., 2018).

Due to the size and complex nature of hospitals, effectively managing resources is imperative yet also a challenge (Morley et al., 2018, Ordu et al., 2021). A potential solution to ED problems is to increase resources however, this is not feasible due to space limitations and budget constraints (Zhao et al., 2015, Salmon et al., 2018). Feasible solutions must target the effective utilisation of existing resources and increasing operational efficiencies (Zhao et al., 2015, Morley et al., 2018). Consequently, limited capacity, budget constraints and inadequate staffing must be considered when proposing solutions (Salimifard et al., 2013).

Furthermore, there have been limitations in the application of solutions. The correct input is needed for the process models to be improved. However, complexities are inherent in healthcare services (Greenhalgh and Papoutsi, 2018). Due to such complexity, this study posits that simply imposing approaches from other areas onto the health service systems will be insufficient. Contextualising the approaches to the healthcare sector generally and to an ED, in particular, will entail applying a systematic framework to first, model the processes of care that are carried out in the ED, quality indicators overseeing care, along with resource usage and associated decision-making that affect the patient's care journey in the department. The next step is analysing the derived model to gain an in-depth understanding of the patient flow. The final step is using the derived knowledge for the development of systematic context-specific methodologies for quality improvement and efficient system performance to meet waiting time expectations.

1.4 The Background of the Research Problem

Several factors have contributed to driving the demand for care in the hospital such as epidemiological trends, changing demography, ageing population, multi-morbidity, process inefficiencies, the rising cost of care, patient expectations, gaps in the availability of care, variations in patient conditions, the severity of patient conditions and insufficient investment in healthcare to address these needs (Derlet and Richards, 2000, Weber et al., 2011, Pines and Bernstein, 2015, Zhao et al., 2015, Jarvis, 2016, Oueida et al., 2018, Moskop et al., 2019, Ortiz-Barrios and Alfaro-Saiz, 2020). In turn, these realities are having a negative impact on the output to patients and the challenge is for hospitals to be able to deliver quality care despite these constraints and conditions. Delivery of quality care promptly is a hospital-wide issue, however; this study focuses on the emergency department as the key department for analysis because (i) it is often the onset of a patient's care journey for a particular condition;

(ii) things done right in ED can potentially have a positive effect on the whole hospital and indeed on the whole healthcare system in the community. The performance of the ED is closely dependent on processes and capacity within the hospital as well as that of the wider health economy comprised of other hospitals, along with primary and social care systems (Ortiz-Barrios and Alfaro-Saiz, 2020, Ordu et al., 2021). Nonetheless, it is the ED that is often used to measure the performance of Acute Hospitals and the whole National Health System (NHS) (Lane et al., 2000, Sakr and Wardrope, 2000).

1.4.1 The 4-Hour Quality Indicator

Funded from general taxation, the UK National Health Service (NHS) was created in 1948 on the principles of providing free access to care at the point of delivery for all based on need rather than the ability to pay. The NHS implemented a 4-hour quality indicator (4HQI) in 2000 as a tool to manage waiting times in EDs (DH, 2000, Day and Oldroyd, 2012) and to ensure quality of care. The QI was modified in 2004 to 98% and then to 95% in 2010 (DH, 2000, DH, 2003, ICF, 2015). Contractually mandated, it stipulates that 95% of patients arriving for care in the ED must be treated, discharged, admitted, or transferred within 4 hours of arrival into the department (DH, 2003, ICF, 2015).

Prior to its introduction, patients waited for several hours to be seen in ED; in some cases for over 12 hours (Letham et al., 2012, Blunt et al., 2015, ICF, 2015) thereby, providing a rationale for having a time-based QI (Bair et al., 2010, Letham et al., 2012, Baker, 2017, Campbell et al., 2017). However, time alone, i.e., the speed at which people move through the ED, is not always a sufficient measure of performance since accuracy and quality of care are equally important. Nonetheless, it is generally accepted that a time-related QI is needed and is useful as a measure of ED performance (Day and Oldroyd, 2012, Blunt et al., 2015, ICF, 2015, Gul and Celik, 2020). It gives hospital managers and policy makers an incentive to prioritise resources for urgent and emergency care (Campbell et al., 2017).

Initial reports published a few years after the introduction of the QI showed an improvement in waiting times, but this was not necessarily an indication of an improvement in the quality of care provided (ICF, 2015, Swancutt et al., 2017). However, the government's Hospital Episode Statistics (HES) involving Accident and Emergency attendance on the NHS Digital website show that in the last few years, hospitals across the country are struggling to meet the QI of 95% of patients to be seen within 4 hours. Indeed, this QI has not been met across the whole of the NHS since 2015 (Blunt et al., 2015, Murray et al., 2017). As seen in Figure 1.1, the performance of the QI has gradually declined over the years.

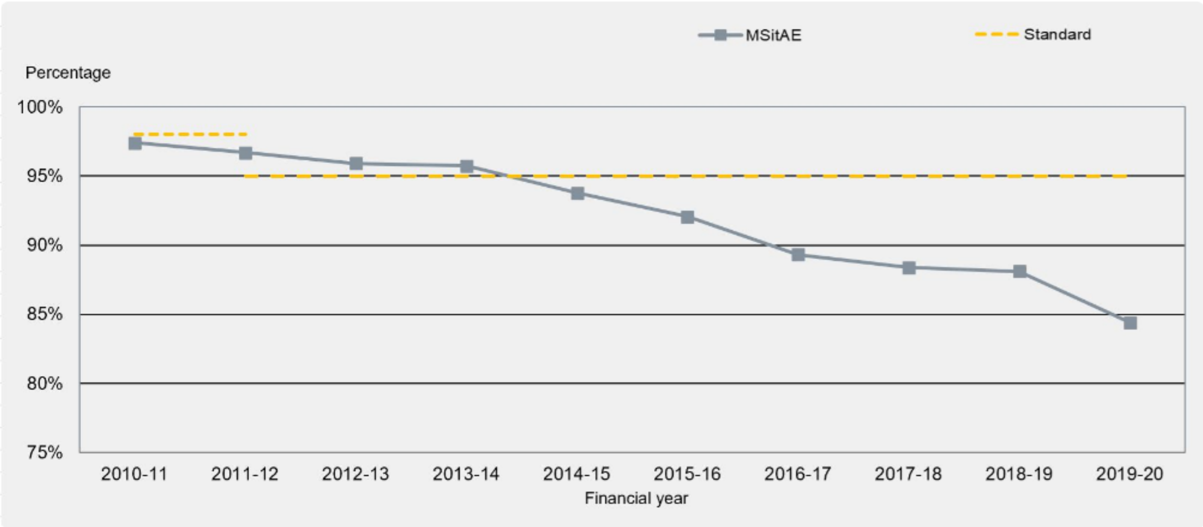


Figure 1.1 Percentage of Patient Attendances Spending 4 Hours or Less in ED

MSitAE- A&E Attendances and Emergency Admissions Monthly Trust Situation Reports.

Source: NHS Digital, 2020

The grey line shows the decline in the performance whilst the yellow dashes show the standard which was at 98% and reduced to 95% as mentioned earlier in this section. The 4HQI is a measure of the performance of the ED therefore inability to meet this QI can have negative implications. In the first instance, it is an indication that a patient has been in the department for over 4 hours which in itself can be unpleasant to the patient and has an impact on the patient outcome. Indeed, some researchers have reported a direct correlation between increased length of stay and patient mortality (Hoot et al., 2008, Bernstein et al., 2009, Sun et al., 2013). Some patients leave without being seen (Goodacre and Webster, 2005, Clarey and Cooke, 2012) leading to a loss of reputation in the healthcare system. Access to an ED which is already struggling to treat its current patients is impaired and may therefore not be able to accept new patients which in extreme situations, results in ambulance diversion (Hoot and Aronsky, 2008). It is therefore crucial for hospitals to meet the QI.

An NHS England planning document released in February 2018 (NHS, 2018) states that this QI and its associated penalty for breaching have been suspended. In practical terms, the government kept the 4-hour requirement in place but temporarily put a waiver on fines to give hospitals and EDs, a window of researching ways to meet the QI in a contextualised manner, which makes the timing of the current study especially meaningful. A time-related quality indicator is necessary to measure the performance of the ED and research is needed to examine how best this can be achieved. When looking at the input-throughput-output model of the ED (Asplin et al., 2003), improvements in the throughput phase are most popular among researchers. The input factors affect demand and output factors influence patients' ability to exit the ED which is often seen as influenced by the wider healthcare system. The throughput part of the patient flow is more under the control of the ED, making this the most attractive and least complicated part to intervene (Vanbrabant et al., 2019a). The focus of this research will therefore be on examining the throughput factors that cause crowding thus making it challenging for hospitals to treat patients timely. This will be achieved by understanding and modelling the system for subsequent improvements to be made in the context of waiting time.

1.5 The Research Problem and Motivation

To date, there have been several studies on quality improvement in the ED (Crabbe et al., 1994, Gill, 2012, Gul and Guneri, 2012, Cohen et al., 2015, Oh et al., 2016, Yang et al., 2016). Some of these have focussed on particular groups of patients or particular conditions. At the same time, there are numerous crossovers and interactions between different conditions, the various processes involved, and the resources required to carry out these processes. With few exceptions, EDs are generally not patient condition specific. Similarly, with a few exceptions, the 4HQI is expected to apply to all patients (DH, 2003). It is therefore important to capture information that will allow examining the quality indicator across the whole department irrespective of patient conditions. Other limitations identified in previous studies on quality improvement involving the indicator include the use of limited data including a lack of granular data, small sample size, and the use of simplified versions of ED process flows to name a few (Au-Yeung et al., 2006, Kolb et al., 2008, Wang et al., 2012, Day et al., 2013, Venugopal et al., 2013, Hurwitz et al., 2014, Kang et al., 2014).

As mentioned earlier, patients used to experience long waiting times in ED before the introduction of the 4HQI; in some cases, for over 12 hours (Letham et al., 2012, Blunt et al., 2015, ICF, 2015). Time alone is too blunt a tool to use as an indicator but criticisms notwithstanding, it is generally accepted that a time-related QI is needed (Day and Oldroyd, 2012, Blunt et al., 2015, ICF, 2015) and equally important, an understanding of processes that must be carried out within the timeframe of the QI. More information about the 4HQI is presented in the next chapter.

The aforesaid discussions indicate that EDs worldwide are complex units with rising and unpredictable demand, providing care in the face of spiralling costs and governed stringent waiting time indicators. This rise in demand is causing bottlenecks and inefficiencies leading to crowding. It will be crucial then to systematically model processes of care in the ED for quality improvement purposes in relation to the ED waiting times. Two fundamental challenges facing the modelling and analysis of health care systems are that patient care is inherently process-intensive and person-specific, the latter giving rise to the issue of variation, both necessary and unnecessary. Hence, techniques applied to model such systems must be able to capture information at a needed level of granularity.

The research problem being examined in this study has emerged because current process modelling techniques used in hospitals adopt ‘simplistic’ process mapping approaches (and tools) with limited capability to identify sources of quality breaches in care processes (Eldabi, 2009, Virtue et al., 2011). These techniques have generally relied on a simplistic understanding of the processes of care in the ED and as such, do not include realities and associated variations (Mohiuddin et al., 2017). The developed models are not accurate or realistic representations of the ED processes. Accurate modelling of healthcare systems such as EDs, in particular, requires effective modelling methodologies to be able to capture and model the processes of care accurately. Solutions must also be contextualised to individual settings to address the local problems in the ED. Detailed descriptions of the study plan for this research are provided in Chapter 3.

As a complex service unit, understanding the ED requires modelling care processes at a granular level to identify and address bottlenecks. This often begins with process mapping. It is generally accepted as an important initial step in modelling complex systems however, there are no guidelines on the level of granularity of information required. This study suggests a level of information that will lead to understanding the processes within the department better to aid in developing meaningful solutions to the waiting time problem. A review of commonly used process mapping methods is presented in Chapter 2. Since patient care processes are activity-rich, the review revealed approaches that allow Role Activity Diagram (RAD) as having the capability to model granularity. They can illustrate roles and associated processes. Such an approach allows a close examination of activities performed to assess process efficiency and identify any deficiencies that can be addressed to enhance improvements. Hence, this technique was used to capture the processes that are followed as patients move along their care journeys in the ED. However, activity-based modelling can be static while ED processes are dynamic with respect to time-related occurrences. Here, simulation approaches such as discrete event simulation (DES), a commonly used method to model EDs which is dynamic and able to incorporate data. It can therefore be said that RAD has granularity, but no time-based data and DES has time-based data but can lack granularity. The current research is addressing this gap by bringing these two methods together where the RAD serves as a complementary tool to DES.

1.6 Research Challenges

A closer examination of the aforesaid discussion underscores the following:

- EDs are struggling to see and treat patients in a timely manner.
- This is because the patient flow is not running smoothly.
- The flow is being affected by bottlenecks.
- The bottlenecks are leading to a crowded ED which is, in turn, impacting the flow.
- The bottlenecks can occur for many reasons as described below.

The ED needs information about the patient to be able to treat them in a timely manner and efficiently. This information may be collected at the pre-hospital stage or various stages during the patient journey. Patients frequently undergo tests in the ED though a delay in requesting and receiving test results is known to affect ED waiting times (Paul and Lin, 2012, Tse et al., 2016, Khanna et al., 2017, Van Der Linden et al., 2017). This delay signifies the lack of information to process patients timely. Hence, emphasis must be also put then to see if already available data about a patient’s condition exists and if so, it must be better utilised, for instance, any information at the pre-hospital stage (Altuwaijri et al., 2019, Stopyra et al., 2020). Moreover, inadequate staffing (Wolf et al., 2018) and delay in receiving consultation from specialty doctor in the diagnosis process are also associated with creating bottlenecks (Qureshi et al., 2010, Brick et al., 2014, Kusumawati et al., 2019, Jung et al., 2020). This can represent the lack of a decision-maker. These are key players who require the right information in processing the patient efficiently which can then ensure smooth flow. In addition to the availability of information and decision-makers, the timeliness of the two factors is vital. Hence, the lack of timely decision-making is also creating bottlenecks (Jung et al., 2020). The required information needs to be generated on time, communicated to the right decision-maker and utilised to process the patient to meet waiting time expectations.

The goal of ED improvement initiatives is to achieve efficiency without an increase in resource utilisation (Morley et al., 2018). Hence, a key aim of this study was to improve patient flow in the ED by exploring improvement suggestions that will lead to better performance of waiting time in the department with minimal additional resource requirements.

1.7 Addressing the Challenges

Using a two-part multi-step study design, this research employed an exploratory framework to model the generic processes of care that were carried out in one of the largest Emergency departments in the UK to identify and examine factors impacting patient flow. First, the model development entailed the use of granular information mapping involving the processes of care to show decisions made, tasks undertaken, information flow and how it was utilised to make decisions for the patient which concluded their LOS.

The second part of the study involved examining anonymised quantitative audit-level patient data to understand service demand and system characteristics. This was conducted by analysing routinely collected hospital data to derive useful parameters for providing the required information to process the patients thus, assessing how information can be accessed and utilised effectively. Statistically significant results, derived from the routine data analysis, formed input into the simulation; results from which yielded valuable insights on managing bottlenecks contextualised to given scenarios. This also demonstrated how available information can be utilised to process the patient in a timely manner.

The study site for this research was a UK-based teaching hospital with a Type 1 ED (Type 1 EDs provide 24-hour consultant-led services and have facilities for full resuscitation). About two-thirds of ED attendances in England take place in Type 1 EDs which is why they are sometimes referred to as ‘major’ emergency departments (Baker, 2017). More information regarding the study's setting, data and ethical considerations is presented in Chapter 3 and the appendices.

1.8 Aim

The overall aim of this research was to address bottlenecks by developing a systematic model-driven approach for assessing emergency department service delivery processes for the improvement of waiting time, as measured by the 4-hour quality indicator.

1.9 Objectives

The aim of the study was realised through the following objectives:

1. To identify factors that lead to breaches of the waiting time quality thresholds overseeing care in the department.
2. To develop a systematic approach that could be followed for waiting time improvement.
3. To derive system design information involving the emergency department by mapping expert procedural knowledge of patient flow.
4. To incorporate routine data to understand decisions made along the patient flow within the system.
5. To develop improvement suggestions that can lead to better performance.
6. To assess the system-level performance of the emergency department using the developed approach to determine the impact of changes on waiting times.

In exploring its aim, this study also makes note of the pandemic. The global pandemic caused by Coronavirus disease (COVID-19) led to governments around the world including the UK, introducing national lockdowns for people to stay at home. This led to attendance at EDs dropping significantly (Morris, 2020). In the UK for instance, the attendance recorded in

April 2020 was the lowest so far since records began in 2010 (Morris, 2020). This decline in attendance, however, did not translate to an improvement in the performance of the 4HQI. Improvements were only seen when hospitals took temporary measures to reschedule elective procedures and operations and to increase hospital capacity (Morris, 2020). The data collection for this research, though undertaken pre-pandemic, continues to be relevant as prevalent problems are still resulting in poor performance of waiting time QIs (NHSDigital, 2021), hence making the outcome of this research still current.

1.10 Thesis Structure

Information in this report is presented in seven chapters and structured as shown in Figure 1.2 and described below.

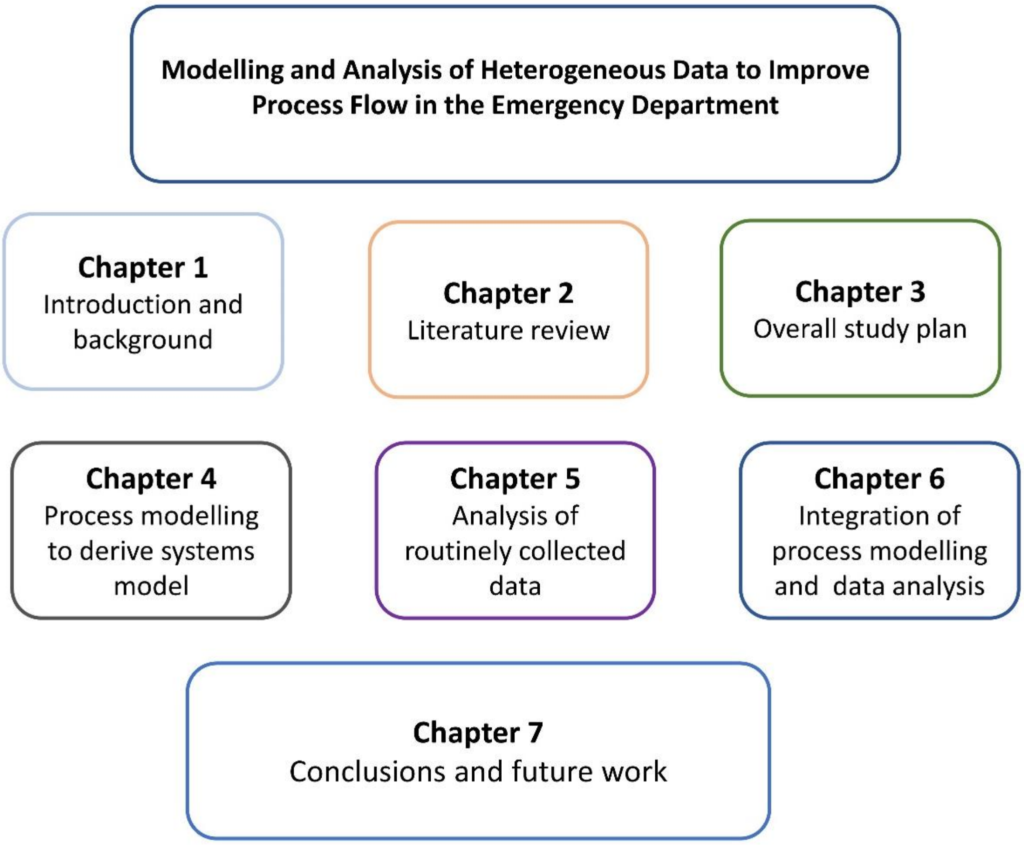


Figure 1.2 Thesis structure diagram

Chapter 2 provides a review of literature on the subject area. It focuses on the emergency department and sheds light on the problems prevailing in this department with an emphasis on crowding which is recognised internationally. The causes, effects and approaches that have been used to address crowding are also reviewed. A case for granularity is made by demonstrating how role activity diagrams provide the required level of granularity when modelling complex systems like emergency departments.

Chapter 3 outlines the overall study plan and provides details of the methodological steps that were followed throughout the research in achieving quality improvement. The steps are presented as generic steps which can be applied in other improvement projects. Further details of the methodological approach are provided in Chapters 4, 5 and 6.

Chapter 4 is about process modelling to derive the systems model. The process modelling is conducted using role activity diagrams. Details are presented about how diagrams were generated from semi-structured interviews. The RADs were analysed, and bottlenecks were identified followed by suggestions from literature and examining the maps.

Chapter 5 presents the analysis of routinely collected data. The improvements to processes cannot be achieved without the use of data therefore statistical methods were utilised to generate models based on logistic regression and generalized linear models. A decision tree method was used to group patients into homogenous groups based on the likelihood to breach or not. An argument was made to focus on the Majors unit as it was identified as the most crowded and therefore warrants more attention. An idea of dividing the length of stay into three time-blocks for monitoring was discussed. It concludes with details of how a model-driven, data-informed alert system could be developed to support smooth patient flow.

Chapter 6 is an integration of the qualitative and quantitative parts of the study in using data to confirm the bottlenecks identified through the RAD. It goes on further to analyse ways of addressing three of the five bottlenecks identified and tests them in a simulation environment using discrete event simulation. The scenario testing reveals how the patient's length of stay can be improved.

Chapter 7 provides the conclusion to this research and lists the contributions that this study is making in addressing bottlenecks in ED to ensure smooth flow. It acknowledges limitations of the study and makes recommendations for future works.

Figure 1.3 below shows how the research objectives presented in Section 1.9 were achieved in the thesis chapters. This provides a visual summary of the information contained in each of the chapters.

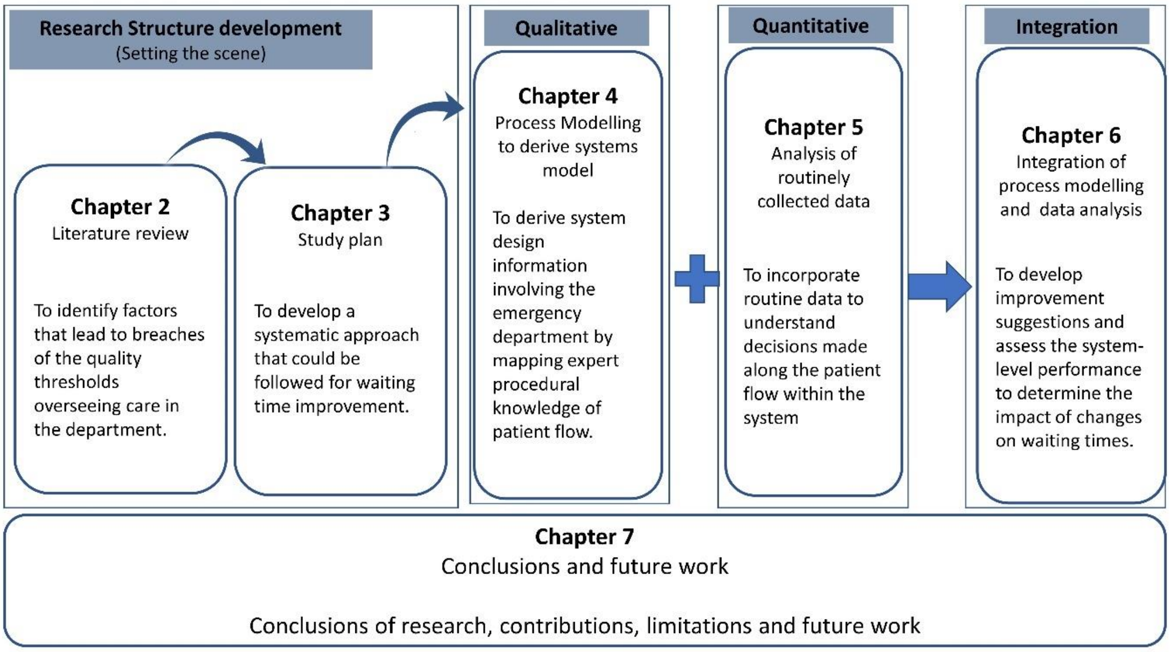


Figure 1.3 Thesis chapters showing research objectives

The next chapter offers an overview of the Literature Review undertaken. It provides more information about the quality indicators, the problems in the ED both nationally and internationally and techniques that have been used to address them.

Chapter 2

Literature Review

This chapter provides a literature review on the Emergency Department and problems faced in the department, especially that of crowding. It discussed the causes and effects of crowding and solutions that have been implemented to address these. It reviews techniques commonly applied to address this problem including challenges. It also discusses the need for granular process mapping and concludes with a recommendation having compared commonly used methods.

The literature review was initiated in January 2016 by conducting a systematic review of the key words: emergency department or emergency room or patient flow or overcrowding. The database used were Web of Science, PubMed, Cochrane Database of Systematic Reviews (CDSR), MEDLINE, Database of Abstracts of Reviews of Effectiveness (DARE), ERIC. All research published in English between 2005 and 2015 were included. The results of this search though not presented as a systematic review in this thesis, formed the basis of the review into the history, complexity, and problems in the ED, particularly causes, consequences, and throughput solutions of ED crowding. The author repeated the searches during the research period to identify newly published papers in the field to ensure that the literature review stayed current.

2.1 Introduction

Rising demand for acute care is reshaping healthcare sectors in the UK and internationally (Derlet and Richards, 2000, Lane et al., 2000, King et al., 2006, Hoot and Aronsky, 2008, Keogh, 2013, Pines and Bernstein, 2015, Jarvis, 2016). In England, the number of patients visiting hospitals has increased over the years. For example, the National Health Service (NHS) handles over 20 million attendances to the emergency department (ED), minor injury units and urgent care centres every year. However, recent figures show a decline in attendance in 2020/2021 due to the Covid-19 pandemic and national lockdown adherence (Keogh, 2013, Baker, 2017, NHSDigital, 2021). A significant number of ED attendances end up in admissions (Keogh, 2013, Baker, 2017), requiring further resources from the hospital compared to treating and discharging patients. The proportion of attendance resulting in admission has risen gradually from 17% in 2011-2012 to 19% in 2019-2020, followed by a rapid increase in 2020-2021 to 24% (NHSDigital, 2021). The rising demand, also worsened by the increasing case mix of patients with complex health needs (Salmon et al., 2018), is leading to longer waiting times. Hospitals are under pressure to improve patient flow to address the waiting time problem (Adler et al., 2003, Fone et al., 2003, Virtue et al., 2011, Mielczarek and Uzialko-Mydlikowska, 2012, Jarvis, 2016). Better flow in the ED is essential for delivering quality care to patients.

The Department of Health (DH) has set numerous expectations over the years in the form of national quality indicators, many contractually mandated, to manage the quality of care. For example, ensuring efficiency led to the introduction of the 4-hour quality indicator (4HQI) to manage waiting times in the ED (Proudlove et al., 2007, DH, 2011, DH, 2012, Letham et al., 2012, Swancutt et al., 2017). Notably, this indicator states that all patients seeking care in the ED must be treated, discharged, admitted or transferred to another provider within 4 hours of arrival into the department (DH, 2010a). However, studies show that many patients experience a length of stay in the ED that exceeds 4 hours, a major factor triggering the problem of crowding in the department (Letham et al., 2012, Blunt et al., 2015, Baker, 2017, Brady et al., 2017). Hospitals in the UK are required to report on the 4HQI but other countries worldwide also report on it even though not mandated (Derlet and Richards, 2000, Sakr and Wardrope, 2000, Finamore and Turris, 2009, Pines et al., 2011a, Pines et al., 2011b, Swancutt et al., 2017).

There exists widespread interest in having a specific time-based waiting time indicator in EDs (Pines et al., 2011b, Boyle et al., 2012, Letham et al., 2012, Mason et al., 2012, Campbell et al., 2013, Higginson et al., 2015). Nonetheless, meeting this 4HQI has been challenging. Since 2015, it has not been met across the whole of the NHS (Blunt et al., 2015, Murray et al., 2017). While the UK government has responded by increasing access to emergency care, even so, as access to emergency care is increasing, the demand for the service is also soaring. This has added to the challenge of hospitals to meet the QI.

2.2 Emergency Department

The Accident and Emergency department (A&E), more recently referred to as Emergency Department (ED), is an integral part of the hospital as a system; and plays a pivotal role in the successful operation of a hospital. Moreover, it often signifies the onset of a patient's care journey. The ED is also where the community and hospital interact (Ortiz-Barrios and Alfaro-Saiz, 2020). Therefore, analysing patient flow in this department provides opportunities for identifying system failures and improving service. To an extent, the ED is also an interesting area to focus on because it is eventful (Sakr and Wardrope, 2000). Over the years, there has been an exponential increase in the complexity and number of problems presented in this department (Sakr and Wardrope, 2000, Salmon et al., 2018).

EDs came into existence in the UK after the report by Sir Harry Platt, chairman of the Accident and Emergency Services Sub-Committee, in 1962 (Platt, 1962, Guly, 2005). They were referred to as Casualty departments. Originally, the term ‘casualty’ meant a seriously injured patient (Sakr and Wardrope, 2000). The number of patients attending the department has grown tremendously over the years. According to the Platt report, there were 789 casualty departments that saw at least one patient per week (Platt, 1962). Only 31 hospitals out of this number saw more than 500 new patients a week, equating to 26,000 new patients each year and 467 saw fewer than 100 patients each week. Essentially, only a few patients were seen in these departments each week (Platt, 1962, Guly, 2005). As time went on, the number of patients increased. The concerns over the level of care provided to the patients attending this department who tend to be injured and seriously ill and the desire to drive improvement in the service provided brought about the investigations, which led to the Platt report. Some of the recommendations were for the department's name to change from casualty to accident and emergency. The report also suggested that every major accident and emergency department should be purpose-built. Its recommendations included that junior medical staff support consultants, staffing was adequate, and general practice (GP) services handled minor cases (Sakr and Wardrope, 2000). It was noted over the years that staffing levels were inadequate for the proper running of the department and that the case mix of ED was changing with more patients presenting with serious medical conditions compared to those with injuries. This increased waiting times, especially for those attending with minor injuries (Sakr and Wardrope, 2000).

2.3 The Complexity of the Emergency Department

The ED was originally designed to care for seriously injured patients. It has evolved over the years with an increasing number of patients and increasing complexities of conditions presented, thus adding to already existing high levels of uncertainties and variations characterising the department. There is also an increase in the attendance of non-urgent patients (Durand et al., 2012). In other words, patients who are not accident victims nor have a medical condition that can be termed an emergency. It could be argued that this is partly due to the lack of easy access to alternative care provisions outside the acute care setting. Notwithstanding, it is also putting enormous pressure on the service delivered by this department, which is, in turn, affecting the performance of the 4HQI (Sakr and Wardrope, 2000, Jarvis, 2016, Higginson and Boyle, 2018).

The ED is an intensely resource-pressured environment and, as such, very expensive to run. As they never know what to expect, it necessitates the employment of staff across all disciplines and levels to provide urgent, emergency, acute, and expert treatment for the various conditions that come through the door (Ordu et al., 2021). In addition, it needs non-clinical staff who assist with care delivery, medical and imaging equipment, specialised point-of-care diagnostic equipment, laboratories, information technology (IT) systems, and suitable clinical space, to name a few resource categories (Ordu et al., 2021). While hospitals try to gauge demand to meet the 4HQI, it is difficult to accurately predict the number of patients who will be attending on a particular day or the type and severity of their conditions due to the volatile and stochastic nature of patient arrival (Wiler et al., 2011, Brady et al., 2017).

It has also been noted that the decision by patients to seek emergency help in the first place can be enhanced by educating patients and their carers to avoid 'inappropriate' ED users (Morgans and Burgess, 2012). This will mean that patients who come through the doors of EDs are those who require emergency care. This will help manage the demands for this service. The introduction of short-stay units, which are referred to by a variety of names, including Clinical Decisions Units (CDU) or Acute Medical Unit (AMU), into some hospitals, has helped address medical emergencies that even though they need to be seen within the day, are not urgent enough for an ED (Damiani et al., 2011, Powter et al., 2014, Zonderland et al., 2015, Leach et al., 2020). The service needs to be managed to improve patient satisfaction because patients are now expecting not only to receive an efficient and quality level of care but also to be done satisfactorily and timely (Çinar et al., 2019).

All patients who visit the ED go through a process called triage, where different scores exist. Additionally, patients are assigned a score known as an early warning score. More details about these scores are provided in the subsequent sections.

2.3.1 Triage Systems and Early Warning Scores

Triage describes a set of algorithms developed to help prioritise patients arriving in emergency departments (Smith et al., 2017). A mismatch between the demand for care and the ability of the system to deliver at the time of patient presentation necessitates the use of triage systems to ensure the identification and prioritisation of patients with the most urgent needs to treat them first (Wuerz et al., 2000, FitzGerald et al., 2010, Farrohknia et al., 2011, Smith et al., 2017, Wolf et al., 2018, Hinson et al., 2019, Gilboy et al., November 2011). Triage is usually performed by a clinical team member who has been trained in a specific method (Smith et al., 2017). Various triage systems have been developed to assist healthcare providers in making accurate triage decisions, such as the Manchester Triage System (MTS), Emergency Severity Index (ESI), Australian Triage Scale (ATS), Canadian Triage and Acuity Scale (CTAS), and South African Triage Scale (SATS) (Christ et al., 2010, Parenti et al., 2014, Smith et al., 2017, Mistry et al., 2018, Tam et al., 2018, Hinson et al., 2019, McCabe et al., 2019). The results from various studies have shown that triage systems are moderately reliable in identifying patients' severity (Parenti et al., 2014, Tam et al., 2018, Hinson et al., 2019).

2.3.2 Triage Systems vs Early Warning Scores

Triage systems are used to prioritise patients where demand exceeds the capacity to fully assess and treat patients within an appropriate time frame (Smith et al., 2017). Early Warning Scores, on the other hand, complement this process by identifying the patient's deterioration based on several clinical factors, thereby helping EDs to identify patients who require early intervention (Smith et al., 2017, Wolf et al., 2018, McCabe et al., 2019). The two systems are not mutually exclusive (Smith et al., 2017). Early Warning Systems were originally designed for use in inpatient areas and subsequently adopted by EDs. They may, therefore, not apply to the full spectrum of ED patients (Smith et al., 2017).

2.3.3 Standardised Early Warning Score and National Early Warning Score

The National Institute for Health and Clinical Excellence (NICE) guidelines recommend a track-and-trigger system to identify early clinical deterioration in patients. The Standardised Early Warning Score (SEWS) is one such system (Gordon and Beckett, 2011). Another is the National Early Warning Score (NEWS) which was first introduced in 2012 and updated in December 2017 to NEWS2 (RCP, 2017). It is a system for standardisation of assessment and response to patient deterioration by allocating scores to patients based on their physiological measurements (RCP, 2017).

2.4 Problems in the Emergency Department

Numerous issues the ED faces make it challenging to satisfy its quality indicators. EDs experience extended length of stay (LOS), prolonged waiting time, excessive patient flow time and high left without seen rates (Clarey and Cooke, 2012, Ortiz-Barrios and Alfaro-Saiz, 2020). Crowding has come about for various reasons, one of which is the growing demand for emergency care and the increasing number of patients who need to be treated in the department. Different countries have tried to manage this increase in demand in different ways yet, ED crowding remains an international problem (Derlet and Richards, 2000, Schull et al., 2001, Asplin et al., 2003, Finamore and Turris, 2009, Pines et al., 2011b, Pines and Bernstein, 2015, Jarvis, 2016, Oueida et al., 2018, Moskop et al., 2019). This study will focus on the main problem of crowding, as presented below.

2.4.1 The Problem of Crowding

Crowding has become a preferred term in place of overcrowding, which some consider redundant (Moskop et al., 2019). As discussed earlier, the demand for care is going up for many reasons and this has triggered the crowding problem, which is considered a global healthcare problem (Derlet and Richards, 2000, Schull et al., 2001, Asplin et al., 2003, Finamore and Turris, 2009, Pines et al., 2011b, Pines and Bernstein, 2015, Jarvis, 2016, Oueida et al., 2018, Moskop et al., 2019). It is a complex issue which cannot be solved in isolation because it represents a broader problem in the healthcare system. Complicating the matter is the fact that it can be seen as both a cause and symptom of the pressures on the healthcare system (Higginson and Boyle, 2018). Crowding has been shown to be directly associated with increased in-patient mortality, decreased patient satisfaction, and increased length of stay and cost for admitted patients (Sun et al., 2013, Chang et al., 2018, Higginson and Boyle, 2018). Crowding further results in resource and bed management inefficiencies and affects confidentiality, patient safety, and privacy (Nugus et al., 2011, Moskop et al., 2019). Some authors state it is the most crucial problem affecting emergency departments in the UK (Higginson and Boyle, 2018). Hence, conducting systematic process improvement in the ED can positively impact the whole hospital (Asplin et al., 2003, Bernstein et al., 2009, Vanderby and Carter, 2010, Sun et al., 2013). Evidence suggests that process inefficiencies contribute to a very high percentage of hospital departments like ED's inability to meet healthcare quality indicators (Francis, 2013, Tucker et al., 2013, DeAnda, 2018).

Crowding also causes boarding and leads to more crowding in that, it places excessive demand on staff in ED who are already busy attending to new patients as they come in whilst looking after patients who are boarding (Asaro et al., 2007, Bowers et al., 2009, Martin et al., 2011, Higginson et al., 2015, Pines and Bernstein, 2015, Brady et al., 2017, DeAnda, 2018, Wallingford et al., 2018). Boarding, also referred to as departure delay or 'trolley waits', is a process where admitted patients receive care in ED whilst they wait for hospital beds to become available (Hurwitz et al., 2014, Khanna et al., 2017, Chang et al., 2018, Moskop et al., 2019, Morris, 2020). Boarding makes it difficult for EDs to attend to new patients in a timely manner resulting in more crowding. It is worth noting that boarding is a leading cause of ED crowding and is not always directly related to the unavailability of inpatient beds (McClelland et al., 2011). Boarding is also greatly influenced by staff shortages, delays in cleaning and preparing rooms or beds to accept new patients and delays in discharging inpatients from the hospital (Lane et al., 2000, Wallingford et al., 2018).

2.4.1.1 Definition for Crowding

Crowding occurs when the demand for patient care in terms of the number and acuity of patients exceeds available resources (Abdelhadi, 2015, Pines and Bernstein, 2015, Saghafian et al., 2015, Jarvis, 2016, Moskop et al., 2019). This mismatch causes a delay in treatment for patients and blockage of emergency beds which then results in patients experiencing poor health outcomes and receiving poor quality of care (Higginson et al., 2015, Pines and Bernstein, 2015, Jarvis, 2016, Brady et al., 2017, Salmon et al., 2018). There is currently no consensus or a general operational definition for crowding, making it difficult to compare crowding between hospitals (Eitel et al., 2010, Moskop et al., 2019, Peng et al., 2020).

Initial attempts by previous researchers led to the identification of three external variables that could result from crowding (Boyle et al., 2014). These measures are internationally recognised (Beniuk et al., 2012, Boyle et al., 2015) and include the following:

1. **Time for ambulances to offload**: A department is considered crowded if it takes ambulances more than fifteen minutes from arrival to offload. There is a shared responsibility between emergency departments and ambulance services to ensure that ambulance patients have a turnaround time that is as short as possible. Fifteen minutes has been agreed upon as an acceptable timeframe for this transfer to take place.

2. **Occupancy of patients on trollies.** EDs have cubicles which are officially designated treatment areas for patients. When these areas are fully occupied, patients may be attended to on trolleys. An ED is considered crowded if the number of patients on trolleys is more than those in cubicles.

3. **Waiting to be admitted**: Once a decision to admit has been made, patients wait to be assigned beds on the inpatient unit and then depart the ED. This period from the decision to admit to patients leaving the ED, which has been defined as boarding, should not be more than two hours for more than 10% of patients waiting to be admitted.

2.4.2 The Input-throughput-Output Model

The most widely used model to describe ED crowding is that of input—throughput—output was developed by Asplin et al (2003) as shown in Figure 2.1 below. The authors looked at the factors that affected crowding in the ED. They developed a conceptual model that describes three interdependent components that can help researchers, policymakers, and administrators understand the causes of ED crowding and support the development of possible solutions. These are input factors that contribute to the demand for the service, throughput factors which affect the length of stay, and output factors influenced by 'boarders', patients who need admission but have no bed. This input-throughput-output conceptual model is said to apply the operations management concept to patient flow in acute care systems. This model highlights the need for a systems approach to viewing the problem of ED crowding and employing integrated solutions.

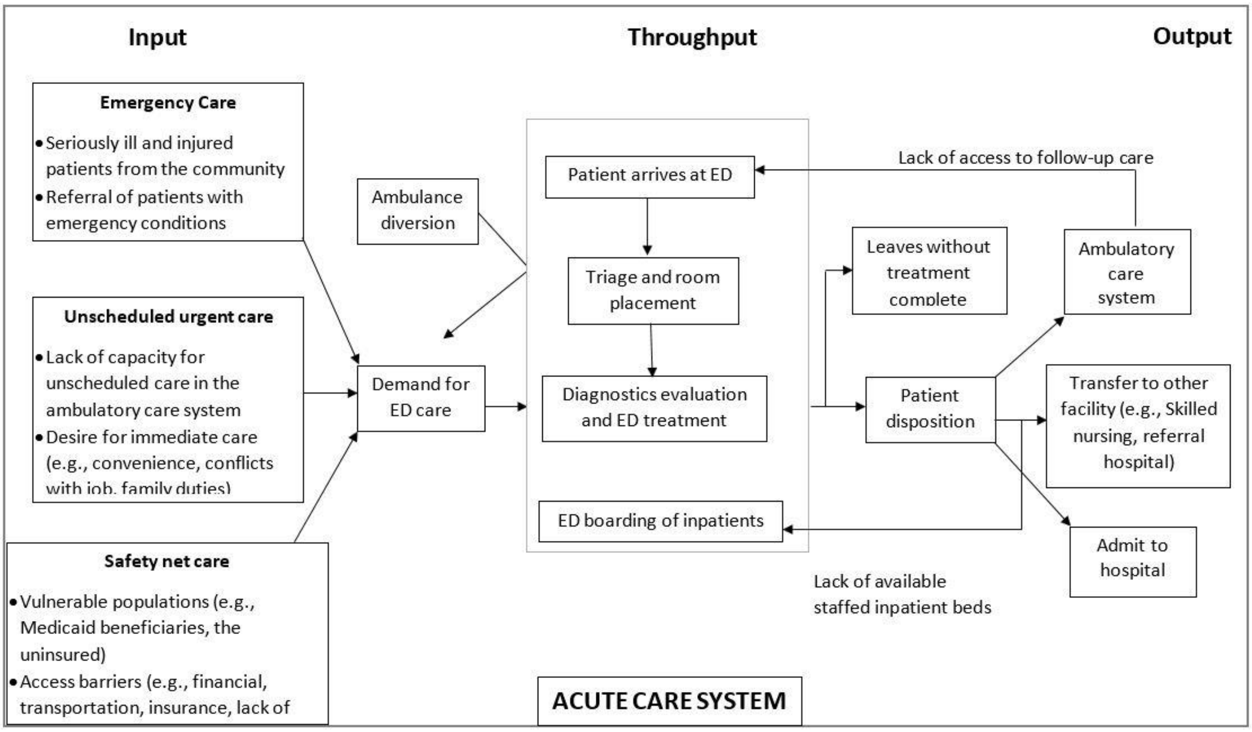


Figure 2.1 The input-throughput-output conceptual model

Source: Asplin et al., 2003

2.4.3 The Structure-Process-Output Model

Another model that is widely used in healthcare, in general, is Donabedian's structure-process-outcome (SPO) model ((Donabedian, 1988)). The three components are the structural attributes of the care setting in which care is delivered, the processes of care and the outcome of care. These three elements are interrelated in that the structure impacts the processes which affect the outcome (Donabedian, 1988). It can be argued that the outcome alone cannot be measured without a close examination of the processes of care that resulted in the outcome and the setting in which the care takes place, which can be described as the structure (Donabedian, 2005). The SPO model can be further described as follows:

Structure: these include attributes of the care session such as the facility, equipment, human resource (staff qualification and ratio) and organisational structure (staff structure and peer review methods) (Donabedian, 1988). The ED facility, the various staff that work in and out of the department to ensure patient care, and the equipment required all form part of the structure.

Process: Processes encompass care activities in relation to patient activities of looking for care and the healthcare practitioner's activities in diagnosing and treating patients (Donabedian, 1988). The processes of care in the ED start from patient arrival to departure.

Outcome: Outcome refers to the effect of the care delivered on the patient's health, including improvement in the patient's behaviour and health status (Donabedian, 1988). Hence working towards improvement by reducing the patient's length of stay; the outcome being measured in the context of this research.

2.4.4 Causes and Effects of Crowding

Understanding the causes of crowding is essential to ensure appropriate interventions. Some might argue that interventions aimed at a single part of the system are unlikely to succeed as there are multiple balancing and competing measures (Nugus et al., 2011, Higginson and Boyle, 2018). Nonetheless, in-depth investigations of each sub-system are necessary since they have their unique attribute. Doing so can generate invaluable lessons that can then contribute to implementing a whole system approach.

The causes of crowding cannot be attributed to only one reason (Higginson and Boyle, 2018, Moskop et al., 2019). At an operational level, the causes and effects of ED crowding can also be classified into three main themes: input, throughput and output factors. The input, throughput and output factors that affect the patient flow and thereby lead to crowding are also known as bottlenecks (Khanna et al., 2017).

Table 2.1 below was generated by the author following the results of the literature on the causes of crowding as per the references provided. The input factors creating bottlenecks, as shown in the table also include the increased number of patients and the acuity of patients, for example, seriously ill and injured patients and those referred with emergency conditions (Asplin et al., 2003, Boyle et al., 2014). An ageing population, advanced medical technology and better pharmaceuticals have increased the complexity and acuteness of the patients presenting to ED (Derlet and Richards, 2000). The patient arrival rate is usually random (Wiler et al., 2011) and can also be affected by unscheduled care and the occurrence of a major incident which can result in mass casualties (Asplin et al., 2003, Di Somma et al., 2015, Waxman et al., 2017). As far as input is concerned, the number of attendances to type 1 emergency departments has increased in line with population growth (Higginson and Boyle, 2018).

Table 2.1 Input, throughput and output bottlenecks causing crowding

Causes of Crowding		
Input factors	**Throughput factors**	**Output factors**
Increased numbers Patient acuteness & complexity Non-urgent visits Frequent-flyers patients Seasonal attendance Referred patients Patient arrival rate Major incident	Internal process delays Treatment delay and waiting for diagnostic test results Resource availability Staff ratio Documentation requirements Physical layout (visibility) Traverse time	Lack of inpatient beds Boarding of admitted patients High left without seen rate

Source: Author

Frequent attendance, non-urgent visits and seasonal increases in attendance, such as increased attendance during influenza seasons, are also input factors causing bottlenecks (Hoot and Aronsky, 2008). Therefore, patient types or classifications need to be examined closely in light of managing patient flow. This flow can be affected by the activities within the ED, and these are referred to as throughput sources of bottlenecks (Asplin et al., 2003, Moskop et al., 2019). The acuteness and complexity of the patient have an impact on internal and exit processes, which are subject to delays, including treatment delays (Khanna et al., 2017) and waiting for diagnosis test results from those conducted outside the ED, e.g., radiology and laboratory tests (Paul and Lin, 2012, Khanna et al., 2017, Van Der Linden et al., 2017). Other sources of throughput bottlenecks are an increased requirement for documentation and duplication of efforts which also induces further delays in internal and exit processes (Derlet and Richards, 2000), awaiting specialty consultation to process complex patients (Qureshi et al., 2010, Brick et al., 2014, Jung et al., 2020). The physical layout of the department impacts visibility and ED throughput (Hurwitz et al., 2014). Bottlenecks generated by output factors such as boarding of admitted patients and the lack of inpatient beds are the most prevailing cause of ED crowding (Hoot and Aronsky, 2008, Hurwitz et al., 2014, Gharahighehi et al., 2016, Van Der Linden et al., 2017, Chang et al., 2018). This includes acutely ill patients being held back in ED because of the lack of beds in Critical Care Units. Lack of bed availability for transfer also leads to boarding in ED while waiting for a bed to become available on an inpatient ward (Boyle et al., 2012, Sun et al., 2013, Gharahighehi et al., 2016, Chang et al., 2018, Salmon et al., 2018, Moskop et al., 2019). There is a correlation between the high mortality rate of admitted patients and ED crowding, which is also associated with increased length of stay in ED and cost (Sun et al., 2013). Other output bottlenecks are discharged patients unable to exit the ED due to lack of transportation and delays with the handover of patients to inpatient units (Brady et al., 2017, Tomar et al., 2019). It was further identified that bottlenecks causing crowding resulted in increased length of stay (Derlet and Richards, 2000). The causal implication of crowding is an increase in both patient dissatisfaction and left without seen rate (Hoot and Aronsky, 2008, Tekwani et al., 2013, Leviner, 2020). The input, throughput and output bottlenecks have also been widely reported by other researchers (Derlet and Richards, 2000, Lane et al., 2000, Schull et al., 2001, Asplin et al., 2003, Brailsford et al., 2004, Asaro et al., 2007, Hoot and Aronsky, 2008, Bowers et al., 2009, Martin et al., 2011, Pines et al., 2011b, Wallingford et al., 2018).

2.4.5 A Causal Loop Model of Emergency Department Crowding

The causal loop model below in Figure 2.2 illustrates the cause and effects of the crowding problem qualitatively. The author developed this to demonstrate how the factors that cause crowding are related to each other following the review of literature presented in Table 2.1 above. The patient arrival rate is positively influenced by factors such as referred patients, seasonal attendance, and the occurrence of a major incident. An increase in crowding results in a delay in the system leading to an increase in the length of stay which leads to patient dissatisfaction and an increase in left without seen rate. The physical layout of the department impacts visibility and traverse time, where an increase in visibility implies a reduction in traverse time and vice versa. Traverse time affects the time required for internal and exit processes. The internal and exit processes are also impacted by the acuteness and complexity of the patients being treated, awaiting specialist consultation, boarding, bed blockage, treatment delay and waiting time for diagnostic test results. However, when the staff ratio decreases, the resource availability also decreases, leading to an increase in the time required for the internal and exit processes, which are also affected by handover delays and lack of transportation for discharged patients. In the causal loop model, plus symbol (+) denote factors that causally increase when the factors linked at the bottom of the arrow also increase while a minus symbol (-) denote factors that reduce when their linked factors increase.

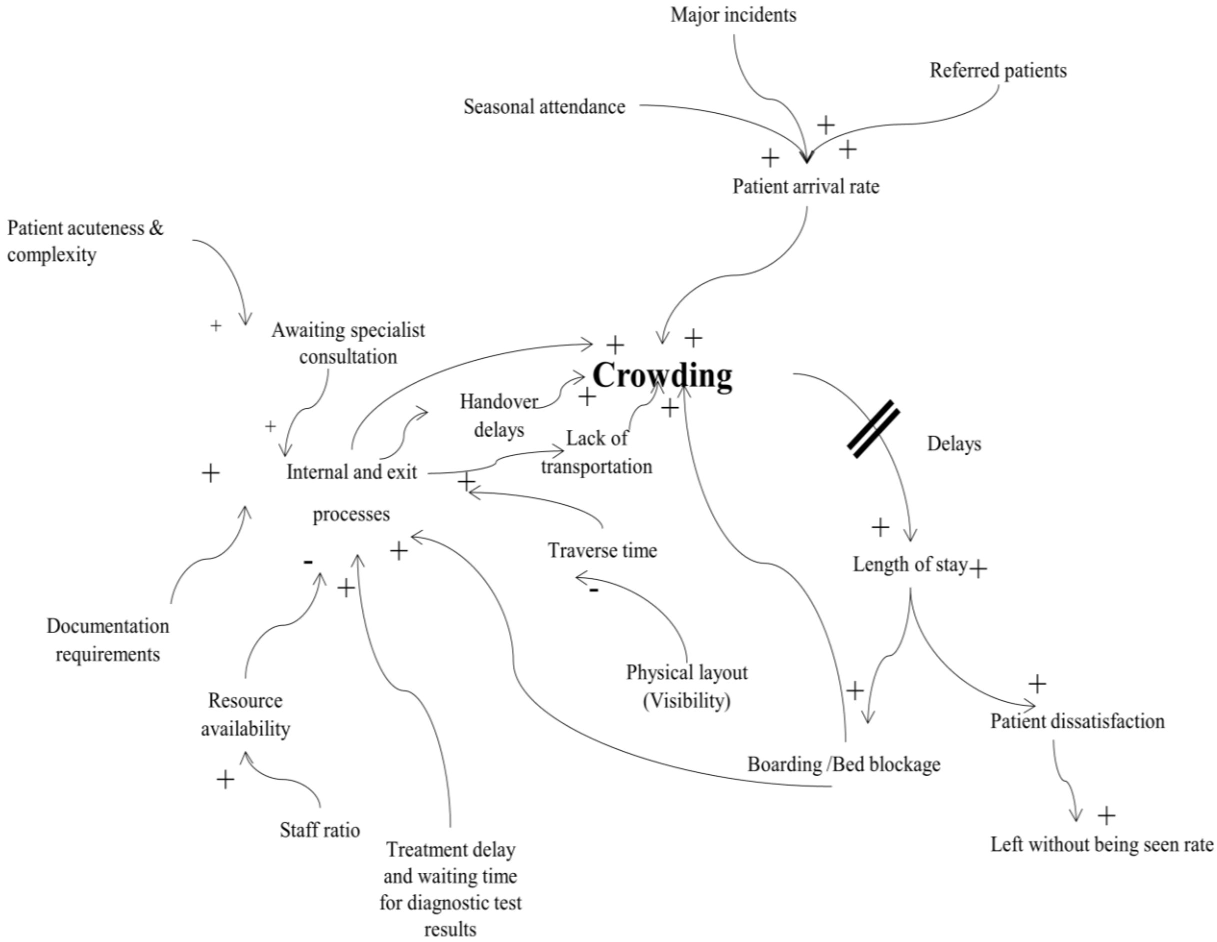


Figure 2.2 Causal loop model of ED crowding

'→' denotes causal link between factors causing crowding
'+' denotes an increase when factors linked at the bottom of the arrow increases
'-' denotes a decrease when factors linked at the bottom of the arrow increases

Source: Author

2.4.6 Solutions to Crowding

ED problems are influenced by their own contexts. Therefore, site specificity is essential in understanding ED patient flow and identifying factors that influence patient LOS, contributing to crowding at an operational level (Nugus et al., 2011, Gill et al., 2018). Understanding the site-specific factors can help develop targeted approaches to address the unique challenges and resources of each hospital to improve ED patient LOS (Nugus et al., 2011, Paul and Lin, 2012, Khanna et al., 2013, Chang et al., 2018, Morley et al., 2018, Valipoor et al., 2018, Ortíz-Barrios et al., 2021).

To date, numerous initiatives have been undertaken to solve the crowding problem. For example, current best-in-class methods for addressing crowding include setting targets in the form of quality indicators that drive the improvement of ED processes (Bowers et al., 2009, Weber et al., 2011, Letham et al., 2012). To that end, NHS quality indicators have brought about improvements requiring the deployment of policies to reduce waiting times (Proudlove et al., 2007, Letham et al., 2012). Due to projected improvements to emergency treatment, strategies mandating a four-hour maximum waiting time for all patients attending ED were established in 2000 and reduced to 95% of patients in 2010 while also allowing for clinical exclusions (Proudlove et al., 2007, Bowers et al., 2009, DH, 2010b, Letham et al., 2012).

2.5 The Focus on Throughput

Managing inputs, throughputs, and outputs is critical in addressing the crowding issue. However, the best solution is unknown as they must be tailored to suit each specific ED's problems. Nonetheless, the throughput aspect of the patient flow is more within the control of the ED compared to input and output aspects though interactions with other departments still make timely throughput a challenge (Paul and Lin, 2012, Elder et al., 2016, Khanna et al., 2017). This explains why is has been a popular area of focus for researchers (DeAnda, 2018, Romeo and May, 2018, Vanbrabant et al., 2019a). Contrary to what was previously believed, throughput has been shown to impact ED length of stay as much as output factors; therefore, improvement efforts should also be targeted at optimising these (DeAnda, 2018, Doupe et al., 2018). Other studies have achieved a reduction in ED LOS by focusing on throughput. Hence this research will also focus on this aspect of the patient flow (Shetty et al., 2012, DeAnda, 2018).

2.6 Techniques for Addressing Emergency Department Problems

The constant pressure to reduce delays and costs has led to the urgent need for researching and improving approaches aimed at patient flow analysis by employing various techniques to address the problems faced in EDs worldwide (Harper, 2002, Katsaliaki and Mustafee, 2011). Some of these are real-world clinical interventions such as fast track, a doctor in triage, streaming, rapid assessment, options for alternative admission when there is an access block, expanded nursing scope of practice, a co-located primary care clinic in ED, and Point of Care Testing (Jarvis, 2016, Morley et al., 2018, O'Neill et al., 2018).

Jarvis, (2016), conducted a literature review to identify evidence-based strategies to reduce crowding by reducing the time patients spend in the ED and improve patient flow. It was identified that ED flow can be improved through the use of point of care testing, doctor triage, rapid assessment, streaming and a co-located primary care clinician in ED. The review concluded that by introducing new technologies such as point of care testing in ED and changing the patterns of work, patient flow can be improved and crowding reduced.

Similarly, Morley et al., (2018) conducted a systematic review to provide a critical analysis and summary of published peer-reviewed studies which had investigated the causes and consequences of ED crowding as well as solutions to address the crowding problem. Most studies that met the inclusion criteria were retrospective cohort studies, with 51% of them modelling or trialling possible solutions to ED crowding. Interestingly, they identified a mismatch between causes and solutions in that, the causes focused mainly on the number and patient type, yet solutions were targeted at efficient flow of patients in the ED. Similar to the conceptual model by Asplin et al., (2003) presented in Section 2.4.2, they broadly categorised the studies that focussed on the causes of crowding as those that identified input, throughput or output causes. The studies that investigated potential solutions were similarly categorised with early physician assessment/physician-led/supported triage, fast-track area, shorter laboratory tests turnaround-times, ED nurse flow coordinator, nurse-initiated protocols, early inpatient consultation and increased ED beds and staff as some of the throughput solutions. They concluded that solutions that yielded promising outcomes were those aimed at whole-of-system initiatives and extending primary care hours.

O'Neill et al (2018), reviewed published papers reporting interventions in improving emergency department operations by analysing their effectiveness. They noted that real-world applications of these interventions are limited, the studies are often restricted in the focus of their reports. Moreover, they vary in how results are reported, making comparisons difficult. Furthermore, cost data is often not reported. They produced evidence maps to provide graphical displays of the interventions to improvement length of stay, waiting-room time and left without being seen rate. Each map displayed the interventions by the type, effect size, data reporting and the resources utilisation i.e., reallocating of existing resources, addition of new resource or in some cases, resource use was unclear. Physician triage was the most common intervention, followed by expansion of nursing scope of practice, fast track, and point of care testing.

Furthermore, process engineering techniques have been applied to model ED at an operational level. These include operational research (OR) methods (integer programming, optimisation, simulation and queuing theory), statistical methods (regression analysis) and quality improvement methods (continuous quality improvement (CQI), lean manufacturing) (Ortiz-Barrios and Alfaro-Saiz, 2020). There appears to be an increase in the use of hybrid methods, particularly the integration of simulation with other techniques (Saghafian et al., 2015, Souza et al., 2021). The most commonly used methods of lean manufacturing and simulation (Holden, 2011, Abdelhadi, 2015, Ortiz-Barrios and Alfaro-Saiz, 2020, Castanheira-Pinto et al., 2021, Tiso et al., 2021) have been reviewed in detail in the subsequent sections.

2.6.1 Lean Manufacturing

Lean manufacturing (LM) methodology, also referred to as lean thinking (LT), is used to improve processes (Dyas et al., 2015, Akmal et al., 2020). Healthcare applications of LT are increasing (Holden, 2011, Abdelhadi, 2015, Dyas et al., 2015, Akmal et al., 2020), with many studies choosing lean because of its continuous process improvement approach (Souza et al., 2021). LT is one of the main approaches being applied in EDs for waiting time improvements due to benefits relating to cost, waiting time and LOS reduction, patient flow efficiency and improvements in patient satisfaction and productivity (Dyas et al., 2015, Castanheira-Pinto et al., 2021). It identifies processes as either value-added or non-value added and therefore helps EDs to detect and remove operational waste and variability in care provision, identify and decrease wasted resources which in turn increases value and leads to a reduction in service lead time (Sfandyarifard, 2010, Akmal et al., 2020, Ortiz-Barrios and Alfaro-Saiz, 2020, Castanheira-Pinto et al., 2021, Tiso et al., 2021). It is recommended that LT be applied through the integration of hard tools such as value stream mapping (VSM) and flow charts, as well as soft tools such as employee involvement and continuous improvement (Tiso et al., 2021). It supports adopting standard operating procedures (SOP) to improve efficiency (Ortiz-Barrios and Alfaro-Saiz, 2020).

The five main principles of LT proposed by Womack and Jones' (1996) provide the following steps as a guide to its implementation:

1. Value must be specified from the customer's viewpoint.
2. All the value-added steps must be identified, and non-value added steps must be eliminated.
3. The process must flow smoothly.
4. Work must be pulled from upstream, not pushed.
5. Perfection must be sought by repeating the above steps until there is no waste and a state of perfect value is achieved.

To contextualise the above steps for healthcare application, Tiso et al (2021) reviewed a framework to structure the methodology for implementing LM projects in ED. The main steps are outlined as beginning with a high-level definition of the project objectives, resource planning and multidisciplinary team creation (Tiso et al., 2021). This is then followed by the collection of quantitative and qualitative data to analyse the current state of the processes involved in the LM project (Tiso et al., 2021). The next step consists of the development of process maps using tools like a flow chart and VSM for the identification of value-added and non-value added activities, i.e., waste ('muda' in Japanese) in the processes (Holden, 2011, Abeidi et al., 2018, Tiso et al., 2021). Any activity that does not add value to the customer (patient) is considered waste (Holden, 2011, Abdelhadi, 2015). In the context of ED, waiting time is mainly identified as waste and, therefore, needs to be eliminated to improve efficiency (Holden, 2011, Radnor et al., 2012, Tiso et al., 2021). This explains why waiting time reduction is reported as the most significant benefit of LM projects in ED (Souza et al., 2021). The next stage is to develop improvement ideas mainly through brain storming activities to discuss proposed ideas for waste elimination (Abeidi et al., 2018, Tiso et al., 2021). Managers and frontline staff must be involved in brainstorming activities to find solutions which often take place during rapid continuous improvement sessions known as kaizen (Holden, 2011). This step could include redesigning existing or developing new processes (Radnor et al., 2012). The solutions are then implemented, with the final step being monitoring and maintaining the improvements achieved (Tiso et al., 2021). Standard operating procedures and performance data can support monitoring (Radnor et al., 2012).

Another systematic review of LT application in healthcare spanning from 1995 to December 2017 identified a myriad of tools and techniques that have been applied over the years including VSM, a type of diagram that shows both current and future processes as well as information, timing, people and products (Holden, 2011, Akmal et al., 2020, Souza et al., 2021); 5S which are Sort, Store, Shine, Standardize, and Sustain as a way to organise and standardise workspaces to make them look neat and organised (Sfandyarifard, 2010, Holden, 2011, Akmal et al., 2020); Ishikawa diagram, also known as a fishbone diagram which is used to show the cause and effects of events (Alowad et al., 2021); A3 report, a problem solving tool for reporting (Holden, 2011, Alowad et al., 2021), Kaizen, rapid continuous improvement sessions (Holden, 2011, Souza et al., 2021); Kanban, a system providing information on products that are ready for pulling to the next step (Holden, 2011); Gemba waste walks, a way of detecting waste by measuring activity durations directly in the field (Akmal et al., 2020, Tiso et al., 2021); 5 Whys, a way of conducting root cause analysis (Holden, 2011); Takt, which measures the interval or exact time cycle required for producing each unit (Abdelhadi, 2015); and Seven wastes, different types of waste that need to be identified and eliminated (Sfandyarifard, 2010) among many others.

2.6.1.1 Challenges to Lean Manufacturing Applications

There are questions about the effectiveness of LM application in the ED and healthcare in general regardless of the growing popularity, firstly due to a lack of consensus on the definition of quality improvement in the context of lean (Holden, 2011, Bucci et al., 2016, Moraros et al., 2016, Akmal et al., 2020). Some argue that, despite abundant research, LM/LT in healthcare is still in its infancy (Akmal et al., 2020). There is a lack of sufficient evidence to support the claim that lean interventions in healthcare lead to quality improvements as gaps remain in their practical and operational applications in the ED (Joosten et al., 2009, Vermeulen et al., 2014, Bucci et al., 2016, Moraros et al., 2016, Tiso et al., 2021). This stems from adopting lean directly from the automotive manufacturing industry without adapting it to suit the healthcare industry's needs amidst the complexity of patient care processes, as the principles are not entirely transferable (Holden, 2011, Mazzocato et al., 2014, Akmal et al., 2020). There are distinct differences between these two industries and how value is defined since, in healthcare, value is provided as services to patients, not as products (Tiso et al., 2021). Also, in healthcare, the customer, in addition to the patient, may include hospital staff, the patient’s family and the commissioners who pay for the service provided. In contrast, in manufacturing, the customer is the same as the commissioner (Sfandyarifard, 2010, Radnor et al., 2012). Another challenge is defining waste in the ED, which is not as simple as doing so in a manufacturing process (Radnor et al., 2012, Tiso et al., 2021).

Furthermore, LT is not being applied in an extended scope of system-wide implementation as expected but rather in a single department at a time which contradicts its theoretical principles (Akmal et al., 2020). True lean has to be applied system-wide rather than in small projects (Radnor et al., 2012). This fragmented approach means that what healthcare calls lean is not lean but simply an attempt to apply lean tools in isolation instead of fully embracing the philosophy of LT (Radnor et al., 2012). Understandably, several studies have raised concerns about the sustainability of so-called improvements (Vermeulen et al., 2014, Bucci et al., 2016, Moraros et al., 2016), with the tool-based approach failing to engage staff to a level where they fully understand LT as a continuous improvement process and shift their attention off the tools (Radnor et al., 2012). The Hawthorne effect, which is the phenomenon where people alter their behaviour when they know they are being watched, may also be to blame for some of the improvements noted in literature (Holden, 2011). As a result, once the projects are completed, the advantages of LM may no longer be as strong. (Holden, 2011). Moreover, many of the studies that reported improvements did not provide details of the techniques applied in the projects, making it difficult to compare results and confirm that LM tools have been correctly adapted and implemented for healthcare settings (Tiso et al., 2021).

The questions around the adaptation of LT/LM in healthcare need to be answered as well as an evaluation of its effectiveness and impact on quality outcomes and patient safety through high-quality scientific research (Holden, 2011, Vermeulen et al., 2014, Moraros et al., 2016). The effect of LT on healthcare staff also needs to be better understood (Holden, 2011), as some researchers have found a negative connection with staff satisfaction (Moraros et al., 2016). Researchers and those seeking to implement lean have been cautioned about its potential to increase workload and reduce autonomy (Holden, 2011).

In summary, LT has the potential to yield improvements in healthcare. Still, the challenges raised must be considered carefully and addressed by researchers and implementers to yield sustainable improvements (Joosten et al., 2009).

2.6.2 Simulation Modelling

The other commonly used process engineering technique is simulation modelling. Its application in healthcare is considered relatively new, especially in terms of the practical application of results, even though it has been applied in areas such as defence, manufacturing and supply chain for a long time (Eldabi et al., 2007, Katsaliaki and Mustafee, 2011, Brady et al., 2017, Castanheira-Pinto et al., 2021). Simulation modelling is used frequently in most planned projects in the military and manufacturing sectors. However, there is still a considerable gap between theory and practice in healthcare applications in terms of the use of derived simulation models (Eldabi et al., 2007, Eldabi, 2009, Brady et al., 2017). Hospitals are complex organisations with interactions between various specialities and departments within outpatients, inpatients and emergency departments (Ordu et al., 2021). For this reason, a simulation model that includes all services provided by a hospital is not feasible to build (Gunal, 2012). The challenges involve modelling the interactions between various departments and the need for heterogeneous data coupled with difficulty obtaining qualitative and quantitative data (Gunal, 2012, Salmon et al., 2018). Due to the collaborative nature of patient care, patient-related data that is generated is stored in different information systems which are not integrated, making data acquisition a challenge (Fitzpatrick, 2006, Dormann et al., 2020). Modelling a single department, such as the ED, is a more realistic objective to set. For this reason, simulation has been widely applied in the ED. It is regarded as a prominent and cost-effect effective tool for analysing and improving ED processes and their performance (Kaushal et al., 2015, Zhao et al., 2015, Mohiuddin et al., 2017, Salmon et al., 2018, Ortiz-Barrios and Alfaro-Saiz, 2020, Peng et al., 2020, Castanheira-Pinto et al., 2021, Ordu et al., 2021). It allows improvement in the ED without necessarily investing more resources (Ordu et al., 2021). Informed decisions can be safely made in the simulated environment (Castanheira-Pinto et al., 2021). The advantage of such an approach means that hospitals, representing environments generally characterised by high levels of uncertainty and resource pressures, can test improvement scenarios and associated costs safely before actual implementation (Harper, 2002, Bowers et al., 2009, Gunal, 2012, Day et al., 2013, Vanbrabant et al., 2019a).

Simulation modelling also aids in planning and decision-making by helping to analyse system and resource utilisation (Davenport, 1993, Brailsford et al., 2009, Mielczarek and Uzialko-Mydlikowska, 2012, Zhao et al., 2015, Mohiuddin et al., 2017). They provide process and product engineers with the opportunity to test their designs in a safe, realistic and complex environment to fully explore how the product or process will be in reality before actually producing or building it (Davenport, 1993, Peng et al., 2020).

Techniques such as discrete event simulation (DES), system dynamics (SD), hybrid model and agent-based simulation (ABS) have been applied in many healthcare settings, including ED (Eitel et al., 2010, Mohiuddin et al., 2017). They provide physicians and managers with an overview of process engineering concepts that can be applied practically to EDs to help address the crowding problem (Eitel et al., 2010, Hurwitz et al., 2014). There is a wealth of research on the application of simulation in understanding the causes of crowding by identifying bottlenecks and testing solutions through 'what if' analysis (Kaushal et al., 2015, Zhao et al., 2015, Mohiuddin et al., 2017, Salmon et al., 2018, Ortiz-Barrios and Alfaro-Saiz, 2020, Peng et al., 2020, Castanheira-Pinto et al., 2021, Ortíz-Barrios et al., 2021).

2.6.2.1 Discrete Event Simulation Modelling (DES)

Discrete Event Simulation (DES), sometimes called process simulation, is a computer simulation method that accurately captures the system's stochastic and dynamic nature (Zapata et al., 2007, Khanna et al., 2016, Vanbrabant et al., 2019a). It is a popular industrial engineering and OR methodology and, indeed, the most popular simulation method that has been applied to modelling healthcare systems, particular emergency departments at an operational level (Gunal, 2012, Karnon et al., 2012, Khanna et al., 2016, Peng et al., 2020). DES is applied by defining entities (i.e. work items or objects such as patients) who have attributes (i.e. properties such as type of illness), consume resources while experiencing events and entering queues over time (Brailsford et al., 2004, Morgan et al., 2011, Gunal, 2012, Karnon et al., 2012, Khanna et al., 2016, Peng et al., 2020). It helps model stochastic systems that change their state in discrete intervals (Brailsford and Hilton, 2001, Brailsford et al., 2004, Gunal, 2012). Due to its flexibility in responding to change, it can handle varying levels of detail, and stochastic factors such as length of stay and random arrivals can be modelled easily. It offers modularity building which allows reusable components of a model to be built (Gunal, 2012). This technique provides a graphical representation of how a care-related process works and how resources are utilised, which can help to understand the overall system performance better and identify any deficits (Jun et al., 1999, Brailsford et al., 2004, Peng et al., 2020). Improvements can then be introduced into the graphical representation in a simulated environment to assess their effectiveness before implementation. DES models have been used to evaluate many healthcare areas, such as hospital scheduling, communicable diseases, and screening (Fone et al., 2003). It is generally considered the preferred method for hospital systems modelling due to the detailed nature of this method, whereby individual patients are tracked through the system (Lane et al., 2000, Brailsford and Hilton, 2001, Chahal et al., 2008, Vanderby and Carter, 2010, Gunal, 2012). The system to be modelled must be accurately defined, and this definition serves as the input. The granularity of the data determines the strength of this input which is also dependent on the experience of the experts providing the required information (Karnon et al., 2012). It is therefore recommended in the DES guidelines for researchers' best practice IV-24 that a diagram, such as a flow chart, should be used to provide information about the system's function and structure to be modelled (Karnon et al., 2012).

In this study, DES is not ranked as the ultimate solution to all ED problems. Instead, what is being highlighted is its potential to address problems as it provides an approach to managing contributing factors at a discrete level. It has the capability of modelling the non-linearity and inherent complexities in a system such as an ED by capturing the dynamics of the system and the various interconnections (Venugopal et al., 2013, Vanbrabant et al., 2019a, Castanheira-Pinto et al., 2021).

2.6.2.2 Challenges to DES Applications

In spite of the advantages mentioned above of DES, it also has challenges. Even though it has been proven an effective tool in manufacturing, defence and business application, there is a lack of implementation of results and follow-up in the healthcare sector (Hamrock et al., 2013, Mohiuddin et al., 2017). Many DES studies reported in literature have had limited success and, therefore, limited impact firstly because of the lack of sophistication in the models used and the analysis techniques applied (Raunak et al., 2009, Best et al., 2014, Mohiuddin et al., 2017). The simplistic nature of the DES models used and, correspondingly, the analytical techniques applied (Au-Yeung et al., 2006) affect the solutions developed. Also, the solutions need to be appropriately managed and targeted; otherwise, they may not have the desired effect on reducing patient flow inefficiencies (Hurwitz et al., 2014).

DES can also be seen as only providing an isolated view of the entire hospital system due to its micro-level nature, which makes it restrictive in modelling entire systems (Lane et al., 2000, Katsaliaki and Mustafee, 2011). It requires large amounts of quantitative data, and the simulation results need intelligent analysis by people with statistical knowledge; otherwise, wrong conclusions can easily be drawn (Brailsford and Hilton, 2001, Vanbrabant et al., 2019a). It is also time-consuming to develop and run for a large number of entities such as ED patients (Brailsford et al., 2004, Defraeye and Van Nieuwenhuyse, 2016).

Furthermore, in most cases, the existing models are not validated using real data since the data collection process can be expensive, time-consuming, and sometimes manual (Kirby et al., 2011). The models developed in studies are also often difficult to use on an ongoing basis as they require a dedicated team to work on fine-tuning and validating the model constantly. This process cannot be managed by hospital management, who are already inundated with other activities due to the complex nature of the ED environment, which is characterised by limited resources, competing priorities and the increasing number of different types of patients requiring care (Au-Yeung et al., 2006, Nugus et al., 2011, Virtue et al., 2011, Ashour and Kremer, 2013, Hurwitz et al., 2014).

Another primary consideration is that appropriate granular information is needed to develop an effective model that works and can address the current problems in ED, which is sometimes not easy to access. As stated in the previous section, the granularity of the data determines the strength of the input. Some patient flow information required to build the model is not collected routinely through the hospital's electronic system. It must be collected manually, adding another level of difficulty (Carmen et al., 2015). Similarly, the data required for continuous validation is challenging to obtain as this may not always be available; therefore, manual data collection may be required (Au-Yeung et al., 2006, Gul and Guneri, 2012). Many of these models are also limited because they focus on clinical or non-clinical factors. Still, patient flow issues are affected by both, and this has to be considered in papers reporting DES studies.

Another challenge of applying DES models is that it is necessary to contextualise information. Models cannot be applied to another hospital without significant modification due to differences in capacity and resource configurations in different EDs, making the study results usually more beneficial to the study site. The solutions to problems causing crowding can therefore be considered typically site-specific (Gul and Guneri, 2012, Hurwitz et al., 2014, Ortíz-Barrios et al., 2021).

Some researchers have broadly categorised some of the limitations above into three main elements as follows (Zeng et al., 2012, Saghafian et al., 2015):

1. A lot of work is required to represent the actual process and flows. Several studies get around this by making assumptions to simplify processes.
2. The quality of data collected is paramount. The output of the model is as good as the data input. When the required data is unavailable, estimates have been used, affecting the results obtained.
3. Correct interpretation and understanding of the outcomes are required before implementing changes. If solutions are not interpreted correctly, they could have a counterproductive effect.

2.6.2.3 System Dynamics (SD)

System dynamics (SD) is a method based on mathematical models and computer simulations and is used to develop management simulators similar to an airline's flight simulators to help understand and learn about dynamic complexity and effectively design policies for implementation (Sterman, 2000). It is used to model the behaviour of complex systems over time and to obtain an insight into how the behaviour is affected by the structure of the system (Sterman, 2000, Morgan et al., 2011, Mohiuddin et al., 2017). This is achieved through the use of stocks and flows. SD is suitable for modelling continuous systems and can track instantaneous changes that occur in a dynamic system. It helps in studying the relationship between elements of healthcare systems and is a suitable method for strategic-level thinking because it looks at the whole system (Sterman, 2000, Brailsford and Hilton, 2001, Chahal et al., 2008, Vanderby and Carter, 2010, Agyapong-Kodua and Weston, 2011, Gunal, 2012, Morgan et al., 2015).

The two main notations, causal loop diagrams (CLDs) and stock & flow models, capture the conceptual relationships in problems and can describe the structure of the system in detail (Brailsford et al., 2004, Chahal et al., 2008). SD is viewed in some studies as the most appropriate tool for modelling ED systems by exploring factors that contribute to long waiting times, bed capacity, and patient flow to inform strategic management decisions about EDs (Lane et al., 2000, Chahal et al., 2008). It is argued that systems should not be modelled in isolation due to the interconnections between different units in a hospital (Lane et al., 2000).

2.6.2.4 Challenges to SD Applications

SD is, however, seen as a deterministic method and does not usually incorporate variability (Brailsford and Hilton, 2001, Vanderby and Carter, 2010). SD is distinct from DES in that it does not lend itself readily to including random variables (Mohiuddin et al., 2017). Thus input parameters are often provided as simple rates (Mohiuddin et al., 2017). Through the high-level view of the system, it captures aggregate instead of individual flows. It is, therefore, not ideal for modelling processes at a granular level as required for a system like the ED (Vanderby and Carter, 2010, Morgan et al., 2015, Mohiuddin et al., 2017).

2.6.2.5 Agent-Based Simulation (ABS)

An emerging method considered highly flexible is Agent-Based Simulation (ABS) (Laskowski and Mukhi, 2008, Siebers et al., 2010, Gunal, 2012, Liu et al., 2017, Sulis and Leva, 2017). It was used mainly in the academic field and not very well implemented in industry, though it was described as having great potential for hospital systems modelling (Gunal, 2012). However, recent publications about healthcare applications, especially the ED, look promising (Gül and Guneri, 2015, Liu et al., 2017). It has three main elements: 1. agents, who possess attributes and behaviours; 2. interactions, which define relationships between the agents; and 3. the environment, which are external factors that affect agents and their interactions (Gunal, 2012, Kaushal et al., 2015). These agents (people and objects) act like entities in a DES but are autonomous and interact with each other based on the state of their environment and make decisions based on a set of rules (Siebers et al., 2010, Laskowski et al., 2011, Gunal, 2012, Kaushal et al., 2015). For example, ABS was applied in modelling the spread of influenza virus infection in an ED by viewing a conceptual model of patient flow and their interactions with each other and healthcare workers (Laskowski et al., 2011). It was concluded that ABS allows modellers to construct a comprehensive representation of the real world (Siebers et al., 2010, Laskowski et al., 2011)

2.6.2.6 Challenges to ABS Applications

The literature on using ABS in healthcare in general and especially in ED is still limited compared to other simulation methods though increasing (Kanagarajah et al., 2008). ABS requires the formulation of rules converted into codes, which is difficult due to the lack of theoretical agreement about human behaviour (Jager, 2017, Badham et al., 2018). However, one of the significant limitations of ABS is that the tools developed (AnyLogic, Repast and NetLogo) require knowledge of programming techniques and Java which are not traits an average ED operations manager possesses, therefore mainly applied by skilled academic researchers (Siebers et al., 2010). Obtaining the relevant behavioural data at the required level of detail is also a challenge (Badham et al., 2018).

2.6.2.7 Hybrid Model

Another technique referred to as the hybrid model, combines both DES and SD to yield benefits of both methods (Brailsford et al., 2010, Zulkepli et al., 2012, Ahmad et al., 2014, Landa et al., 2017, Palmer and Tian, 2021). As described earlier, DES is used to analyse operational-level problems, whereas SD models often look at strategic-level problems (Sterman, 2000, Brailsford et al., 2010). The operational research community has debated this idea for over a decade (Brailsford et al., 2010). It combines the operational tool nature of DES which views system performance at a very detailed level with the strategic tool of SD which views the overall system behaviour (Chahal et al., 2008, Brailsford et al., 2010, Zulkepli et al., 2012). Due to the interconnected nature of hospital systems, the hybrid model is considered ideal because it meets the needs of looking at detailed operational activities in a unit of the hospital while also being able to view its impact on other departments of the hospital. It is argued that effective decision-making requires tools capable of comprehending both detail and dynamic interactions of healthcare hence justifying the need for a hybrid model whereby DES and SD complement each other (Chahal et al., 2008). A proposal for implementing the hybrid model was made for three different formats: the Hierarchical Format, Process-Environment Format and Integrated Format (Chahal et al., 2008). In a case study by Brailsford et al (2010), data from a DES model using Simul8 was passed to an SD model using Vensim via an excel interface.

2.6.2.8 Challenges to Hybrid Model Applications

Researchers have attempted to combine both SD and DES to create a hybrid model though some argue that a genuinely hybrid model has not yet been created because it will be more than just integrating DES and SD in a single model; though a lot has been learnt along the way (Brailsford et al., 2010). Transferring the output of one model as input for the other can be challenging and, therefore, advisable to look at results from both models when interpreting them (Zulkepli et al., 2012). Also, there is difficulty in adapting hospital systems for the required information for the hybrid model (Landa et al., 2017). There is a lack of reporting on the details of how these models have been implemented, which makes it challenging to reproduce reported results (Morgan et al., 2016, Palmer and Tian, 2021). Furthermore, this methodology is not well defined and may mean different things (Palmer and Tian, 2021).

2.7 The Need for Granular Process Modelling

Patient care in the ED is complex due to its activity-rich nature (Nugus et al., 2011). Several processes take place simultaneously and sequentially, involving interactions with other units outside the departments in addition to interactions between various staff within its boundaries. EDs also interact with the community and the broader healthcare system (Ortiz-Barrios and Alfaro-Saiz, 2020). The crowding problem has worsened over the years, with crowding causing more crowding, thereby presenting a significant risk to the safety of patients (Moskop et al., 2019). Addressing this problem has led to an increasing trend in the use of different methods, as previously mentioned; particularly an increase in the integration of simulation with other OR techniques and justifiably so due to the complex nature of EDs (Saghafian et al., 2015, Souza et al., 2021). The complexity of some of these methods can be a barrier to their adoption, requiring collaboration between OR researchers, ED managers and stakeholders at an early stage (Saghafian et al., 2015, Salmon et al., 2018). Financial constraints, especially in developing countries, have limited the broad application of these approaches (Morley et al., 2018, Ortiz-Barrios and Alfaro-Saiz, 2020).

While studies have endeavoured to generate solutions aimed at solving bottlenecks in ED, some of these solutions have had limited success due to the reliance on a simplified understanding of ED process flow (Best et al., 2014, Hurwitz et al., 2014, Mohiuddin et al., 2017). Such studies have not incorporated detailed information about the realities on the ground and associated variation. There is a lack of accurate, realistic models of the real ED system as these simplistic models do not account for the complexities in the patient journey. Simulation studies often use assumptions to produce models for ‘what if’ analysis (Peng et al., 2020). Furthermore, throughput-focused solutions have been shown to yield comparative results to input and output ones hence necessitating the need to accurately model these factors as part of steps towards addressing ED problems (Proudlove et al., 2007, Eatock et al., 2011, Weber et al., 2011, Mason et al., 2012, Doupe et al., 2018). Moreover, solutions that have been successful in other settings may not be useful in varied situations (Saghafian et al., 2015, Ortíz-Barrios et al., 2021), providing avenues for more research.

Granularity is vital in overcoming these barriers and is hence essential for modelling complex systems. The first step towards improving any process is to understand the existing processes, which can be achieved through process modelling techniques. These techniques are useful in effectively modelling and analysing improvement suggestions in complex systems (Zhao et al., 2009). They have been predominantly used in industrial engineering, manufacturing and complex services and recently applied in the healthcare sector, such as in modelling process flow in the emergency department (Eldabi, 2009, Zhao et al., 2009, Katsaliaki and Mustafee, 2011, Jahangirian et al., 2012).

Granularity is significant, yet few studies address it directly (Maier et al., 2017). More studies have to focus on this topic as the granularity of data affects its strength as an input (Karnon et al., 2012). However, the challenge with granularity is finding an appropriate balance between providing enough detail without confusing or altering results (Maier et al., 2017). This study proceeds to emphasise this point by further reviewing process mapping and comparing commonly used methods.

2.7.1 Process Mapping

Process mapping (PM) provides a snapshot of activities in a moment in time to visualise the flow (Bicheno, 2004, Calder et al., 2012). The development of process maps involves interviews with key knowledge holders and is also based on observation (Jurishica, 2005, Calder et al., 2012, Johnson et al., 2012). Focus groups can also be used to develop process maps, which can be very enlightening as it highlights common themes of error in the processes. One such study aimed at improving patient safety in relation to EDs disposition decisions (Calder et al., 2012). The mapping helps to see how experts address a problem, hence providing the opportunity to explore, clarify and challenge stakeholders' views of the workflow (Johnson et al., 2012). This could highlight the need to improve communication between stakeholders.

In addition, process mapping requires the use of qualitative data, which can be challenging to obtain from those who have knowledge and experience of the process being mapped. Process maps cannot capture the dynamics involved in a system such as that in EDs and can get very complicated for complex systems (Calder et al., 2012). They do not include time dependencies or consider interconnections of systems hence limited in their application to dynamic systems. (Agyapong-Kodua et al., 2009). In principle, they mainly help visualise and identify waste in systems and show the relationships between information and physical flows (Hines and Rich, 1997, Bicheno, 2004, Calder et al., 2012, Johnson et al., 2012). However, they serve as an important first step in modelling complex systems (Zhao et al., 2009). Some of the commonly used techniques are flowcharting (Crabbe et al., 1994, Aguilar-Saven, 2004, Shukla et al., 2014), dataflow diagrams (Hunt, 1996, Shukla et al., 2014, Shukla et al., 2015), Value Stream Mapping (VSM)(Kaale et al., 2005, Gill, 2012, Al-Balushi, 2017, Swancutt et al., 2017, Souza et al., 2021) and Role Activity Diagram (RAD) (Ould and Roberts, 1986, Ould, 1992, Odeh et al., 2002, Ould, 2007, Shukla et al., 2015).

Table 2.2 Comparing process mapping methods provides a comparison of these methods based on their ability to model different attributes at various levels of granularity. Each technique has certain advantages, though RAD, by contrast, provides a more in-depth and realistic representation of the system.

Table 2.2 Comparing process mapping methods

Capabilities / Methodology	Process mapping and modelling						
	Show start and end of a process	Show sequential flow and steps in a process	Show sub-processes	Show decision questions & possible outcome	Show simultaneous processes	Show roles performing activities within a process	Show interactions between roles
Data flow diagram	Yes	Yes	No	No	No	No	No
Value Stream Mapping	Yes	Yes	Yes	No	No	No	No
Flow chart	Yes	Yes	Yes	Yes	No	No	No
Role Activity Diagram (Proposed in this study)	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Adapted from Amissah and Lahiri, 2022

They provide a detailed yet easily understood solution for mapping complex systems and can be used to analyse and improve complex processes by enabling the detection and removal of bottlenecks (Abu Rub et al., 2008, Zhao et al., 2009).

RADs can serve as a communication tool for those with an in-depth knowledge of processes by facilitating communication about processes to identify areas that need attention (Abu Rub et al., 2008, Zhao et al., 2009). They focus on roles that perform activities and the interactions that occur within the processes including multi-level interactions. These processes are sometimes parallel and collaborative and can also occur with simultaneous and sequential activities. RADs can help healthcare organisations understand their processes well before embarking on process improvement steps (Abu Rub et al., 2008). RADs can be used on their own or to support inputs to dynamic techniques such as simulation; therefore, a decision was made to use this over other available tools. Also, there is no reported ED application outside of this study though applied in other areas of the healthcare system (Martinez-Garcia, 1997, Shukla et al., 2014, Shukla et al., 2015).

2.8 Conclusion

In this chapter, the problems facing EDs have been reviewed with a particular emphasis on crowding. The causes and solutions of crowding have been explored in light of the commonly used input-throughput-output model, with throughput emerging as the area of focus. The review of process engineering techniques showed that what is being hailed as lean application in healthcare is simply an application of tools in isolation rather than a complete acceptance of the lean philosophy. Simulation modelling, particularly DES, offers benefits of its usage in ED. Irrespective of the methodology of choice, the point has been made that the input is significant, making granularity key in any process improvement project. A review of commonly used process mapping methodologies that provide the requisite input was conducted and concluded that RADs provide the level of granularity needed to explore complex systems such as ED.

The next chapter provides information about the Research Methodology, detailing the study design and the methods for data gathering and analysis.

Chapter 3

Overall Study Plan

This chapter provides details about a model-driven methodology that served as an overall plan for the study. It outlines the detailed methodological steps of how quality improvements can be achieved. As discussed in Chapter 2, several approaches have been utilised in hospital process improvements, particularly in solving ED problems such as crowding, yet the problem remains. Therefore, it was important that the current research could provide upfront, a step-by-step guide towards addressing the problem of bottlenecks in the ED with the subsequent chapters operationalising these.

3.1 Introduction

This research examined care processes in the ED to develop a model-driven approach to solving the problems identified. As described in Chapters 1 and 2, the ED is a complex unit with rising and unpredictable demand expected to provide quality care to patients in a timely manner. It was essential to capture information that would help to examine care processes and quality indicators across the ED. Quality improvements relating to ED waiting times have been recorded extensively in literature. Yet, limitations identified in previous studies include using small sample size, along with limited and non-granular data (Best et al., 2014, Hurwitz et al., 2014, Mohiuddin et al., 2017). Effective and innovative methodologies are required to capture and model care processes accurately to identify and address bottlenecks. The systematic modelling of ED care processes would lead to quality improvement in relation to the 4HQI.

3.2 Review and Selection of Research Methods

Healthcare modelling needs to move beyond just having state-of-the-art models to ones that have been developed through analysis of various information and data, including best practices and evidence. In Figure 3.1 below, the state-of-the-art models (M1) are usually tried and tested in a local setting where they are contextualised based on the service delivery, system expectations and the funds available to provide the services required (M2). Given the aforementioned complexities involved in the provision of care and the nature of the ED, an exploratory framework was used to model and analyse the generic processes of care that were carried out in an emergency department to understand and examine the flow of patients into the department and the variations that exist. This entailed the use of a mixed-method approach that combined both qualitative and quantitative data. The information captured on the actual design of the system (M3) would inform the future design of the ideal flow model (M4) with improved processes and system performance. The diagram below represents the transition from a state-of-the-art model to a model that shows ideal flow as described above.

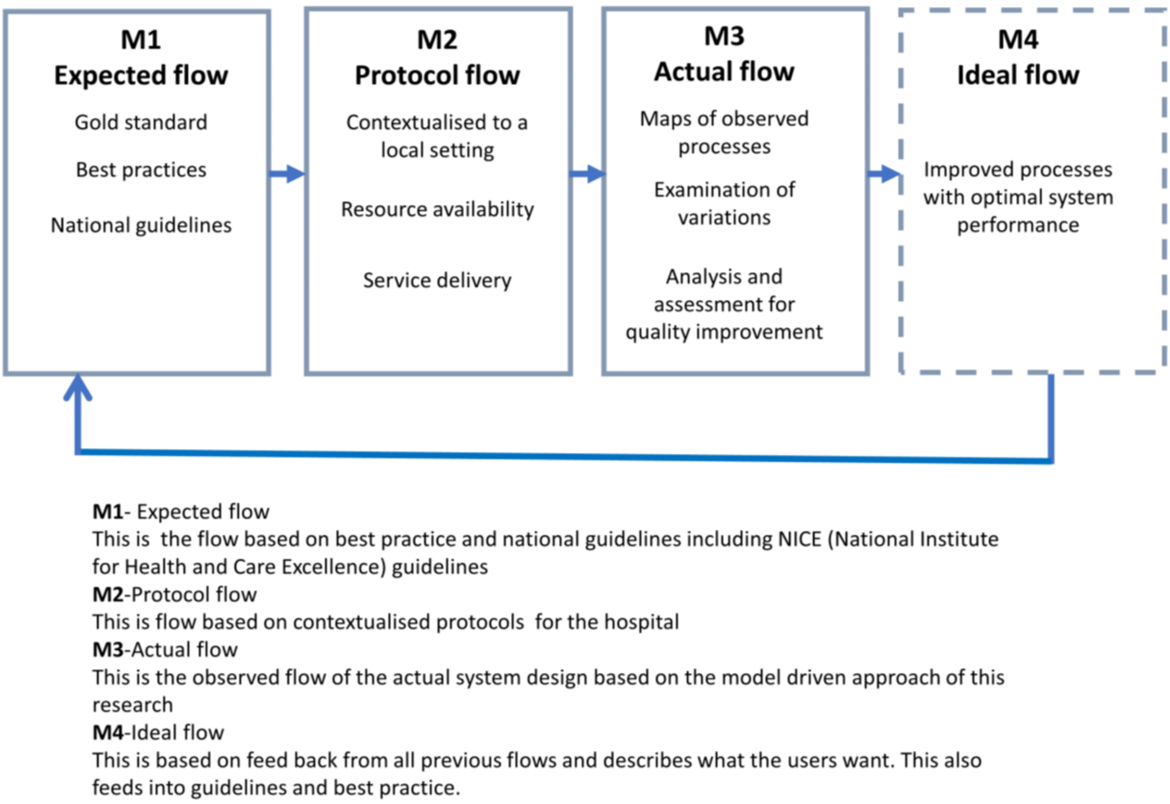


Figure 3.1 Healthcare modelling

Source: Author

3.3 Study Design

Given the exploratory nature of this study, it was advisable to utilise multiple sources of data (Yin, 2009). After reviewing both qualitative and quantitative methods, it was decided that this research would benefit from both approaches to capture the information required. Data gathering and analysis in the study first involved semi-structured interviews followed by the analysis of standard anonymised routinely collected hospital data.

Applying Donabedian's structure-process-outcome model that was introduced in Chapter 2, this study focused on the following elements:

Structure: Ethical approval, study setting, sampling, and recruitment of staff.

Processes: The processes were measured through qualitative and quantitative methods. Process modelling through RAD was used to capture the detailed maps of the processes in 7 steps; whilst statistical analysis was used to analyse the quantitative data.

Outcome: Steps were taken to address the identified bottlenecks, and the outcome of the improvements was measured using simulation modelling.

3.4 Research Resources

Primary sources of data:

- Observation
- Informal consultation
- Semi-structured interviews with stakeholders
- Anonymised routinely collected hospital data

Secondary sources of data:

- Hospital Episode Statistics (HES) data (Data warehouse containing details of all admissions, outpatient appointments and ED attendances at NHS hospitals in England)
- Existing data from case study hospital(s) (Floor plan, staff rota, shift patterns, etc.)
- Journal papers and other publications
- Textbooks

3.5 Details of the Research Methodology

The qualitative data were derived from stakeholder interviews, as depicted in the diagram below. The topics for the semi-structured interview questions are detailed in Appendix C.1. The interview started with the role of the individual in the ED care process, requesting details of activities and interactions the individual had with other staff, the critical decisions they made and the supporting documents for the decision. The participants were also asked about the quality indicators they must follow, how they manage breach scenarios, and what resources and information they needed to perform their role. Any previous involvement in process improvement was also ascertained as well as suggestions they had on processes that could be changed to bring about improvements. The participant information leaflet is in Appendix C.2, and the interview de-brief information can be found in Appendix C.3. Gathering stakeholder data were essential because of the need to capture the system design. These interviews provided accurate information, which was used as inputs in modelling patient flow for simulation and analysis. Results were then used in a DES model for quality improvement, where changes in process and resources could be analysed in the simulated environment.

An iterative step-by-step methodology was used in conducting this study which involved four main steps, as shown in Figure 3.2 below. This chapter provides an overview of each of the steps, while further details are provided in subsequent chapters. Chapter 4 provides details about step 1; Chapter 5 provides details about step 2. Finally, details about steps 3 and 4 are provided in Chapter 6.

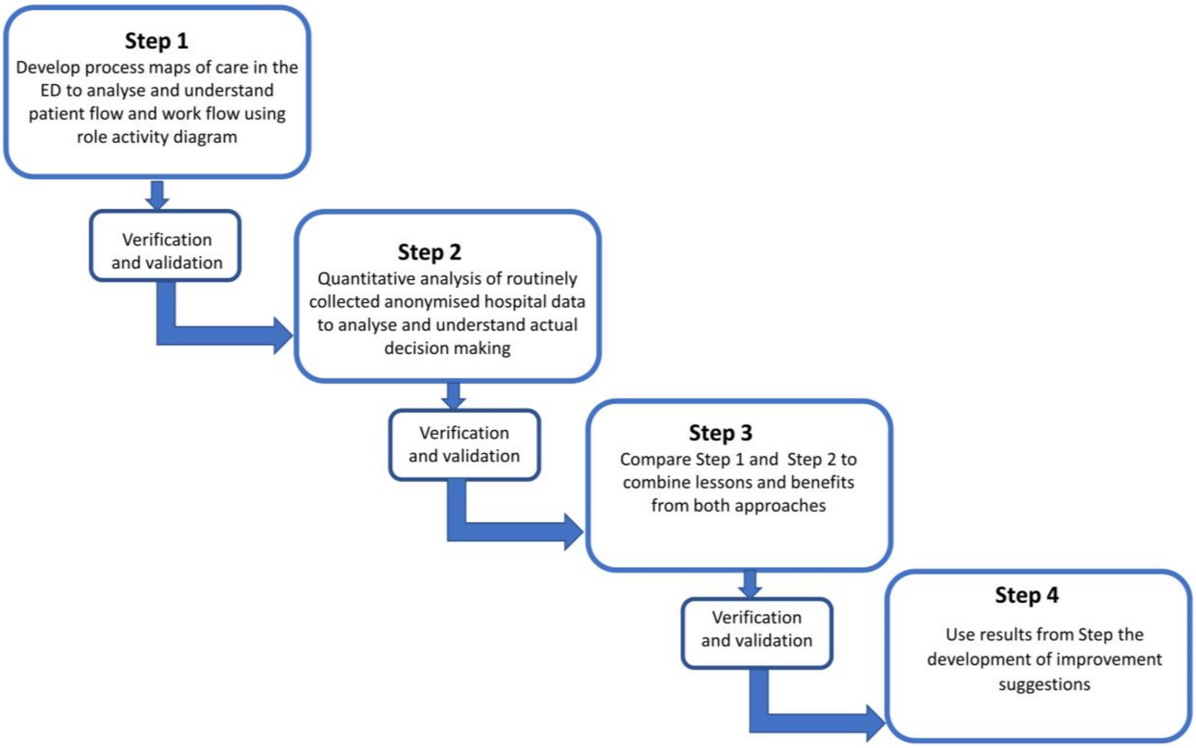


Figure 3.2 Research methodology

Source: Author

Interviews conducted supported the development of process maps to help understand and examine the patient and workflow; step 1. This was achieved through the use of RAD. The next step was quantitative analysis of routinely collected hospital data to analyse decision-making and provide further insight into the patient flow; step 2. In step 3, the models developed in step1 were compared to the statistical data analysis from step 2. Simulation and analysis of both quantitative and qualitative data supported the development of improvement suggestions, forming the methodology's final step.

Each of the four steps described in Figure 3.2 above required the use of software and equipment to complete the various tasks involved. The resources required and tasks completed to execute each step are detailed in Table 3.1 below. In the first step, the development of the process maps required the use of an audio recorder, Microsoft (MS) Word and Visio for conducting the interviews, developing the RADs and undergoing verification and validation processes. The quantitative analysis employed the use of MS Excel and IBM SPSS (International Business Machines Statistical Package for the Social Sciences) software.

Table 3.1 Research steps

1. Development of process maps	2. Quantitative analysis	3. Integration of qualitative and quantitative data	4. Solutions for improvement
Software/equipment used			
Audio recorder, MS word and MS Visio	MS Excel and IBM SPSS	IBM SPSS, MS Excel and MS Visio	IBM SPSS, MS Excel MS Visio and Simul8
In-depth interviews with stakeholders to gather information to derive systems models within the ED RAD development of selected processes Verification and validation of the model	Checks for errors, duplications, outliers and missing values. Baseline descriptive statistical examination into breaches Univariate, bivariate and multivariate analysis to determine statistically significant variables and derive predictive models. Verification and validation of models	Quantitative data analyses to ascertain the existence of bottlenecks identified in Step 1 Verification and validation of RAD models against data Results from the quantitative data analysed against RADs to assess current system performance.	Identification of areas for improvement. DES model development. Verification and validation of DES models Case study to test improvement suggestions Iterations of models to analyse the effects of changes in the input parameters on LOS reduction.

Source: Author

The data were first cleansed by checking for errors, duplication, outliers and missing values. Baseline analysis was then conducted, and statistical methods were applied. Integration of qualitative and quantitative data followed an analysis of the quantitative data against the bottlenecks. The final step involved testing the improvements suggestions through DES using available data.

3.6 Data Gathering

Data gathering entailed various steps starting with an application for ethical approval, followed by a plan for the acquisition of qualitative data from the study site. This included sampling and recruitment to conduct interviews for the RAD development. Further details are provided in the subsequent sections.

3.6.1 Ethical Approval Application

Interviewing was necessary to fulfil the objective of obtaining details about the ED's system design. A study protocol was submitted to BSREC (Biomedical & Scientific Research Ethics Committee) for ethical approval, which was granted on 11th December 2015. l. A copy of this approval is in Appendix C.4 with a reference code of REGO-2015-1715. This was followed by an application for ethical approval from the Research and Development (R&D) office of the study site.

3.6.2 Qualitative Data

Patient care, a process-intensive service, generates highly granular information, requiring a methodology that can effectively model such granularity. Several approaches have been used during process modelling to help visualise the process and support decision-making. A review of literature shows that RAD, compared to other approaches, has the ability to model granular information by capturing parallel processes and the interactions between roles, including multiple interactions, responsibilities, sequential and simultaneous decisions made (Ould, 2005). The resulting model from this approach can illustrate the interrelations between patient care processes with that of system-level factors in an in-depth way and therefore selected as a suitable tool for this study (Ould, 1992). RAD is also useful in capturing the structure that exists in an organisation (Odeh et al., 2002). It is effective in representing features of a hospital's interactions, such as communication at multiple levels and parallel and collaborative processes. Using the RAD methodology, this study developed detailed system models of the crucial multidisciplinary collaborations involved in the care of patients in ED. The data required to construct the RAD was obtained by conducting semi-structured interviews with stakeholders who were staff at the study site to understand the roles, responsibilities, information sharing, and interactions with patient care processes. This assisted in the development of detailed processes that were carried out and resource models used in the ED and other associated departments such as the Clinical Decisions Unit.

3.6.3 Study Setting

The study site for this research is a large teaching hospital with a Type 1 emergency department. As a Type-1 site, it is a major ED that provides consultant-led 24-hour service seven days a week with full facilities for resuscitation. It is a regional centre for cancer and provides highly specialist services for liver, cardiac, burns and plastic. The average patient attendance at this ED during the interview period was 315 patients per day (NHSDigital, 2017), making it a very busy department with approximately 150 medical and clinical staff comprising consultant doctors, trainee doctors, emergency department practitioners (ENP), emergency department technicians (ECT), charge nurses, staff nurses, and auxiliary nurses (Study-site, 2017). The ED is made up of four main areas comprising a Resuscitation (Resus) unit where patients with life-threatening conditions are seen and a Minors unit, also known as See and Treat where patients with minor injuries are treated. It also has a Majors unit for patients with complex conditions and a GP-in-ED area for simple conditions that can be managed by a GP (general practitioner).

Patient attendance at the hospital has increased over the years. The increased growth in attendance contributed to the 95% waiting time QI not being achieved in any month in 2017/2018 due to the increased pressure on the department. This also led to delays in ambulance handover (Study-site, 2018). Similar to other EDs in England, this ED has not achieved the 4-hour QI since Dec 2015 (Blunt et al., 2015, Murray et al., 2017).

3.6.4 Sampling

Due to the operational nature of the tasks performed, interviewees were skewed towards nursing staff (Saville et al., 2019). The types of staff interviewed included nurses, senior sisters, charge nurses, ED coordinators, doctors, matrons, and staff members from other departments and teams in the hospital, such as staff from the clinical decisions unit and site management. Furthermore, since different staffing levels during out-of-hours have been shown to affect care processes in hospitals (Keogh, Jul 2013), staff who work different shifts were also interviewed. The subtopics for the interviews are provided in Appendix C.1. The semi-structured interviews were designed according to techniques by Newcomer et al. 2015 (2015) in terms of drafting topics for the interview, setting up and also conducting the interviews. The questions were aimed at gaining an understanding of the roles undertaken by each individual, decisions made along the patient journey, data and resource utilisation as well as improvement suggestions. In all, the study aimed to interview a broad group of staff, totalling 30 participants, given that a sample size of 20 to 30 interviews is generally an accepted range for qualitative interviews of this nature (Boddy, 2016).

3.6.5 Recruitment

This process involved emailing the ED staff explaining the study and requesting their participation. Given the relevance of the topic and existing relations between the researcher and the participating hospital, a high response rate to the request for participation was expected. The participant information leaflet given to the interviewees and the interview de-brief information are presented in Appendix C.2 and Appendix C.3, respectively. To protect the confidentiality of study participants, study materials identify individuals only by professional function. With written consent obtained using the consent form in Appendix C.5, the interviews were audio tape-recorded and the tape-recordings transcribed unless in cases where consent for audio recording was not granted. The transcript responses to the semi-structured interviews formed the raw data for analysis.

3.7 Development of Process Maps

The generic steps for developing the RAD process maps are described below. The application of these steps is described in Section 4.5 (Chapter 4).

Step 1- As described by Shukla et al. (2014), the process of developing an RAD begins by first identifying the key roles involved in the process to be modelled and clearly identifying the scope of the process; this is step 1.

Step 2-This involves conducting interviews with the key roles identified to generate the interview transcripts. The interviews need to be audio recorded where permission has been granted and then transcribed, or notes taken if there is no consent for an audio recording.

Step 3 – The transcripts are then marked up in Microsoft word to identify the critical procedural terms that will be useful for constructing the RADs. These include specific roles carrying out specific processes of care, activities performed, interactions between roles, resources, decisions and decision questions. The terms are extracted to form operational statements. Table 3.2 shows the colour coding for the markup.

Table 3.2 RAD Legend

Item	**Colour code**
Roles	
Activities	
Interactions	
Decisions	
Resource	
decision questions	

Source: Author

Step 4 - The next step is to provide an initial overview of the flow as derived from the interview information by constructing several flow diagrams to depict the processes described by the operational statements. This serves as a visual guide in developing the detailed RAD.

Step 5 –To provide a quantitative basis for the RAD development, intermediary matrices have to be generated to show relationships amongst the operational statements. These matrices are Action-Type (AT), Action-Role (AR) and Interaction-Role (IR) matrices. The extracted terms from step 3 are used to develop these operational statements. The development begins by listing all the key operational statements extracted from the transcripts and carefully indicating the type of action, i.e., activity, interaction, part refinement, case refinement, trigger or an encapsulated process. For the interactions, the interaction driver and receivers have to be indicated and a 'yes' or 'no' as applicable to case refinements. The roles involved must also be specified in addition to the interaction drivers and receivers. The description of the matrices, including the equations and tables presented below, have been adopted from earlier works by Shukla et al (2014).

3.7.1 Action-Type Matrix

This matrix provides a relationship between the extracted operational statement depicting actions and the type of action that it represents, be it an activity, interaction, trigger, part refinement, case refinement or an encapsulated process. The rows in the matrix represent the statements, and the columns indicate the RAD notation relating to the action being described. A value of 1 shows that relations exist otherwise, the value is set to 0. Table 3.3 below illustrates an AT matrix with the operational statement as ‘Action 1, Action 2,….Action N’ which can be represented mathematically as:

‘Action 1, Action 2, …, Action N’. Mathematically,

$$[AT]_{ij} = \begin{cases} 1, & if\ Action\ i\ is\ of\ type\ j \\ 0, & otherwise \end{cases} \quad (1)$$

Table 3.3 Action-type matrix

Action - Type	*Activity*	*State*	*Trigger*	*Start Role*	*Case Refinement*	*Part Refinement*	*Encapsulated Process*
Action 1	*0*	*0*	*1*	*0*	*0*	*0*	*0*
Action 2	*1*	*0*	*0*	*0*	*0*	*0*	*0*
:	*:*	*:*	*:*	*:*	*:*	*:*	*:*
Action N	*1*	*0*	*0*	*0*	*0*	*0*	*0*

Source: Shukla et al., 2014

3.7.2 Action-Role Matrix

This matrix provides a relationship between the actions in the extracted operational statement and the role performing the action. This is useful when drawing the RADs as it begins with first drawing the roles before other RAD concepts are illustrated. The rows in the matrix represent the statements, and the columns indicate the roles. In Table 3.4 below, an AR matrix is illustrated with the ‘N’ number of actions performed by ‘R’ roles and can be represented mathematically as:

$$[AR]_{ij} = \begin{cases} 1, & if\ Action\ i\ is\ of\ type\ \ j^{th}\ role \\ 0, & otherwise \end{cases} \quad (2)$$

Table 3.4 Generic Action-role matrix

Action - Role	*Role 1*	*Role 2*	...	*Role 'R'*
Action 1	*0*	*0*	...	*0*
Action 2	*1*	*0*	...	*0*
:	*:*	*:*	*:*	*:*
Action N	*1*	*0*	...	*0*

Source: Shukla et al., 2014

3.7.3 Interaction-Role Matrix

This matrix shows the interactions that exist between two or more roles. The details of the interactions are represented by the rows and roles interacting are represented by the column with an indication of the role driver and receiver (s). Table 3.5 below illustrates an IR matrix with a 1 to I number of interactions. The driver of the role is indicated by 1 and receiver (s) by 2, otherwise, 0. This can be represented mathematically as:

$$[IR]_{ij} = \begin{cases} 1 \;\; if \;\; j^{th} \; role \; is \; a \; driver \; of \; i^{th} \; Interaction \\ 2 \;\; if \;\; j^{th} \; role \; is \; a \; receiver \; of \; i^{th} \; Interaction \\ 0 \qquad\qquad\qquad\qquad Otherwise \end{cases} \tag{3}$$

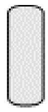
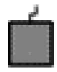
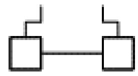
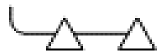
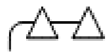
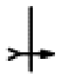
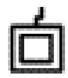
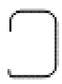
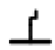
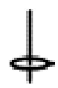
Table 3.5 Generic Interaction-role matrix

Interaction - Role	*Role 1*	*Role 2*	*Role 3*	...	*Role 'R'*
Interaction 1	*0*	*2*	*1*	...	*1*
Interaction 2	*1*	*0*	*0*	...	*0*
:	*:*	*:*	*:*	*:*	*:*
Interaction I	*1*	*0*	*1*	...	*0*

Source: Shukla et al., 2014

Step 6 – Using Microsoft Visio software, the matrices are then followed through step by step and represented graphically by the RAD notations in Table 3.6 below to plot each item

Table 3.6 A description of RAD concepts and corresponding graphical representation

RAD Concept	General description	Graphical notation
Role	A role performs a set of activities to achieve a particular goal. A role can be an individual, a group of people or equipment.	
Activity	A unit of work performed by a role is an activity	
Interaction	Interaction represents a collaboration between roles to achieve the objective of the process	
Case Refinement	A case refinement represents a decision question and the possible outcomes.	
Part refinement	The part refinement symbol represents activities done simultaneously by a role.	
Trigger	A trigger represents an event that starts the activity thread.	
Encapsulated process	An encapsulated process symbol represents a sub-process on the main diagram. The sub-process is then expanded on a separate diagram	
Loop	A loop symbol is used to represent part of the process that repeats itself	
Stop	The stop symbol marks the end of a process by ending a thread.	
State	The state symbol is used to describe what is true before or after an action	

Source: Adapted from Ould and Roberts, 1986, Shukla et al., 2014 and produce the diagram. The table provides a description of each of the RAD concepts, a general description, and a graphical notation for the concept.

Step 7- This entails the verification and validation process. The RADs must be cross-checked against the transcripts to ensure that they accurately represent the information provided in the interviews. They have to be presented to the staff who were interviewed to verify them, and any additional information provided must be used to update the diagrams. For validation, the diagrams must be presented to staff who were not interviewed but have in-depth knowledge about the process. Again, further information supplied must be incorporated in finalising the RADs.

3.8 Quantitative Data Request

Quantitative data were also required in addition to the qualitative data obtained through the RAD development to provide further information about decisions that were made along the patient journey. The data were needed for analysis to identify factors that led to the breach and explore solutions to address waiting time challenges. The subsequent sub-sections provide information about the data requested; both for ED patients and inpatients and a brief description of the statistical analysis.

Data request for standard anonymised routinely collected hospital data from the study site was submitted to the Research and Development office. It was agreed that the data would be stored on the university's secured server and could only be accessed via a password shared with the researcher. The only people who had access to the data were the researcher and academic supervisor. Several variables were required to investigate the complexity of patients' length of stay when attending the emergency department.

3.8.1 ED Patient Data

Retrospective data covering a period of 2 years from January 2017 to December 2018 were requested with the following variables of interest:

Pseudo identification, demography (age and gender), mode of arrival, presenting complaint, referral source, partial patient post code, partial postcode data of primary care providers, date and time data of arrival, time seen, assessments, date and time of medical decision, primary and secondary diagnosis, primary and secondary investigations, procedures, disposal status, departure time and date, EM-HRG.

3.8.2 Inpatient Variables

Making changes in the ED alone is not enough, as what happens in this department impacts the overall hospital. Therefore, looking at the inpatient data for the patient who gets admitted following an ED visit was essential. For these patients, the following were the variables of interest:

Spell number, admission date and time, number of episodes, first and last ward of discharge, ICD (International Classification of Disease) and diagnosis code, associated category, description of the diagnosis, primary and secondary diagnosis, FCE-HRG (Finished Consultant Episodes Healthcare Resource Groups) code, inpatient activity data including discharge date and time, discharge destination.

Exclusion Criteria: This study only examined data involving patients aged 17 or older.

3.8.3 Data Received

The data request was followed by several discussions with the information governance team and informatics department, which took place over the telephone, via emails and through face-to-face meetings. This spanned six months to arrive at a set of variables that provided the information required for the research without compromising patient safety in ensuring that information governance principles had been adhered to. The data were initially sent to the researcher's NHS address and then transferred to a secured drive provided by the university, which was password protected and could only be assessed by the researcher and academic supervisor.

3.9 Quantitative Analysis

Before analysis, the data were checked for errors, duplications, outliers and missing values. Descriptive statistics were used to describe the sample and to conduct a baseline examination of the sample's health service utilisation, including hospital visit patterns. The data were then compared to understand the differences in health service utilisation patterns between patients who experience longer lengths of stay in the ED and those who do not in relation to the 4HQI. The use of both bivariable and multi-variable analysis was employed. For dichotomous measures, Pearson's Chi-square to test the equality of proportions was used for categorical variables in addition to the Kruskal-Wallis test for the continuous variables.

Regression analysis helped to identify statistically significant predictive variables. Specifically, logistic regression was used to examine decision-making processes at the time of the patient visit of the sample that led to breaches in the quality indicator. A generalized linear model was used to model the patient's length of stay and understand factors that have a strong association with predicting how long a patient will stay in ED. It was hypothesised that; the rich texture of the collected data would generate interesting analysis opportunities, especially towards understanding some of the non-obvious factors that trigger quality breaches. Statistically significant results, along with the activity-based systems models, became inputs to the simulation modelling. Additional details of the statistical analysis are provided in Chapter 5.

3.10 Integration of Qualitative and Quantitative Data

The quantitative data were further analysed to confirm the existence of trends discovered in the qualitative analysis. The two elements of data were integrated to derive suggestions to address the bottlenecks identified. The solutions were tested using discrete event simulation as briefly described in the next section. Further details about the DES model development and analysis are provided in Chapter 6.

3.11 Solution for Improvement

Improvement solutions were developed and tested using simulation modelling. The important steps for developing a discrete event simulation model can be listed as beginning with a formulation of the problem, setting the objectives of the simulation and then developing a conceptual model (Peng et al., 2020). This is then followed by data collection, design and building of the model, which is verified and validated before analysing to arrive at a set of solutions (Peng et al., 2020). In this regard, the information from the qualitative interviews was used to develop process maps of the care process in the form of a condensed RAD-informed flow chart. Commercially available simulation software, specifically Simul8 from Simul8 Corporation, was utilised to transform the flow chart into a discrete event simulation model for the operational-level process analysis.

Results from the quantitative data analysis were used as input for the developed models and also used to assess the current system performance. Once the model was validated, it was then used to develop suggestions and recommendations for improving the ED patient flow performance. Several iterations of the models were undertaken to analyse the effects of changes in the input parameters on waiting time output.

3.12 Conclusion

This chapter has provided an overview of the overall study plan, which was applied, and details of the steps followed in the model-driven methodology. This methodology could also serve as a useful generic guide for waiting time improvement initiatives in various settings. The next chapter provides further details about the process modelling of an ED to derive the systems model using role activity diagrams in a case study application.

Chapter 4

Process Modelling to Derive Systems Model

This chapter provides information about process modelling to derive the systems model of the emergency department using role activity diagrams. It provides information on how the steps outlined in Chapter 3 were applied in an emergency department of an Acute hospital in the UK to derive process maps. These maps revealed bottlenecks that impacted flow and affected patient length of stay. It concludes with recommendations on how the bottlenecks could be addressed.

4.1 Introduction

Emergency departments are fast-paced environments that experience complexities at all levels (Smith and Feied, 1999). The need for sufficient information to support decision-making when processing a patient sometimes requires interactions with staff both within ED and with other departments (Shukla et al., 2015). These interactions can generate variations affecting patient flow that lead to bottlenecks. Modelling ED processes at a granular level provide the necessary information to facilitate a better understanding of the clinical and non-clinical sources of variations so that they can be managed better. Simulation studies have been conducted to address ED bottlenecks (Gunal and Pidd, 2010, Vanbrabant et al., 2019a, Castanheira-Pinto et al., 2021). Yet, these studies do not always use realistic models as inputs to the simulation, which then affects the improvement suggestions made (Vanbrabant et al., 2019b). The systems model can then serve as input to simulation studies. The collection and modelling of granular information emerged as a necessary initial step in deriving the model through process mapping.

4.2 Informal Consultation

Process maps (Bicheno, 2004, Calder et al., 2012) are one of the most commonly used tools in business and industry to support quality improvement strategies for complex systems (Anjard, 1996, Zhao et al., 2009). As demonstrated in Chapter 2 through the comparison of the role activity diagram to other process modelling techniques, an RAD has the ability to model processes of care that take place in an environment as complex as an ED. In this research, the process mapping started with direct observation of processes in the ED at the chosen hospital, followed by a number of informal consultations, which commenced in January 2014. This formed part of the initial scoping exercise to understand patient demand and to gain a practical in-depth understanding of the situation in the department and the processes that were carried out.

The aforesaid initial exercise provided beneficial information about the processes performed. The data collected during these processes assisted with the sampling and selecting the types of information to be collected. Figure 4.1 below is a rough physical layout of the ED at the study site developed during the informal consultation period. This figure provides a diagrammatic view of the setting in which the process modelling was conducted. It can be seen that there are two main entry routes into the department: one for ambulance arrivals and the main entrance for self-presenting patients. The Resuscitation area has six bays, and the Majors area has sixteen cubicles, five of which have patient monitors as indicated by an asterisk. A streaming nurse is stationed in a small room with a glass window close to the main entrance and a waiting area for patients to sit in after registering at the reception. The main role of this nurse is to direct patients to the appropriate unit to be attended to following a brief description of their presenting complaint. Triage is undertaken in the assessment room marked AR for patients waiting to be seen in the Majors unit, whereas those who are to be seen in Minors are directed to the Minor injury unit. Imaging facilities such as computer tomography (CT) scans and X-rays are located within the department though managed by staff from the imaging department. The unmarked rooms are offices, seminar rooms and storerooms.

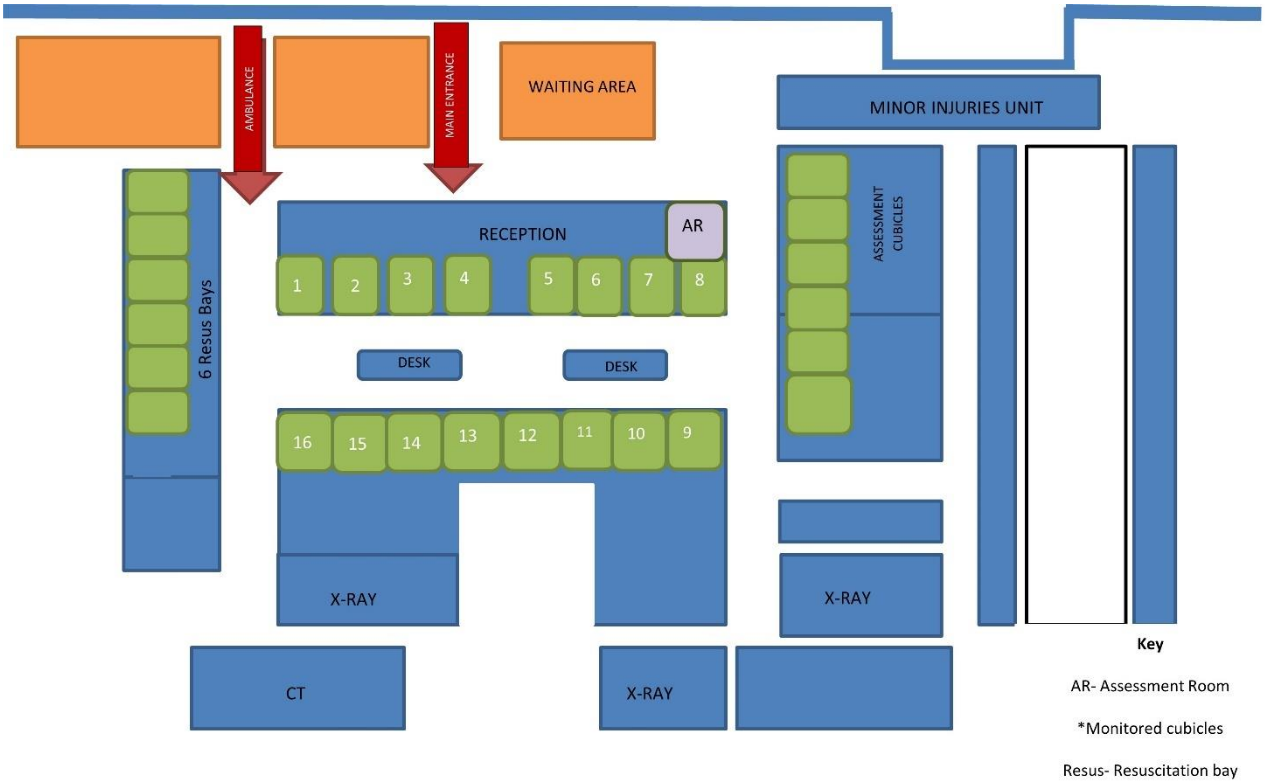


Figure 4.1 Layout of Emergency Department

Source: Author

The initial conversations during the informal consultation period were with a senior staff member of the ED, a senior staff member from the Clinical Decisions Unit, the process improvement manager and a process improvement officer. The informal consultations supported the development of 'higher-level' illustrations of the processes of care at the ED, as shown in Figure 4.2 below. There are two entry routes into the ED where a patient either arrives in an ambulance or without one. The patient who arrives by ambulance is booked in by a coordinator after being offloaded and proceeds with initial assessment (i.e., triage). After being entered into the system and having their information forwarded to the appropriate printer, the patient who arrives without an ambulance also undergoes an initial assessment. The patient follows the same path after triage, where they are assessed by a doctor who requests tests if required. This process is followed by results being analysed and a decision made regarding the patient disposition or more tests requested if required. The patient leaves the ED by being discharged to go home, transferred to CDU or admitted directly to a department.

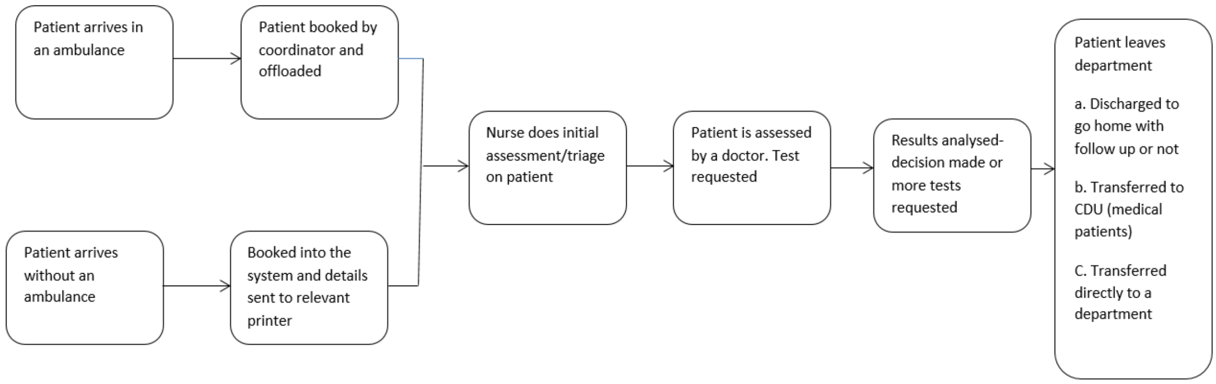


Figure 4.2 Initial view of ED processes

Source: Author

The processes shown in the diagram above (Figure 4.2) was based on the information about the flow of patient, which confirmed information previously obtained from literature (Lane et al., 2000, Hoot et al., 2008, Bair et al., 2010). It provided an elementary illustration of the processes of care in the ED. Direct observation, informal consultation and then conducting formal semi-structured interviews, done with ethics approvals, to enable the development of the RAD was a very useful methodology that assisted in an evolving understanding of processes. This ongoing gradual process of understanding flow in the ED was essential to conducting an accurate system modelling for improvement.

4.3 National and Regional Data

During the informal consultation period, a review of the publicly available hospital episode statistics (HES) data revealed that the study site, similar to other hospitals across England and the region, had not met crucial waiting time expectations, including the 4HQI. Table 4.1 compares the study site data against the national and regional data for 2015-2016. It features the hospital's performance of 91.8% against the 4HQI. The national performance at 89.1% and the regional at 88.9% all fall short of the expected 95%. The total number of patient attendances to the ED and the number of those who were seen within 4 hours which yielded the percentages are also provided in Table 4.1. The low performance of the hospital generated interest in finding out the reason behind it. The hospital's 2013/2014 annual report showed that there had been a 2.78% increase in patient attendance to ED in 2014-2015 compared to 2012-2013 data (Study-site, 2014). This raised questions about the rise in patient attendance being a potential reason for the decline in performance. A review of the literature confirmed that possibility in addition to other factors that might have contributed to declined performance such as an increase in patient complexity and acuity, seasonal attendance and a rise in non-urgent visits (Asplin et al., 2003, Hoot and Aronsky, 2008, Boyle et al., 2014).

Table 4.1 ED attendances (excluding planned attendances)

Description of provider	HES (2015-2016)			HES (2016-2017)			HES (2017-2018)		
	Total Attendances	Number of patients who spent less than 4 hrs in ED	% of patients who spent less than 4 hrs in ED	Total Attendances	Number of patients who spent less than 4 hrs in ED	% of patients who spent less than 4 hrs in ED	Total Attendances	Number of patients who spent less than 4 hrs in ED	% of patients who spent less than 4 hrs in ED
England	20,168,071	17,975,204	89.10%	20,603,774	17,775,238	86.30%	21,011,705	17,959,517	85%
Region in England	5,210,271	4,630,053	88.90%	5,361,990	4,548,235	84.80%	5,472,885	4,576,330	84%
Study Site	108,463	99,625	91.90%	115,226	94,216	81.80%	117,460	97,370	83%

Source: HES Data

Furthermore, informal information obtained from being embedded in the hospital also indicated that the hospital's performance was not improving. Hence, the decision was made to observe the site's ED processes more systematically to better understand the patient flow. There was also a need to comprehend what was happening on the shop floor. This was due to informal observations made in the department that the current statistics did not fully capture the information needed to identify bottlenecks causing this decline in performance. The HES data were continually reviewed to monitor the hospital's performance during the interview period and the following year, 2018. Similar to the information provided for 2015-2016, Table 4.1 also includes information for 2016-2017 and 2017-2018. As the total number of patients attending the ED in these two years increased consecutively compared to 2015-2016 data, the percentage of patients who were seen within 4 hours declined, as shown in the national, regional and hospital data presented in the table. The hospital's performance reduced to 81.8% in 2016-2017, with a slight improvement of 83% in 2017-2018.

The aforesaid observations shaped the next steps of the study which led to the request for ethical approval to formally gather data. Details about sampling, recruitment of interviews, the interview process and data transcription have been provided in Chapter 3 as part of the study plan. The following sections detail how they were applied to generate the role activity diagrams.

4.4 Description of Role Activity Diagram Generation

The analysis of data derived from the semi-structured interviews provided a detailed representation of the sequence of activities that were carried out while caring for a patient. This allowed for viewing the patient journey in greater detail, including the interrelations between processes involving multiple roles, multi-level communications, and inter-departmental interactions, both sequential and simultaneous as well as parallel and collaborative processes; common features when providing patient care.

4.5 Steps for Role Activity Diagram Development

The detailed steps followed to develop the RAD is described below. This is a case application of the steps outlined in Section 3.7.

4.5.1 Identifying Key Roles (Step 1)

The key roles identified for the development of the interviews were nurses, as they were primarily involved in the day-to-day operations of the various units in the ED (Saville et al., 2019). Each shift was staffed by an Emergency Department Coordinator (EDC), a position that is held by experienced senior nurses who coordinates the activities of the department by means of an overarching role. Each unit was also staffed by nurses who gave feedback to the EDC. The staff in Resuscitation work closely with the doctors to respond to alerts, whilst the operations of the Majors unit were led by a Majors lead who worked with the nurses, healthcare assistants (HCAs) and Emergency Care Technicians (ECTs) in the department while also coordinating with the EDC. The Minors unit was often led by an Emergency Nurse Practitioner (ENP) who could see and treat patients without needing a doctor to confirm discharge. The ENP also worked with nurses in the Minors unit. Another key role was the Triage nurse, who triages patients into the Majors unit or redirects them as required and worked closely with the ECTs.

4.5.2 Conducting Interviews to Generate Transcripts (Step 2)

The interviews focused on understanding the roles, responsibilities and key decisions made by staff when providing care, along with interactions and sequential, simultaneous as well as collaborative activities that occurred along the patient flow. Additionally, the staff were interviewed regarding the resources they needed to carry out their duties, such as equipment, instruments, laboratory results, the availability of inpatient beds, and input from other departments while treating patients with complex presentations. They were also interviewed about additional tasks that needed to be carried out by another unit, such as multidisciplinary expertise and the time required to gather information.

From January 2017 through December 2017, a combination of direct observations, discussions with staff, and semi-structured interviews were used to gather procedural knowledge for the study. Staff were informed about the study through emails. A meeting with the ED manager was held afterwards to continue the conversation and plan the interviewing process. Interview dates were agreed then followed up with a phone call. Staff were also informed at handover meetings in advance of the interviews. Before the interviews, all participants were given the participant information sheet (Appendix C.2) and the interview de-brief sheet (Appendix C.3) to provide more details about the study. The interviews lasted approximately one hour and took place either in seminar rooms in the department or in the clinical area, ensuring that confidentially was maintained. The interviews were audio recorded with participant permission obtained through signing a consent form. Nineteen participants consented to have their interviews recorded, and the responses of the remaining two participants were recorded on paper.

A minimum of two EDCs and two nurses per unit, i.e., Majors, Resuscitation and Minors, were interviewed to ensure that information about each unit was being gathered from more than one individual. The main nursing shifts were a long day which was from 7:30 to 20:00 or a night shift which was from 19:30 to 08:00. The staff to be interviewed were identified by the shift lead (EDC) from the daily rotas, stratified such that each of the required staff roles was interviewed until the minimum numbers were achieved. Staff from other units who worked closely with ED were also interviewed. These staff included the Clinical Decisions Unit, which is a short-stay unit for medical patients, the Old Persons Assessment and Liaison team (OPAL), which assists in managing care for older patients, the Site management team and medical staff. Table 4.2 provides the specific roles and numbers of staff interviewed. An early intention was to interview 30 staff to get their perspectives on these staff responsibilities, as indicated in the sampling Section 3.6.4. However, in all, twenty-one staff were interviewed for the study.

This number provided the required information due to the staff's experience level and therefore saturation was reached. Hence, it was not required to conduct further interviews. Even the least experienced staff had fifteen months (1.25 years) of experience with the most experienced staff having four hundred and nineteen months (34.92 years) of experience. Altogether, more than half of the staff interviewed had over ten years of experience. To provide some context, initial and intermediary skills are achieved in the first twelve months of working in the ED. Staff then progress to Senior nurse band five roles from one to two years. All the nurses interviewed were either a senior band five or a higher banding.

Table 4.2 Staff title and number interviewed

Title of role	Number of staff interviewed
ED Manager	1
Streaming nurse	2
ED coordinator	2
Resuscitation nurse	2
Emergency Care Technician (ECT)	2
Triage Nurse	2
Minors nurse	2 (1 ENP and 1 Staff nurse)
Majors' coordinator	2
OPAL (Old Persons Assessment and Liaison) team	1 Charge nurse
ED consultant	1
Site Manager	1
ED Matron	1
CDU coordinator	1
CDU sister	1
Total	**21**

4.5.3 Marking up Transcripts to Extract Operational Statements (Step 3)

The interviews were transcribed by the author who ensured that the transcripts were fully anonymised. The transcribed interviews formed the raw data for analysis, which was then used to derive flow diagrams and role activity diagrams (RAD) to understand decisions and processes in the ED. The transcripts were marked up using Microsoft word to identify the key procedural terms required for building the RAD, as shown in Table 3.2 in Section 3.7 (repeated below as Table 4.3). The key procedural terms make up operational statements that describe the processes. Excerpts from the marked-up script for the interview with the Majors lead are shown below in Example 4.1.

Table 4.3 RAD Legend

Item	Colour code
Roles	
Activities	
Interactions	
Decisions	
Resource	
decision questions	

Source: Author

Interviewer: *What is the starting point of your role? What activities do you do as a Majors coordinator/lead?*

> ***Participant:*** *The Majors coordinator/lead is running the department, so this is a side-line to the ED coordinator, so my job is to manage the Majors cubicles from 1 to 16. Duties will include ensuring that staff are assessing patients appropriately, the correct drugs and observations are done. I get the handover for each patient, and I use my experience to list jobs that the nurses are required to do for each patient in order to speed up the process, make sure they have all the appropriate tests back in time for when the doctors need them*

Example 4.1 An excerpt from the Majors lead interview script

4.5.4 Developing flowcharts (Step 4)

Several flowcharts were developed from the operational statements to depict the care processes followed in the emergency department in addition to the one presented in Figure 4.2. These flowcharts were updated and combined to result in one "high-level" diagram summarising the processes in the various units in the department, which is displayed in Figure 4.3 below.

Figure 4.3 illustrates a two-panelled ED patient flow, with Panel A showing a generic flow comprising five key steps (I to V) that are commonly followed in an ED. Upon arrival, a patient registers at reception (I) and undergoes triage (II). The patient is then seen by an ED physician, i.e. a Doctor (III), which involves assessment, diagnostics, and if necessary, a re-evaluation (Smith et al., 2017). These steps allow for reaching a medical decision (IV) and subsequent discharge from the ED (V) (Alexander et al., 2016) either to the usual place of residence, admission, or transfer to another provider.

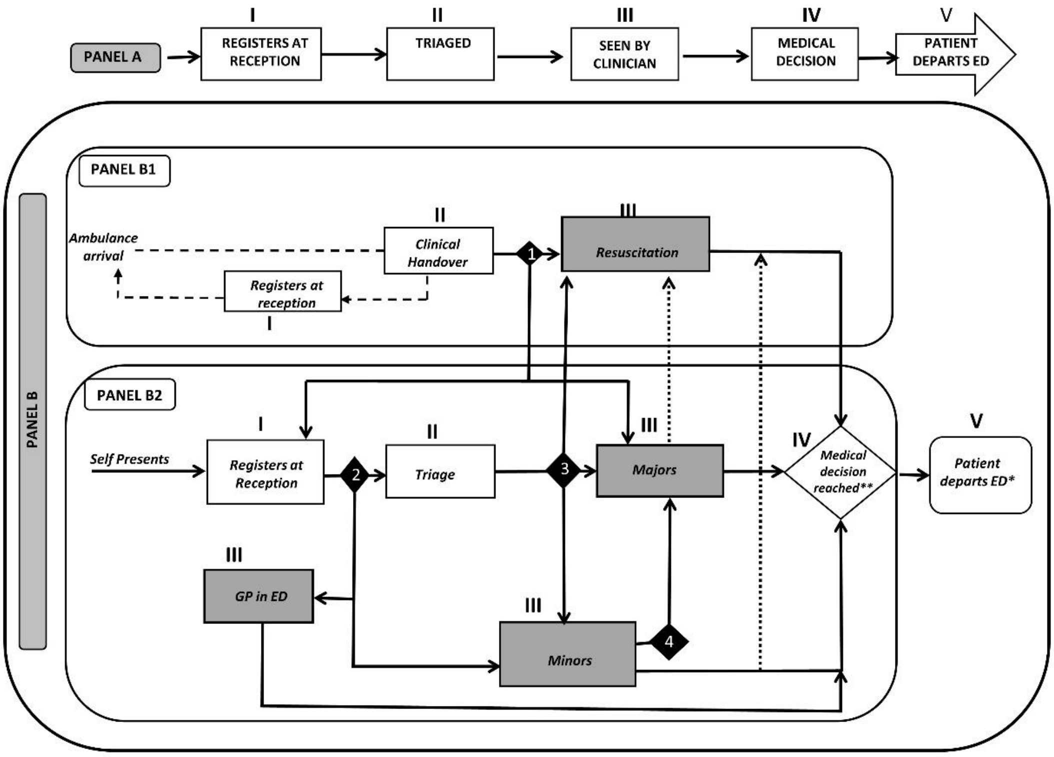


Figure 4.3 High-level flow chart of ED processes.

Note: *Patient outcome: Admitted, Discharged, Transferred, Left without Seen. **Medical decision made in Majors, Minors, Resuscitation or GP-in-ED. GP- General Practitioner. Source: Adapted from Amissah and Lahiri, 2022

There are two modes of arrival for patients presenting to the ED, i.e., ambulance and self-presenting. Sub-panel B1 illustrates the main steps that are carried out for patients who are ambulance conveyances. Paramedics do a clinical patient handover to ED staff upon arrival. Next, paramedics egress the department after checking with reception post-handover and provide a copy of the patient report form. The ED staff receiving the handover performs a rapid assessment of the patient to reach a decision point (DP1) on the most appropriate unit or area to send the patient next. This could be to Resuscitation or to Majors, the unit that sees serious and complex illnesses or injuries. Also, patients deemed suitable to wait are sent to the regular waiting area.

Sub-panel B2 illustrates the route for self-referrals wherein a streaming nurse conducts a visual assessment of the patient upon arrival. The patient then registers at reception and is directed to the most appropriate area (DP2). This can either be a general practice clinic located within the ED for patients meeting a set of criteria, Minors (See & Treat) unit for conditions which are not life-threatening or Triage. The Triage nurse sees patients going into Majors but also ensures that patients are redirected to either Minors or Resuscitation (DP3) if necessary. Emergent conditions can also affect care flow in the ED (Xu et al., 2013, Ross et al., 2019). Consequently, Minors patients can be redirected to Majors (DP4); likewise, deteriorating patients in Majors or Minors could be transferred to Resuscitation. These movements are illustrated with dotted lines in the figure as they happen infrequently. Once treatment is completed, the patient leaves ED.

Figure 4.3 above can be described as a "high-level" depicting the processes in the ED, which helps to understand the general flow. However, the system does not run in this simple form since numerous steps and procedures occur within each box, triggering myriads of variation, as illustrated in the subsequent steps with the developed RADs. Even if the system runs in this simpler form, there will still be problems since the sheer number of patients coming into the department is enormous.

4.5.5 Developing matrices from the operational statements (Step 5)

This stage involved the development of matrices, namely action-type, action-role and interaction-role matrices from the operational statements for the construction of the RADs.

The key processes derived from the transcripts were listed for all the operational statements describing the actions performed in the various units. The statements were then identified by the type of action taking place, i.e., activity, interaction, case refinement etc. The roles performing these actions were specified in addition to the interaction drivers and receivers for each interaction. The individual matrices for all the RADs generated were developed by employing the use of Python programming language to write a script that would simply do a count to establish the action-type, action-role and interaction-role matrices as explained in

Chapter 3. The python script is provided in Appendix D.1. As explained in Section 4.2, the extracted operational statements are used to construct flow charts for the units. The statements pertaining to the Majors unit are used for developing the matrices for the unit. Section 4.6 below provides further details about these operational statements. An excerpt from these statements relating to Majors unit processes P8 to P13 is listed below. The subsequent matrices developed are also presented to illustrate the level of detail involved in developing the RADs.

For example, operational statement P8 in Table 4.4 is captured in Table 4.5; activity type matrix as an interaction, same as P11 and P12. However, P9, P10 and P13 are indicated in Table 4.5 as activities. Table 4.6 shows the role performing the action. Operational statement P8 is being performed by the EDC, P9 and P13 by the patient, P10 and P11 by the Majors lead, and P12 by the staff nurse.

4.5.6 Matrix Tables

Table 4.4 Operational statements and details for matrix tables (Majors Unit)

Process number	Activities	Action_type	Case refinement (Y/N)	Role	Interaction_driver1	Interaction_receiver1	Interaction_receiver2	Interaction_receiver3
P8	Patients assigned to the Majors unit are handed over to the Majors lead	Interaction	--	ED Coordinator	ED Coordinator	Majors lead	Patient	Paramedic
P9	Patient waits	Activity	--	Patient				--
P10	Majors lead lists, on a centrally located whiteboard, all the assessments and tests that the patient must undergo	Activity	--	Majors lead	--	--	--	--
P11	Majors lead discusses listed tasks with the Staff nurse and HCA	Interaction	--	Majors lead	Majors lead	Staff Nurse	HCA	--
P12	Tasks are assigned and completed by the Staff nurse and HCA	Interaction	--	Staff Nurse	Staff Nurse	Patient	HCA	--
P13	The patient waits to be seen by the treating physician	Activity	--	Patient	--	--	--	--

Table 4.55 Action Type Matrix

Process number	RAD Statements	Interaction	Part refinement	Case Refinement	State	Case refinement	Activity	Encapsulated process
P8	Patients assigned to the Majors unit are handed over to the Majors lead	1	0	0	0	0	0	0
P9	Patient waits	0	0	0	0	0	1	0
P10	Majors lead lists, on a centrally located whiteboard, all the assessments and tests that the patient must undergo	0	0	0	0	0	1	0
P11	Majors lead discusses listed tasks with the Staff nurse and HCA	1	0	0	0	0	0	0
P12	Tasks are assigned and completed by the Staff nurse and HCA	1	0	0	0	0	0	0
P13	The patient waits to be seen by the treating physician	0	0	0	0	0	1	0

Table 4.6 Action Role Matrix

Process number	RAD Statements	Receptionist	ED Coordinator	Paramedic	Patient	Majors lead	Staff Nurse	HCA	Doctor	Porter
P8	Patients assigned to the Majors unit are handed over to the Majors lead	0	1	0	0	0	0	0	0	--
P9	Patient waits	0	0	0	1	0	0	0	0	--
P10	Majors lead lists, on a centrally located whiteboard, all the assessments and tests that the patient must undergo	0	0	0	0	1	0	0	0	--
P11	Majors lead discusses listed tasks with the Staff nurse and HCA	0	0	0	0	1	0	0	0	--
P12	Tasks are assigned and completed by the Staff nurse and HCA	0	0	0	0	0	1	0	0	--
P13	The patient waits to be seen by the treating physician	0	0	0	1	0	0	0	0	--

Table 4.57 Interaction Role Matrix

Process number	RAD Statements	Receptionist	ED Coordinator	Paramedic	Patient	Majors lead	Staff Nurse	HCA	Doctor	Porter
P8	Patients assigned to the Majors unit are handed over to the Majors lead	0	1	2	2	2	0	0	0	--
P11	Majors lead discusses listed tasks with the Staff nurse and HCA	0	0	0	0	1	2	2	0	--
P12	Tasks are assigned and completed by the Staff nurse and HCA	0	0	0	2	0	1	2	0	--

Finally, Table 4.7, the interaction role matrix, indicates the interaction driver denoted by 1 and the interaction receiver (s) denoted by 2. This only applies to the statements identified as interactions from Table 4.5, which were P8, P11 and P12. Table 4.6 then shows the interaction drivers (denoted by 1) as EDC for P8, Majors lead for P11 and staff nurse for P12. All other roles were interaction receivers (denoted by 2).

4.5.7 Plotting the RAD Notations (Step 6)

Microsoft Visio software was used to plot the RAD notation items, using the matrices as a guide. Several RADs were developed to focus on key processes and roles in the ED. The five main diagrams developed are listed below:

1. High-level RAD of ED processes
2. Majors unit RAD
3. Streaming and Triage RAD
4. Minors unit RAD
5. ED coordinator RAD

The interviews indicated Majors to be the most crowded unit, as Gillian et al. reported (2015), therefore, a decision was made to mainly focus on modelling the care processes in this unit. The Majors RAD has been provided below in Figure 4.4. The Streaming and Triage RAD shows the pre-majors stage and is available in Appendix D.2. The Minors RAD has also been provided in Appendix D.3 to illustrate processes in another unit other than Majors. Due to the restricted quality of the RAD images provided in this document, electronic versions are available via this link: https://osf.io/64tbr/

4.5.8 Verification and validation (Step 7)

For purposes of verification, a two-step approach was employed. Firstly, the RADs were cross-checked against the transcripts to ensure accurate representation. Follow-up meetings were conducted with the interviewees to explain the developed diagrams and seek their input on the diagrams. Additionally, validation was carried out by presenting the diagrams to staff who were not interviewed initially. Any feedback received was incorporated to update the diagrams. On occasions where information from one staff about a particular process differed from another, the research staff followed up with additional meetings to seek further clarification. In total, six staff provided information regarding verification and validation, as shown in Table 4.8.

Table 4.8 Staff involved in the verification and validation process

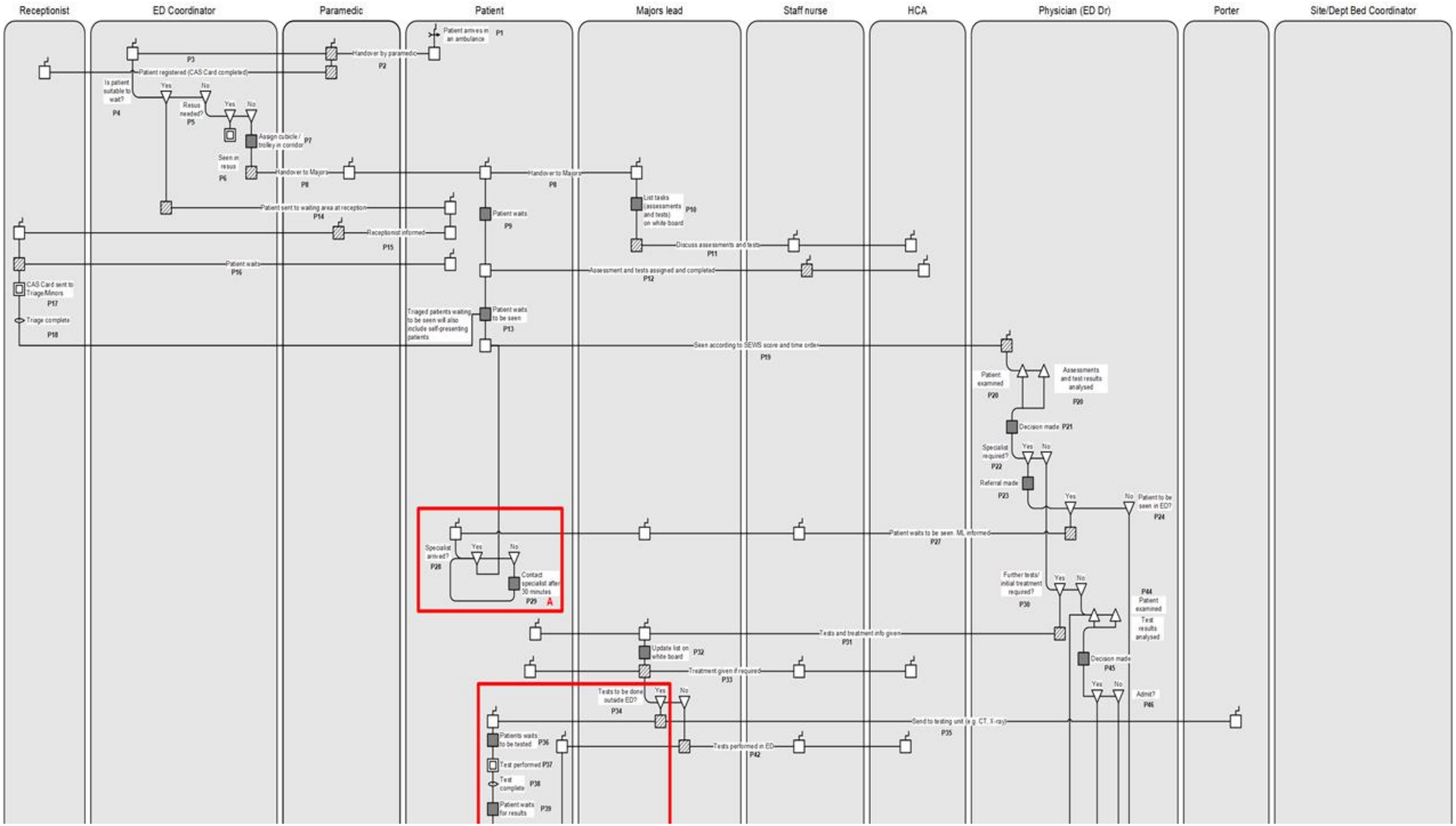
Verification	**Validation**
Majors lead	EDC
ENP	Senior nurse minors
EDC	Majors lead

A note is made here that a follow-up meeting was arranged in the summer of 2021 with an ED Senior Charge nurse, the role centrally responsible for ensuring the department's functions to discuss changes in processes since the start of the global pandemic. The discussion revealed that processes related to the primary focus of this research have not changed. Further details about the Majors unit RAD are provided in the subsequent sections.

4.6 Majors Unit Role Activity Diagram

From the flow chart in Figure 4.3, the entry (panel B) into Minors and GP-in-ED is by self-presenters only. The Resuscitation unit typically receives ambulance arrivals though self-presenters could sometimes be directed here. However, the Majors unit receives patients from both routes, i.e., self-presenters and ambulance conveyances with emergent conditions, sometimes necessitating redirection to Majors from other units. All of these factors signify the complexity and variation of care in this unit.

The Majors unit RAD is shown in Figure 4.4 below. Numerous roles interact to provide care in the Majors unit: an ED Coordinator (EDC), Majors Lead (ML), ED physician, staff nurse, HCA, receptionist, paramedic, site manager, and porter. A total of 73 processes, denoted as P1 to P73, can be divided into 12 main steps to describe the patient flow in Majors.



Receptionist
ED Coordinator
Paramedic
Patient
Majors lead
Staff nurse
HCA
Physician (ED Dr)
Porter
Site/Dept Bed Coordinator
Patient arrives in an ambulance P1
Handover by paramedic P2
P3
Patient registered (CAS Card completed)
Is patient suitable to wait? P4
Yes
No
Resus needed? P5
Seen in resus P6
Assign cubicle / trolley in corridor P7
Handover to Majors P8
Patient waits P9
List tasks (assessments and tests) on white board P10
Discuss assessments and tests P11
Assessment and tests assigned and completed P12
Patient waits to be seen P13
Triaged patients waiting to be seen will also include self-presenting patients
Patient sent to waiting area at reception P14
Receptionist informed P15
Patient waits P16
CAS Card sent to Triage/Minors P17
Triage complete P18
Seen according to SEWS score and time order P19
Patient examined P20
Assessments and test results analysed P20
Decision made P21
Specialist required? P22
Referral made P23
Patient to be seen in ED? P24
Patient waits to be seen. ML informed P27
Specialist arrived? P28
Contact specialist after 30 minutes P29
A
Further tests/ initial treatment required? P30
Tests and treatment info given P31
Update list on white board P32
Treatment given if required P33
Tests to be done outside ED? P34
Send to testing unit (e.g. CT, X-ray) P35
Patients waits to be tested P36
Test performed P37
Test complete P38
Patient waits for results P39
Tests performed in ED P42
P44 Patient examined
Test results analysed
Decision made P45
Admit? P46

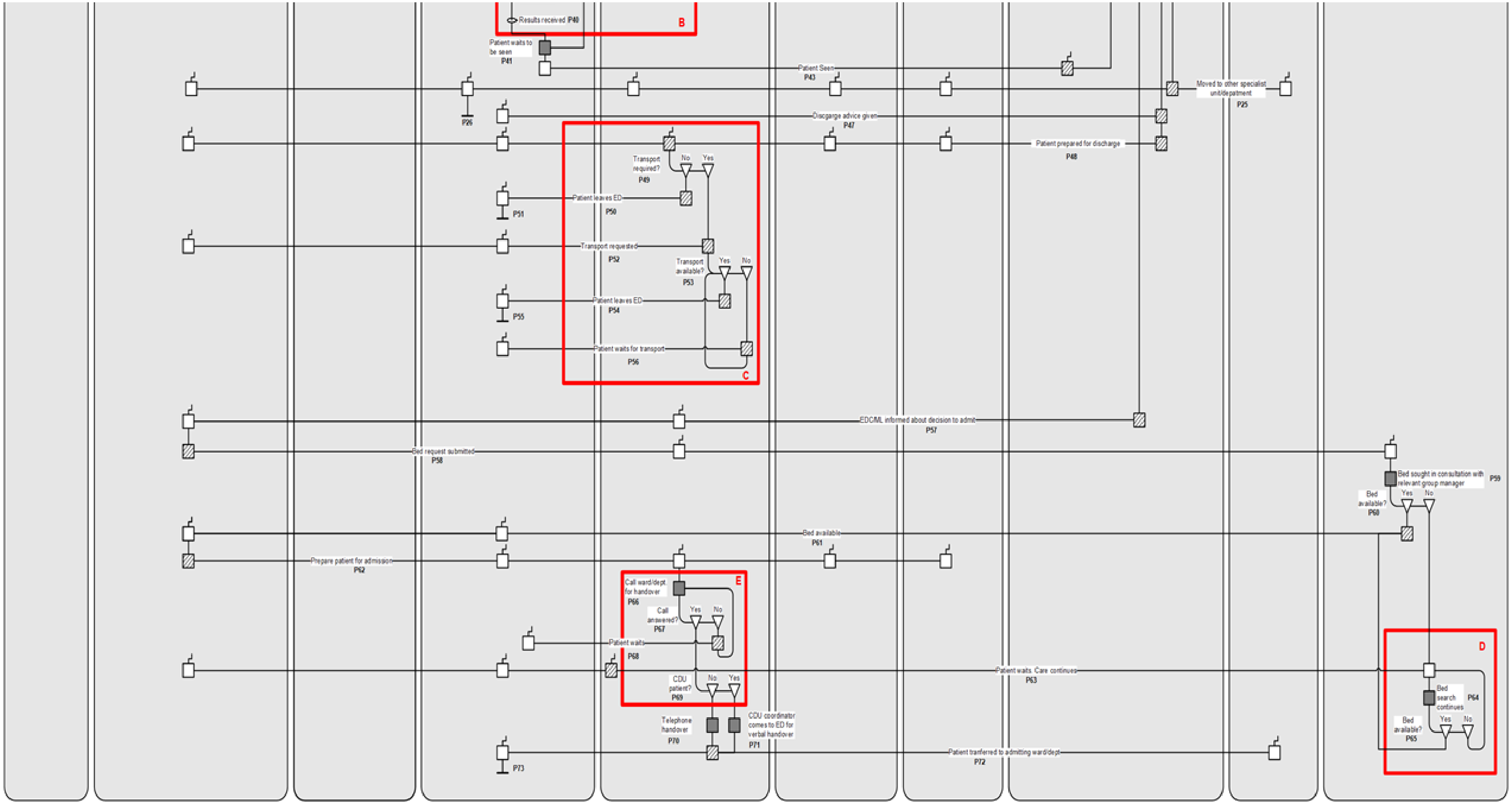


Figure 4.4 Majors role activity diagram

Note: Resus- Resuscitation area; SEWS-Standardised Early Warning Score; CT-Computerised Tomography; A- Awaiting specialty input; Bottleneck B- Test outside ED; Bottleneck C- Awaiting transportation; Bottleneck D- Bed search; Bottleneck E- Handover; CDU- Clinical Decision Unit. Source: Adapted from Amissah and Lahiri, 2022

Step 1 – Handover (P1-P4). For patients arriving via ambulance, paramedics carry out a handover to the EDC who conducts a rapid assessment to determine if the patient is suitable to wait. The patient is also registered at reception by the paramedics, where the ED CAS (casualty) Card is completed from the information on the patient report form (PRF), which the ambulance services use.

Step 2 – Resuscitation/Majors (P5-P8). For patients who are not suitable to wait, the decision question of 'Resus needed?' can either be 'yes' resulting in the patient being sent to Resus or 'no' wherein the patient is assigned a cubicle (or trolley if a cubicle is unavailable) in Majors. Patients assigned to the Majors unit are handed over to the ML.

Step 3 – Assessments and tests (P9-P13). While the patient waits, the ML lists all the assessments and tests that the patient must undergo on a centrally located whiteboard and assigns these to the HCA and staff nurse, who ensure that the tasks have been carried out. The patient waits to be seen by the treating physician.

Step 4 – Waiting area/Minors (P14-P18). A patient assessed as suitable to wait is sent to the waiting area and waits either in reception to be triaged or in Minors to be seen. The receptionist sends the ED Casualty (CAS) card to the relevant printer in Triage or Minors for sub-processes per the encapsulated process notation usage. The patients wait to be seen after triage has been completed.

Step 5 – Seen by ED Physician (P19-P26). The ED prioritises patients using the Standard Early Warning Score (SEWS). The order in which the physician sees patients is determined by a combination of the SEWS score and time order of arrival. The physician examines the patient and reviews the results of any assessments and tests, including blood pressure, temperature and electrocardiograph (ECG). Based on the obtained values, a decision is made by the physician on the next course of action as to whether the patient needs to be seen by a specialist. If affirmative, then a referral is made to the appropriate specialty. The specialist may see the patient within or outside the ED. If the patient is to be seen outside the ED, the physician informs the EDC, who coordinates with the ML, the staff nurse and a porter to move the patient to the appropriate department or unit. The clock stops once the patient leaves ED, concluding their LOS.

Step 6 – Seen by Specialist (P27-P30). If the patient is to be seen in the ED by a specialist, the ML is informed while the patient continues to wait. A question arises, i.e., 'has the specialist arrived?' If the specialist does not arrive within 30 minutes of referral, then a reminder telephone call is made by the ML while the patient continues to wait, which can impact on patient's LOS. Where more than one patient is waiting to be seen, the specialist also attends to patients based on the SEW priority. If upon assessment, the specialist reaches a medical decision that the patient is more suitable for a different specialty, then another referral is made by the attending ED physician. The referral chain continues until the appropriate specialist has seen the patient. The results of which can lead to a decision question about whether additional tests or initial treatments are required.

Step 7- Additional tests/treatment (P31-P37). All information about treatment and tests required is given to the ML who updates the whiteboard of tasks to be performed by the HCA and staff nurse. Some tests may be performed outside the department, for example, x-rays and computerised tomography (CT) scans. Therefore, the next decision question is whether the test will be performed outside the ED. If the decision is 'yes', then the patients are sent to the testing unit with the help of the porter, where they await their turn for the test to be performed. This is denoted as an encapsulation.

Step 8 – Medical decision (P38-P46). Once the test is complete, the patient continues to wait in Majors until the arrival of test results and again waits to be seen. This also applies to patients who had tests performed in ED, such as POCT, or blood samples sent to the laboratory. While being seen by a physician; test results are analysed together with further patient examination. A medical decision is made on whether the patient is to be admitted.

Step 9 – Discharge (P47-P48). An outcome of 'no' for admit is followed by discharge advice given to patients by the physician, after which the patient is prepared for discharge. Discharged patients who require medication will have it dispensed directly from ED if it is in stock or requested from the pharmacy as part of this process.

Step 10 – Departure from ED (P49-P56). Discharged patients may be able to leave on their own or require transportation. Patients leaving the department denotes the end of the ED care process and RAD notation usage. At this point, the clock monitoring patient LOS is stopped. However, the clock continues to monitor LOS for patients requiring transportation while the ED makes the necessary arrangements. The availability of transport determines whether the patient can leave the department immediately upon a decision to discharge or wait until such time when transportation becomes available, which can prolong the LOS.

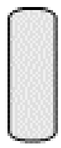
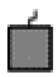
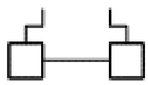
Step 11 – Admission/Bed search (P57-P65). An outcome of 'yes' for admission will require the EDC and ML to be informed. The EDC raises a request for a bed to the site manager, and the search begins in consultation with the relevant group manager for that specialty. At times, the request may be made directly to staff in the receiving area. The availability of a bed determines how quickly a patient can exit the ED. The patient is prepared for admission. The availability of a bed is constantly assessed while the patient remains in ED, which prolongs the overall LOS. If there is no bed available, the search continues while the patient waits and is continuously monitored and cared for.

Step 12 – Handover to admitting area (P66-P73). Once a bed becomes available, a call is placed to the receiving area by the ML for handover, followed by a decision question of ‘call answered?’ If the call goes unanswered, the ML or staff nurse delegated to perform this task will continue calling until answered. Meanwhile, the patient waits. If the patient is to be admitted to CDU, the unit coordinator arrives in ED for a verbal handover. For admissions to other wards, the handover is done over the telephone. With the help of a porter, the patient is moved to the receiving ward, and the clock overseeing ED LOS is stopped.

A concurrent process of scanning all notes into the electronic patient records system is undertaken by one of the staff looking after the patient as part of both P48 and P62. This happens because some aspects of the patient notes are still recorded on paper though an electronic patient record system is in use.

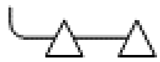
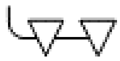
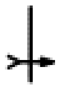
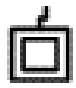
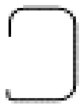
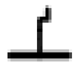
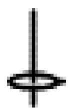
Table 4.9 below provides some examples of the notations used in developing the Majors RAD. This illustrates how the concepts presented in Table 3.6 in Chapter 3 converts to an actual RAD.

Table 4.69 Examples relating to RAD notations from the Major's unit RAD

Process Number	**RAD Concept**	**General Description**	**Example Majors RAD**	**Graphical Notation**
P1	***Role***	A role performs a set of activities to achieve a particular goal. A role can be an individual, a group of people or equipment.	ED Coordinator, paramedic and patient	
P10, P66	***Activity***	A unit of work performed by a role is an activity	Majors lead lists assessments and tests on a whiteboard, Call ward/dept for handover	
P8, P11	***Interaction***	Interaction represents a collaboration between roles to achieve the objective of the process	Patients assigned to the Majors unit are handed over to the Majors lead. Majors lead discusses listed tasks with the Staff nurse and HCA	

Source: Adapted from Ould and Roberts, 1986, Shukla et al., 2014

Table 4.9 Examples relating to RAD notations from the Major's unit RAD (cont'd)

Process Number	RAD Concept	General Description	Example Majors RAD	Graphical Notation
P60	***Case Refinement***	A case refinement represents a decision question and the possible outcomes.	Decision question: Bed available? Outcome: Yes or No	
P20	***Part refinement***	The part refinement symbol represents activities done simultaneously by a role.	Patient examined, assessments and test results were analysed simultaneously	
P1	***Trigger***	A trigger represents an event that starts the activity thread.	The patient arrives in an ambulance	
P37	***Encapsulated process***	An encapsulated process symbol represents a sub-process on the main diagram. The sub-process is then expanded on a separate diagram	Tests performed outside ED	
P65	***Loop***	A loop symbol is used to represent part of the process that repeats itself	Bed available? If 'no', then the steps are repeated until the answer is 'yes'.	
P73	***Stop***	The stop symbol marks the end of a process by ending a thread.	After the patient leaves ED, the thread ends.	
P38	***State***	The state symbol is used to describe what is true before or after an action	Test complete	

Source: Adapted from Ould and Roberts, 1986, Shukla et al., 2014

4.7 Areas excluded from process modelling

In this study, the resuscitation area was not modelled. Even though it is a highly intensive unit in terms of resource requirement and urgency, resuscitation patients formed a small percentage of the overall attendance (Virtue et al., 2011) which was 6.76% in this dataset. Hence, RADs were not developed for this unit. Also, no RADs were developed for patients who were seen by the GP-in-ED. This group of patients constituted only 3.61% of the overall attendance and was also deemed outside the scope of this research.

4.8 A Review of Role Activity Diagrams

The role activity diagrams developed provided a very detailed granularity of activities that occur from when the patient arrives in the ED to when they leave, i.e., discharged, transferred, or admitted. Examining the RADs further helped identify processes that create bottlenecks in the ED, some of which were outside the department's control. Even though the RADs are static because they are not embedded with time-based data, the sheer number of activities illustrated indicates that a considerable amount of time will be required to complete these. The time stamps collected via the electronic patient system are mainly Arrival time, Triage time, Seen time, Medical discharge time and Departure time. However, the RADs reveal that several activities occur between these recorded times. In the case of complex patients, i.e., the group mostly seen in the Majors unit, it is easy to see from the RADs how four hours may not be enough to go through all the processes required. This provides insights into the performance of the 4HQI.

As the processes show, several roles must interact for many activities to be completed successfully, leading to variation. These are the receptionist, ED coordinator, paramedic, Majors lead, staff nurse, healthcare assistant, ED doctor, porter and site manager, with the patient at the centre of it all. The greater the number of roles required to complete the activity, the more complex the interaction is. All the roles involved must agree and work harmoniously to complete the interaction. The shared decision element of interaction adds to the complexity. Encapsulated processes (Figure 4.4: P6, P17 and P37) represent detailed sub-processes which can be expanded into their separate RADs. Generally, the RAD allows managers and policymakers to review processes for improvements. A close review of the RAD showed several potential issues. There are several times when the patient is waiting (e.g., Figure 4.4: P9, P13, P27, P36, P39, P41, P56, P63 and P68), which contributes to the overall time the patient spends in ED. In the Majors RAD, diagnosis tests such as x-rays and scans performed outside the ED are not within the control of the ED. The results must be received before the patient can progress further through the processes which cause delays. Also, for patients requiring specialty input, there is sometimes a delay between when the referral is made and when the specialist arrives in the department, which can be more than the estimated 30 minutes.

Similarly, patients requiring transport also add to the waiting time as the clock cannot be stopped until the patient is physically out of the ED. In total, five bottlenecks were detected following an examination of the patient journey in the Majors unit. These bottlenecks have been marked with red boxes on the RAD in Figure 4.4. Box A -patients awaiting specialty input, Box B-tests conducted outside the ED, Box C- patients awaiting transportation after discharge, Box D- bed search after admission and Box E-Call to admitting ward for handover.

4.9 Solutions for Bottlenecks from Literature

It is noteworthy that four of the five bottlenecks that were identified through the RAD modelling involved loops. These bottlenecks are not unique to the ED of this study site but are common ED patient flow problems (Baboolal et al., 2012, Hurwitz et al., 2014, Gharahighehi et al., 2016, Khanna et al., 2017, Higginson and Boyle, 2018, Kusumawati et al., 2019, Moskop et al., 2019). Consequently, the bottlenecks were first examined based on suggestions in literature about how they may be addressed. These are presented in the sub-sections below as recommendations and trade-offs. Secondly, suggestions are being made in the context of insights derived from the process modelling, demonstrating how the RAD is a useful technique not only for the identification of problems but also for developing solutions. The suggestions can be broadly classified under four groupings: reallocation of resources to the bottleneck area, tests moved upstream, creation of buffer zones and better handling of data and information (Amissah and Lahiri, 2022).

4.9.1 Reallocation of Resources

To address the bottleneck of awaiting specialty input, senior decision-makers from inpatient units should be free of elective commitments and non-clinical activities for a certain period to ensure prompt response to ED referrals (Higginson et al., 2015). The benefit is that patients will be processed faster, resulting in reduced waiting times. However, the trade-off is that speciality doctors prioritising ED work over inpatient consultation may lead to longer waiting times for inpatients to be seen.

4.9.2 Tests Moved Upstream

The test outside ED bottleneck can be addressed by enabling front-loading of tests (Higginson and Boyle, 2018). Point Of Care Testing can be used to speed up results in addition to having agreements in place for turnarounds times for laboratory and radiology tests so that requests from ED will be prioritised (Higginson et al., 2015, Jarvis, 2016, Chang et al., 2018). An agreement at the study site of a maximum two-hour turnaround time for blood tests can be extended to other tests. The trade-off is that additional resources may be required to meet service-level agreements. Test results for non-ED patients might take longer, potentially impacting inpatient activities.

4.9.3 Creation of Buffer Zones

To address awaiting transportation bottleneck, a discharge lounge located close to ED can be used to facilitate quicker discharges for patients needing transport (Franklin et al., 2020, Woods et al., 2020). This will enhance the timely discharge of patients during the daytime when the lounge is in operation and reduce the number of patients boarding in ED. However, additional resources will be required to manage the increased patient load. This can serve as a buffer zone for discharged patients.

Furthermore, in addressing the bed search bottleneck, evidence supports that admitted patients waiting for beds to become available can wait on the inpatient ward, which is safer than an unassessed patient waiting in an ambulance (Higginson et al., 2015, Chang et al., 2018, NHSImprovement, July 2017). This will create a buffer zone for admitted patients. Moreover, processes such as clinician rounds should be planned earlier in the day to facilitate the discharge of patients from the inpatient wards and utilisation of the inpatient discharge lounge to free up beds early in the day (Higginson et al., 2015). Inpatient discharges must also occur during weekends and bank holidays (Higginson et al., 2015, Chang et al., 2018, NHSImprovement, July 2017). This will result in a reduction in the number of patients boarding in ED hence, staff will be available to attend to new patients. However, the disadvantage is that beds may not be available in the inpatient ward for an extended period leaving patients to board on the inpatient ward for a long time. The hospital will also incur extra operational costs in the additional resources required to facilitate discharges at weekends and bank holidays.

4.9.4 Better Handling of Data and Information

The handover bottleneck can be addressed by reducing the need for verbal handover and its duration by using an integrated system with electronic patient notes & handover reports (Chang et al., 2018). Moreover, the admission processes could be better documented to reduce duplication (Higginson et al., 2015). This will enable patients to leave the ED on time thus reducing the number of patients boarding in the department though, the resources required to develop and integrate electronic systems will be an additional cost to the hospital.

Further steps towards finding solutions to address the identified bottlenecks necessitated understanding the patient journey prior to entering Majors. The Streaming and Triage RADs (Appendix D.2) were further investigated to achieve this. An enhanced version of this RAD with points where information is being recorded (denoted by), points where the patient is waiting (denoted by), and entry points into Majors (denoted by) is presented in Figure 4.5.

4.10 Exploring Entry into Majors- Streaming and Triage Role Activity Diagram

The Streaming and Triage RAD comprises 29 processes, as shown in Figure 4.5 labelled P1 to P29, involving interactions between the patient and five roles: Streaming nurse, Receptionist, Triage nurse, Emergency care technician (ECT) and ED doctor. Following the arrival of a self-presenting patient to ED (P1), a brief conversation takes place with the streaming nurse (P2), who performs a quick visual and verbal assessment of the patient and provides a colour-coded card (P3) which indicates the relevant unit for that patient to be registered at reception (P4). A patient who meets the GP in ED (P5) criteria is sent to the area (P6) to be seen by the GP (P7). After registering the patient, the receptionist generates and sends the CAS card to the printer in the relevant unit (P8). Patients who are not registered to be seen in Majors, i.e., do not meet Majors criteria (P9), are sent to Minors or Resuscitation (P10). The Majors patients wait to be triaged (P11) and are called in time order and according to the urgency of presentation as recorded on the CAS card (P12). The Triage nurse performs an initial assessment (P13) and quickly determines if the patient has chest pain (P14), as there exist time-bound protocols for such patients. An electrocardiograph (ECG) is performed immediately (P15) if the patient has chest pain. The results are quickly given to a doctor to review (P16), and the patient is immediately sent to Majors or Resus (P18) if an assessment of the normality of results (P17) has a negative outcome. This marks an entry point into Majors. A patient whose ECG is normal is asked to wait (P19) to be seen while the CAS card is put in a queue, marking an entry point into Majors (P20).

A patient who does not have chest pain will be assessed for other urgent conditions (P21). If they do not have any urgent conditions, the patient is asked to wait (P22), and the CAS card is again put in the Majors queue (P23), marking another entry point into Majors. Alternatively, the patient is sent to Minors if they are deemed to have been incorrectly assigned. Patients with urgent conditions may require more assessments to be conducted or medication to be given immediately, such as pain relief or antibiotics (P24). Sometimes a blood test may be required (P25). If this is so, the request is made to the ECT (P26), who obtains the sample from the patient and sends it off to the laboratory (P27). The patient waits (P28) until the results are ready (P29) for them to be seen. If a blood test is not required, the patient waits (P22) to be seen and the CAS Card is placed in the queue.

The Streaming and Triage RAD emphasises the point that information from the CAS card can support predictive planning even before the patient goes into Majors. Information is collected at several stages throughout the patient journey (Figure 4.5: P2, P4, P13, P15, P24, and P29). The RADs also highlight several instances where the patient is simply waiting, some of which though necessary (Figure 4.5: P11, P19, P22 and P28), nonetheless add up to the patient's length of stay. P18, P20, and P23 are entry points into Majors.

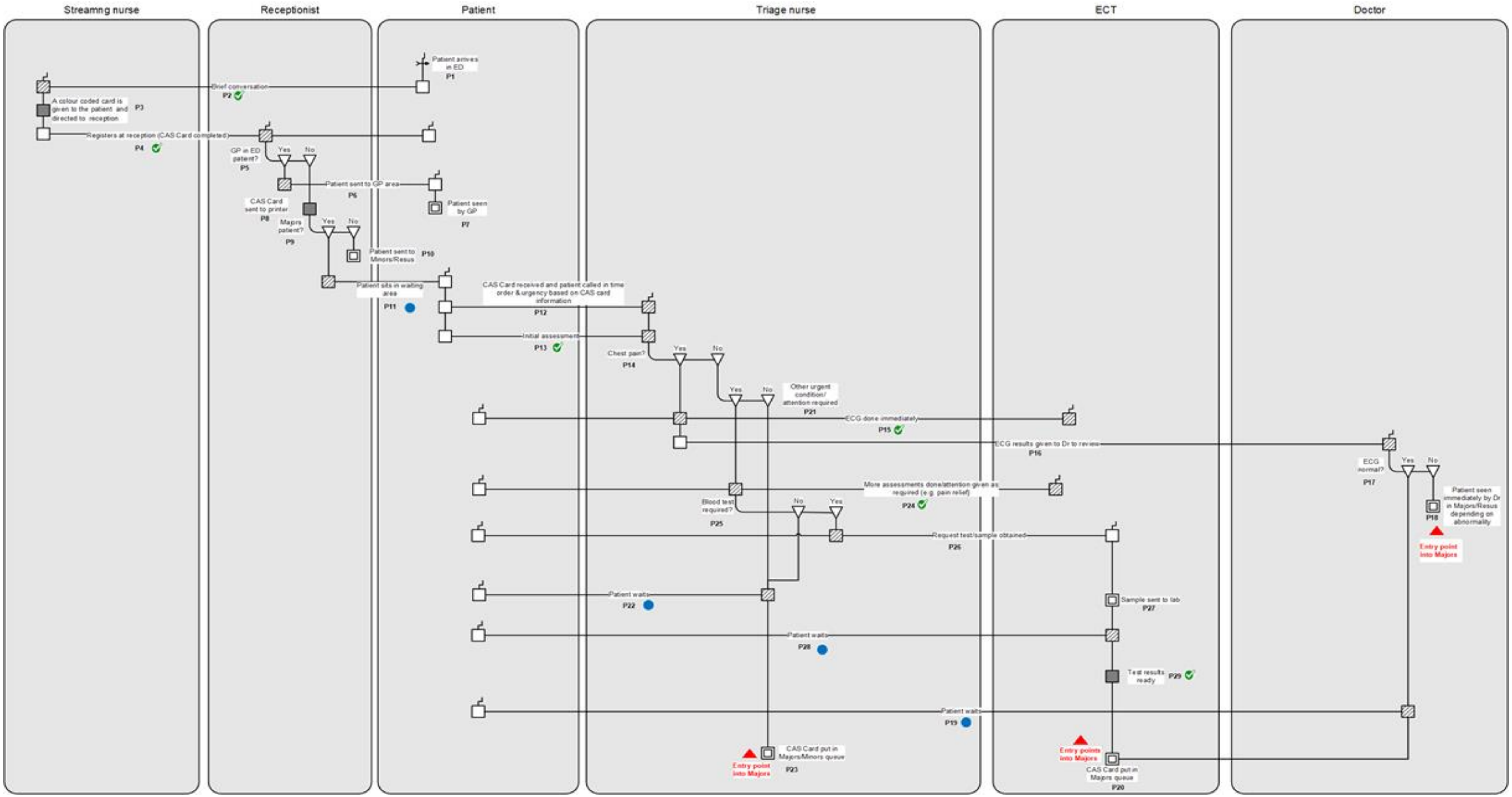


Figure 4.5 Streaming and Triage RAD. Note: ECT-Emergency Care Technician

Source: Amissah and Lahiri, 2022

4.11 Suggestions Derived from Process Mapping

Figure 4.6 below illustrates the bottlenecks against the five-time stamps presented in Panel A of Figure 4.3. Test outside is symbolised by a broken line between Triage and Seen. Test outside might happen at this stage in circumstances where the Triage nurse is authorised to request tests. Otherwise, tests are normally requested between Seen and Medical decisions after requests from doctors. Awaiting specialty input bottleneck also occurs at this point. Furthermore, the bottleneck of discharged patients awaiting transportation and admitted patients waiting for bed search and handover occurs between medical decision and departure.

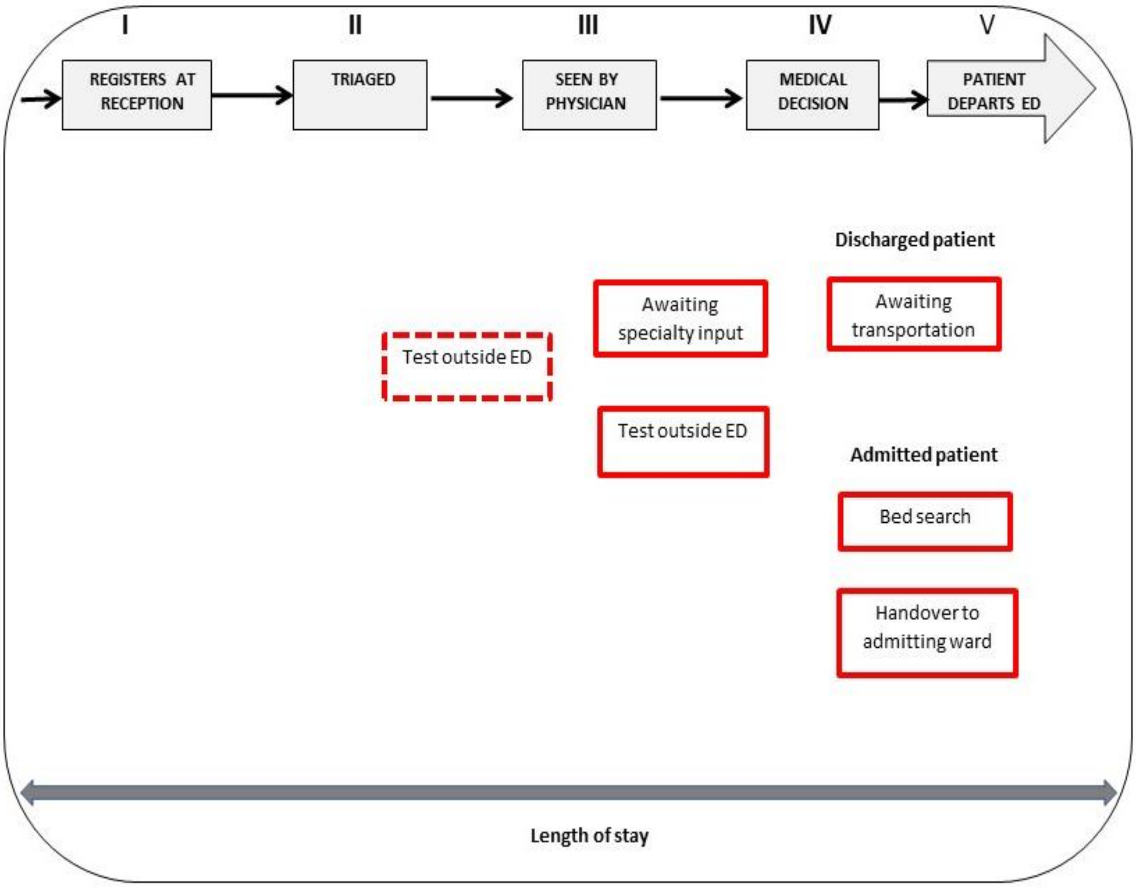


Figure 4.6 Majors unit bottlenecks against time stamps

Source: Author

It was identified from the Majors RAD (Figure 4.4) that four out of the five bottlenecks were loops, therefore necessitating the development of an appropriate approach to eliminate them. This approach will be referred to as Loop Disintegration Approach (LDA), which will entail:

1. Using information that the ED already has access to, hereafter referred to as precedence information, the loop is disintegrated into a collection of activities.
2. Generating information earlier in the process in the absence of precedence information to bring decision-making forward and speed up processes.
3. Deriving processes as alternative routes for patients who would have otherwise fallen into a looping process.

The LDA can also be applied to bottlenecks that are not loops in nature, as the principles are applicable.

These suggestions, in line with the principles of LDA, can be divided into three as listed below:

1. Better use of available data and information, i.e., using precedence information to reduce repeat tests. CAS Card and PRF can be harnessed earlier, for example, Pre-Majors (at Triage)
2. Introduction of a new role in Triage, an Advanced Clinical Practitioner to bring decision-making forward. The ACP's role in collecting the correct information about the patient at Triage will provide an early indication of specialty input requirements and order tests in support of early decision-making.
3. Bringing the transportation question earlier in the process (at Triage) and using a discharge lounge can also support improvement with the transportation bottleneck.

The principles of LDA and how they match the suggestions presented above are outlined in Table 4.10 below. They show how each of the three principles is addressed through the suggested solutions.

Careful consideration was given to selecting bottlenecks to address due to this research's time and resource constraints. The declining bed base in the UK (Higginson et al., 2015, Higginson and Boyle, 2018) impacts the availability of beds for admitted patients which is linked to the bed search bottleneck. This output problem reflects more significant concerns in the healthcare system and is therefore deemed outside the scope of this research. Moreover, Covid-19 led to the problem of the availability of beds becoming even more unpredictable due to repurposing and reallocation of beds (Nepomuceno et al., 2020).

Consequently, the handover over to admitting ward was also not tackled. It was anticipated that insight gained from exploring Figure 4.5 would help manage the three bottlenecks: tests outside ED, and awaiting specialty input and transportation, including potentially reducing their occurrence. Further information on how the LDA principles are applied to solving these three bottlenecks is provided in the subsequent sections.

Table 4.10 Applying the principles of the Loop Disintegration Approach

	LDA principles	**Solutions to implement the LDA principle**
1.	Disintegrating the loop into activities using precedence information.	Better use of available data and information. The use of precedence information to reduce the number of repeat tests.
2.	Generating information earlier in the process to bring decision-making forward.	Placing an Advanced Clinical Practitioner in Triage. Processes need to be brought forward to support early decision-making.
3.	Deriving processes as alternative routes.	Discharge planning and the use of a discharge lounge.

Source: Author

4.11.1 The use of precedence information to reduce the number of repeat tests

The process mapping revealed that staff have access to information about the patient's health, collected before their entry into Majors. This information could be utilised in addressing some of the identified bottlenecks. The Patient Report Form (PRF) is completed (Jenkin et al., 2007, Altuwaijri et al., 2019) by the paramedics (Altuwaijri et al., 2019) for all patients arriving by ambulance. A copy of the PRF or its electronic version; ePRF, is provided to ED staff as part of the handover process (Altuwaijri et al., 2019). In addition to the incident date and time, the PRF collects details pertaining to (a) demographics; (b) health history; (c) vital signs and observations; (d) cardiac health and ECG reading; (e) cerebrovascular events, such as suspected stroke; (f) medications; (g) GP name; and (h) mental health among others. Furthermore, a CAS Card is completed at registration for both ambulance arrivals and self-presenting patients, with additional information collected along the patient journey starting as early as during triage (Snooks et al., 1998, Montan et al., 2017). Information on the CAS card includes (a) date and time of arrival; (b) speciality; (c) date of birth; (d) source of referral; (e) number of previous attendances; (f) GP detail; (g) if a patient was transported with an alert; (h) observations; and, (i) falls risks. Such information is typically collected by all EDs worldwide (Snooks et al., 1998) and becomes available to ED staff before performing any tests.

The details available through the PRF and the CAS card play a significant role in ensuring appropriate care. The information can also be valuable in preventing identified bottlenecks and reducing overall LOS.

Undertaking tests, especially outside ED, is time-consuming, yet these variables obtained from the PRF and CAS Card could be used in place of some of the tests hence, reducing the need for repeat tests. For example, patients requiring a blood test for diagnosis can utilise pre-hospital blood test results to expedite decision-making on arrival to ED hence reducing the likelihood of long waiting times for blood test results (Harrison et al., 2010, Goodacre et al., 2011, Goyder et al., 2020). Another source of bottlenecks is imaging; these examinations are time-consuming (Van der Veen et al., 2018). However, the emerging use of pre-hospital ultrasound (Delorenzo and Meadley, 2018) signifies that EDs can use these results if available to decrease bottlenecks due to this test (Roantree et al., 2021). Information about the patient's health history, presenting complaints and vital signs, and observations can be utilised to process the patient efficiently. These variables could provide information in advance about tests which will be required to reach a diagnosis so that requests can be submitted at Triage. By so doing, the results would be available when the patient is being seen, leading to better management of bottlenecks and shorter patient waiting times.

4.11.2 Placing an Advanced Clinical Practitioner in Triage

Another bottleneck is specialty input, where referrals are made, and reminders are sent every thirty minutes until the specialist arrives. This loop can also be broken and converted into activities by bringing decision-making forward. Patients with medical conditions are sent to the clinical decisions unit. Those with conditions requiring surgery are sent to the surgical assessment unit (SAU). All other direct admissions to the wards require specialty input, as ED doctors cannot admit directly into a specialty ward. Indications of patient health history, numbers of previous attendances and cardiac health provide initial insights into the complexity of the condition. These could suggest a need for speciality input. This information can be used by an Advanced Clinical Practitioner (ACP) at Triage to make a decision on the need for specialty input for undiagnosed patients (HEE, 2017). The role of the ACP encompasses different specialities involved in tasks requiring complex decision-making such as diagnosis, prescribing, and discharge of patients (Smyth and McCabe, 2017, Lockwood et al., 2022). They can request investigations such as X-rays and CT scans before a patient is seen by a doctor and can also prescribe and start urgent treatment such as antibiotics (Moxham and McMahon-Parkes, 2020). ACPs have questions surrounding their level of clinical autonomy (Lockwood et al., 2022) as they work within strict guidelines and protocolised pathways (Smyth and McCabe, 2017, Crouch and Brown, 2018). Nonetheless, considerations can be given to expanding their role in helping to address the bottleneck caused by specialty input. Therefore, the ACP can notify the specialties before the patient is examined by an ED doctor and confirm after reaching an agreement with the ED doctor. This will speed up the referral process for the relevant patients, reducing the delay caused by awaiting specialty input. For example, the introduction of an ACP in Triage within the cardiology service yielded benefits for the patient group in terms of improvements in patient outcomes for those with acute coronary syndromes (ACS) (Comer, 2021).

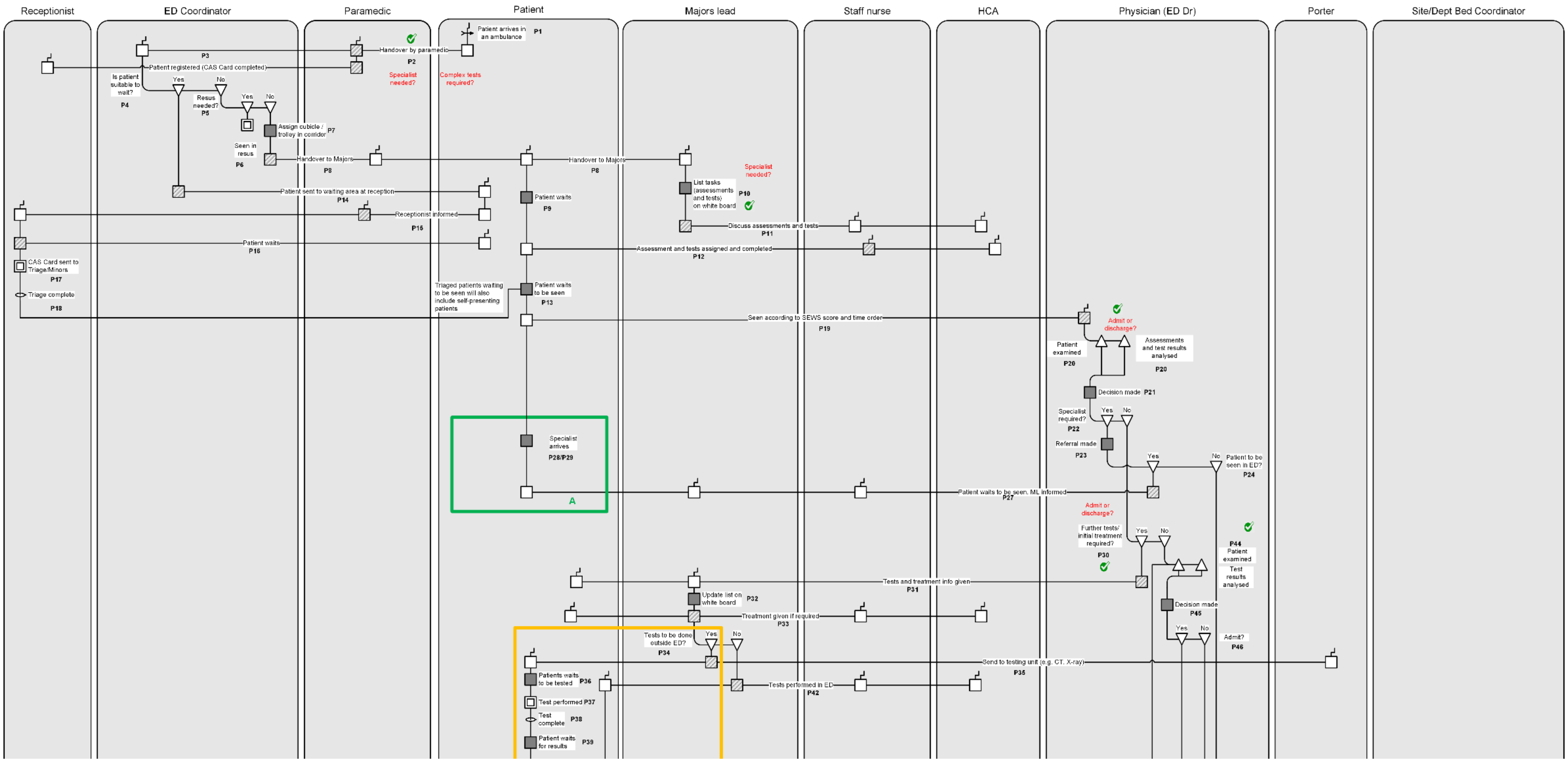
4.11.3 Discharge Planning and the use of a Discharge Lounge

The loop for transport can be broken up by changing it into activities. Discharged patients unable to leave the ED due to transportation delays have also been recorded in literature (Liu et al., 2015, Tomar et al., 2019). These patients continue to be cared for by ED staff who also need to attend to new patients arriving, therefore causing a crowded ED (Tomar et al., 2019). The CAS Card has information recorded regarding the need for transport. This requirement can be assessed earlier such as at Triage. Having this information early in the patient's care journey means it can be sent in advance to the discharge team to help better plan the discharge process, including arranging transport, thereby reducing the likelihood of delays due to transportation. The patients can also be sent to a discharge lounge while awaiting transport to free up space in ED. This has significantly reduced ED LOS for discharged patients by improving patient flow and reducing crowding in ED (Nasr Isfahani et al., 2020, Woods et al., 2020).

Discharge lounges are typically used for inpatients (Hernandez et al., 2014, Franklin et al., 2020, Zainuddin and Balakrishnan, 2021). However, utilising this facility for discharged patients from ED will be very beneficial in reducing crowding in the ED (Woods et al., 2020). This lounge will have to be located within close proximity to the ED so that a proportion of discharged patients during the day requiring transport can be sent there to wait for a final departure from the hospital.

4.12 Implementing Solutions

An improved Majors role activity diagram in Figure 4.7 below shows that the loops for specialty input (Bottleneck A) and transport (Bottleneck C) problems can be converted to activities when addressed through the principles mentioned above. The boxes around these two bottlenecks have been converted from red boxes to green ones. The need for tests outside ED (Bottleneck B) cannot be eliminated entirely, hence is an amber box. But using precedence information (pre-hospital tests) and moving tests upstream can bring decision-making forward and reduce repeat tests which will improve LOS. There are several instances in the Majors RAD indicated by green ticks (Figure 4.7: P2, P10, P20, P30, P43 and P44) where information can be collected about the patient to support predictive planning regarding the likelihood of encountering any of the bottlenecks downstream. The need for specialty input, complex tests which will be conducted outside ED, and prediction about patient disposition, i.e., admitted or discharged, can be constantly assessed at these points.



Receptionist
ED Coordinator
Paramedic
Patient
Majors lead
Staff nurse
HCA
Physician (ED Dr)
Porter
Site/Dept Bed Coordinator
Patient arrives in an ambulance P1
Handover by paramedic P2
P3
Patient registered (CAS Card completed)
Specialist needed?
Complex tests required?
Is patient suitable to wait? P4
Resus needed? P5
Seen in resus P6
Assign cubicle / trolley in corridor P7
Handover to Majors P8
Patient sent to waiting area at reception P14
Receptionist informed P15
Patient waits P16
CAS Card sent to Triage/Minors P17
Triage complete P18
Patient waits P9
List tasks (assessments and tests) on white board P10
Discuss assessments and tests P11
Assessment and tests assigned and completed P12
Triaged patients waiting to be seen will also include self-presenting patients
Patient waits to be seen P13
Seen according to SEWS score and time order P19
Admit or discharge?
Patient examined P20
Assessments and test results analysed P20
Decision made P21
Specialist required? P22
Referral made P23
Patient to be seen in ED? P24
Specialist arrives P28/P29
A
Patient waits to be seen. ML informed P27
Further tests/ initial treatment required? P30
P44 Patient examined
Test results analysed
Tests and treatment info given P31
Update list on white board P32
Treatment given if required P33
Decision made P45
Admit? P46
Tests to be done outside ED? P34
Send to testing unit (e.g. CT, X-ray) P35
Patients waits to be tested P36
Test performed P37
Test complete P38
Patient waits for results P39
Tests performed in ED P42

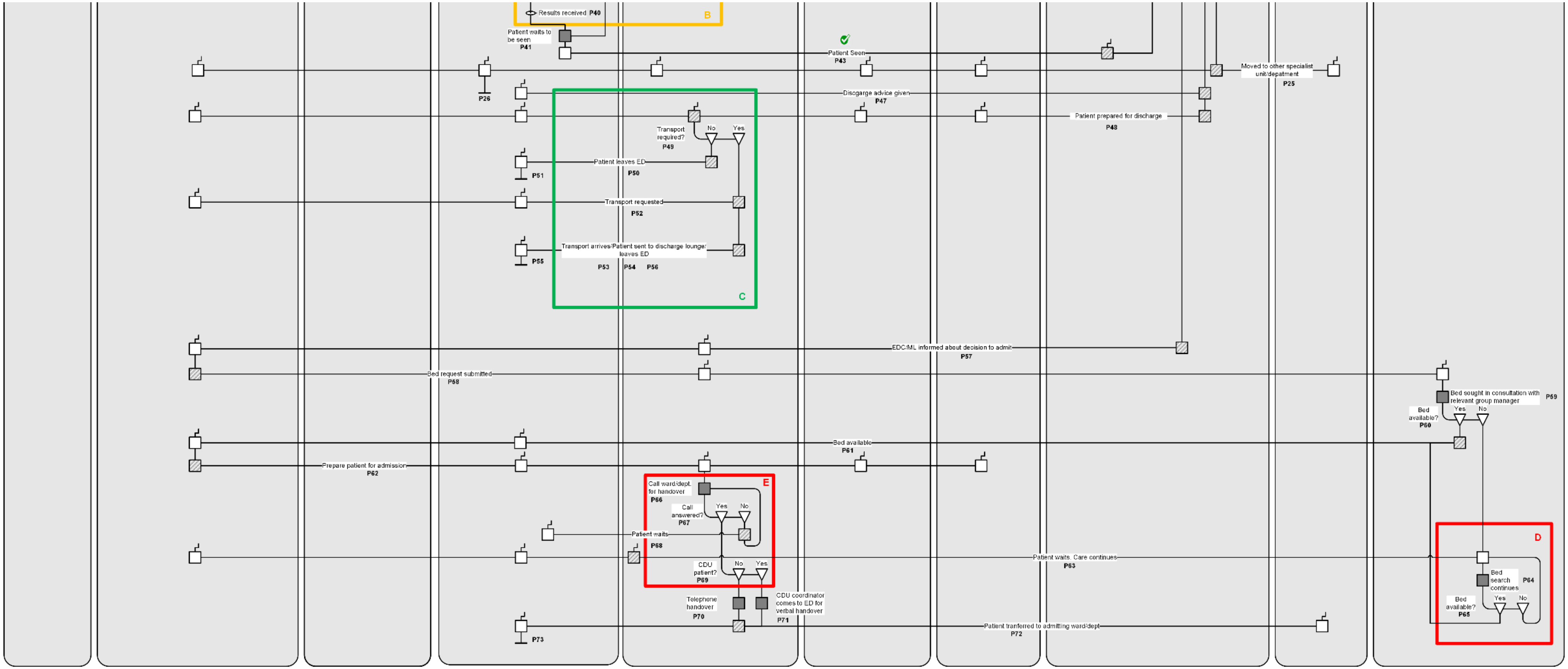


Figure 4.7 Improved Majors role activity diagram

Source: Author

4.13 Conclusion

This chapter has provided a report of how RAD was applied in the study site to map processes in ED and identify bottlenecks, specifically in the Majors unit, which emerged as the most crowded unit. Information from literature and the process mapping revealed insights into how the bottlenecks can be better managed, emphasising granularity. After developing the systems model using RADs, the outcome of decisions made in processing patients needed to be reviewed by analysing the information routinely collected along the patient journey. Chapter 5, therefore, provides the data analysis report. Following that, the recommendations for addressing the bottlenecks were tested using discrete event simulation and reported in Chapter 6.

Chapter 5

Analysis of Routinely Collected Data

This chapter provides the details of the quantitative data analysis conducted about the patient journey from arrival to when they leave ED. This was done to gain insight into decisions that were made about the patient and the outcome of those decisions. Statistical analysis was conducted to develop models for predicting breaches and length of stay. The length of stay was also examined for suggestions on how it can be monitored to support decision-making and timely care delivery.

5.1 Introduction

The lessons learnt from the RAD and the improvements suggested to address the bottlenecks cannot be implemented without the use of quantitative data. It was, therefore, necessary for hospital data to complement efforts undertaken by the RAD modelling. This study relied on routinely collected hospital data (RCHD) for further analysis. The use of RCHD can support QI initiatives in providing a better understanding of ED patient waiting times (Brady et al., 2017, Dormann et al., 2020). However, only a small proportion of UK studies are accessing RCHD due to difficulties with accessing and matching data to the purpose of the research (Lensen et al., 2020). Other barriers include accuracy, timeliness, and comprehensiveness of the data (Hirshon et al., 2009). Barriers notwithstanding, researchers are encouraged to use RCHD due to the huge potential to improve patient outcomes in ED studies (Hirshon et al., 2009). Large volumes of data are available through electronic platforms increasing access and potential for use (de Lusignan and van Weel, 2005, Hirshon et al., 2009).

Anonymised RCHD was requested from the study site to coincide with the qualitative data timeline. Data were therefore requested for visits from January 2017 to December 2018. It was important that having understood the patient journey through the RAD, the decisions that were made regarding the patient and the associated data collected were also analysed. Prior to embarking on the data analysis, a review of what other researchers had reported concerning factors that influence the length of stay was undertaken. This review is presented in Section 5.6 below.

5.2 Data Files

The data were sent through secured file transfer in the form of three files as shown in Table 5.1 below. Most of the data were provided as codes therefore the informatics department was contacted to seek clarification on the meaning of the codes to understand the variables. The first file, File1a comprised data involving 74,050 visits from 1st January 2017 to 31st August 2017. The second one, File 1b was for 65,776 visits from 1st September 2017 to 31st March 2018 and finally, File 1c for 89,268 visits from 1st April 2018 to 31st December 2018 all totalling 229,094 visits. Once received, the original CSV (Comma Separated Values) files were converted to Microsoft Excel format.

The dataset comprised 38 variables as illustrated in Appendix E.1. Some of the variables requested were modified by the hospital's informatics department to ensure that the data were completely anonymised. Age for example was provided in five-year groups starting from 17 years to 21 years up to 77 years to 81 years and then patients from 82 years onwards were put into one group. All patients who were below 17 years of age were excluded from the study.

Table 5.1 Files received with data

Name of file	Number of visits	Dates of visits
File 1a	74,050	01/01/2017 to 31/08/2017
File 1b	65,776	01/09/2017 to 31/03/2018
File 1c	89,268	01/04/2018 to 31/12/2018
Total	229,094	

Additionally, new variables were created from the existing data. These were number of diagnosis, number of procedures, number of investigations, arrival time (In/Out of hours), day of arrival, weekday/weekend, year of arrival and month of arrival. Furthermore, variables for different time-blocks and measures were computed such as Arrival to Triage, Triage to Seen, Seen to Medical Decision (MD), MD to Departure (boarding), total length of stay (LOS), and QI violation (breach and no breach).

The systems knowledge derived from the RAD construction informed the data analysis described in this chapter. The Majors RAD (Figure 4.5) and the Streaming and Triage RAD (Appendix D.2) were both carefully examined to extract quantitative data related to the RAD processes. Figure 5.1 below shows the Majors RAD and the stages in the processes at which this data is collected. Patient demographics such as age and gender are collected when the patient arrives. It can be seen that data were collected throughout the patient journey from P1 when the patient arrives to P73 when the patient leaves the department.

Following a similar process as described above to examine the Streaming and Triage RAD in Appendix D.2, additional variables related to processes in that RAD were also identified. Variables such as GP postcode, partial postcode, activity number and those related to the inpatient activity were excluded at this stage. These variables together with process numbers and descriptions are illustrated in Table 5.2 below.

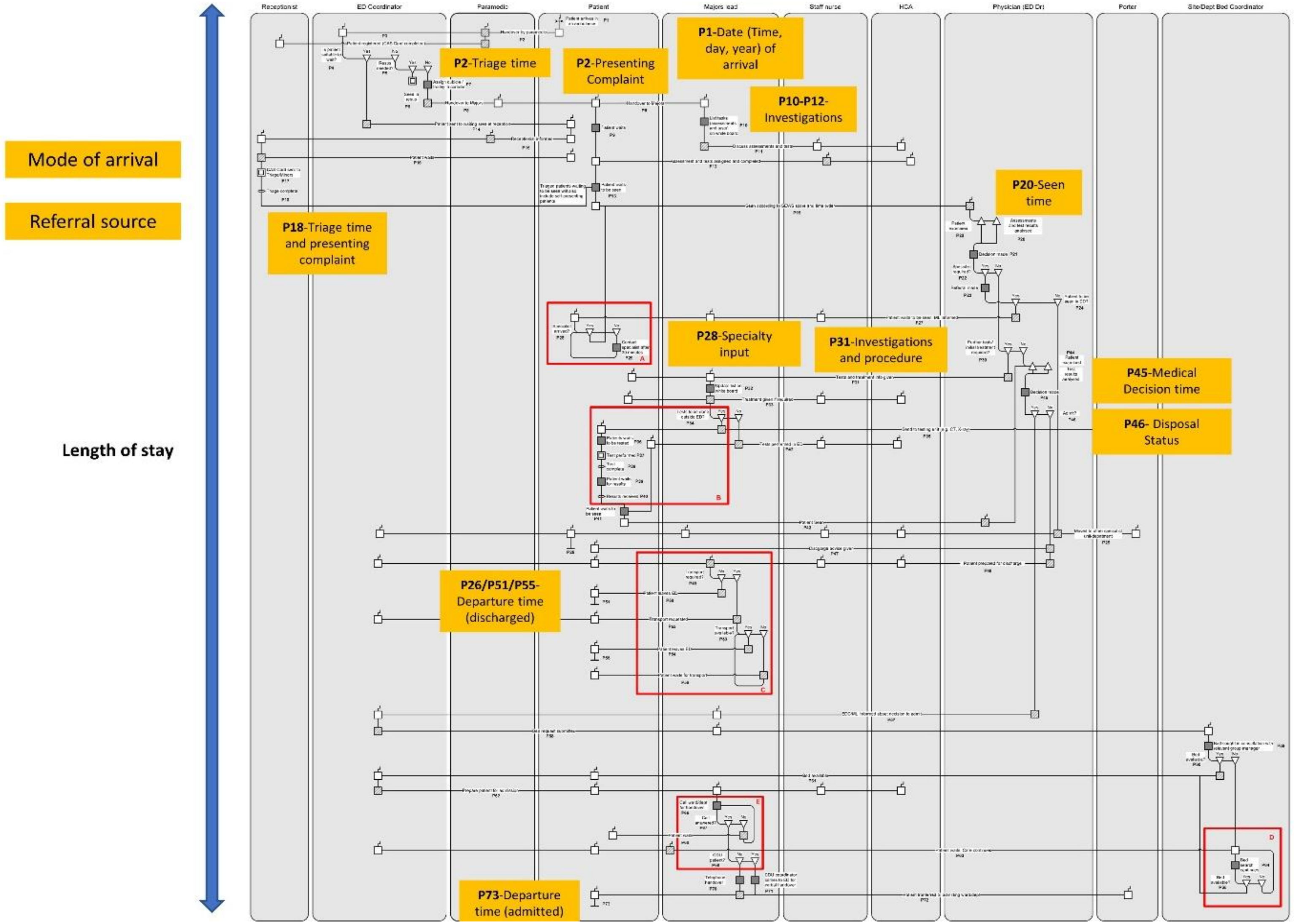


Figure 5.1 Majors RAD showing relevant quantitative data received

Source: Author

Table 5.2 RAD processes and associated quantitative data

Number	RAD process numbers (Fig 4.4: EMS arrival)	RAD process numbers (Fig 4.5: Non-EMS arrival)	RAD process name	Quantitative data
1.	P1	N/A	Patient arrives in an ambulance	1. Arrival time (In/Out of hours) 2. Day of arrival 3. Arrival month 4. Arrival year 5. Mode of arrival
2.	P2	N/A	Handover by paramedic	6. Presenting complaint 7. Triage time 8. Arrival location 9. Age 10. Gender
3.	P3	N/A	Patient registered (CAS Card completed)	11. Referral source
4.	P10-P12	N/A	Listing, discussing, and completing assessments and tests	12. Investigation type 13. Number of investigations
5.	P3	N/A	Registers at reception	14. Frequent user
6.	N/A	P1	Patient arrives in ED	Mode of arrival
7.	N/A	P4	Registers at reception (CAS Card completed)	Arrival time Day of arrival Arrival month Arrival year Referral source Arrival location Age Gender Frequent user
8.	N/A	P13	Initial assessments	Investigation type Number of investigations
9.	P18	N/A	Triage complete	Presenting complaint Triage time
10.	P20	N/A	Patient examined, assessment and test results analysed	15. Seen time 16. Diagnosis type 17. Number of diagnosis
11.	P28	N/A	Specialist arrived? Yes/No	Specialty input requirement (inferred from data)
12.	P31	N/A	Tests and treatment information given	Investigation type Number of investigations 18. Procedure type 19. Number of procedures
13.	P45	N/A	Medical Decision	20. Medical Decision time
14.	P46	N/A	Admit? Yes/No	21. Disposal status
15.	P26/P51/P55	N/A	Stop (after patient leave ED)	22. Departure time Transportation requirement (inferred from data)
16.	P73	N/A	Stop (after patient leave ED)	Departure time

Variables already numbered were excluded from the numbering to illustrate a total of 22 variables identified relating to 16 processes. These 16 processes from the two RAD formed the basis of the conducted analysis.

5.3 Statistical Analysis

The data set was imported into IBM SPSS Version 27. This was used for statistical inference and regression analysis. The data were first imported, and labels were created. The variable view was edited as required to ensure the correct data types and measures were selected.

The data went through various forms of data cleaning processes beginning with the removal of three categories of dead patients which came to a total of 358 patients as shown in Figure 5.2 below and Appendix E.2. This reduced the number of visits to 228,736. A further 516 patients who left without being seen (LWBS) were removed leaving 228,220. Once the initial analysis began, it was discovered that 11,009 patients left before treatment was completed and therefore excluded from further analysis resulting in 217,211 visits. The sample for the quantitative analysis comprised live patients who were discharged based on clinical advice upon treatment completion. Hence, all patients who had died in the department, those who left without being seen (LWBS) and left before treatment were further excluded from the sample.

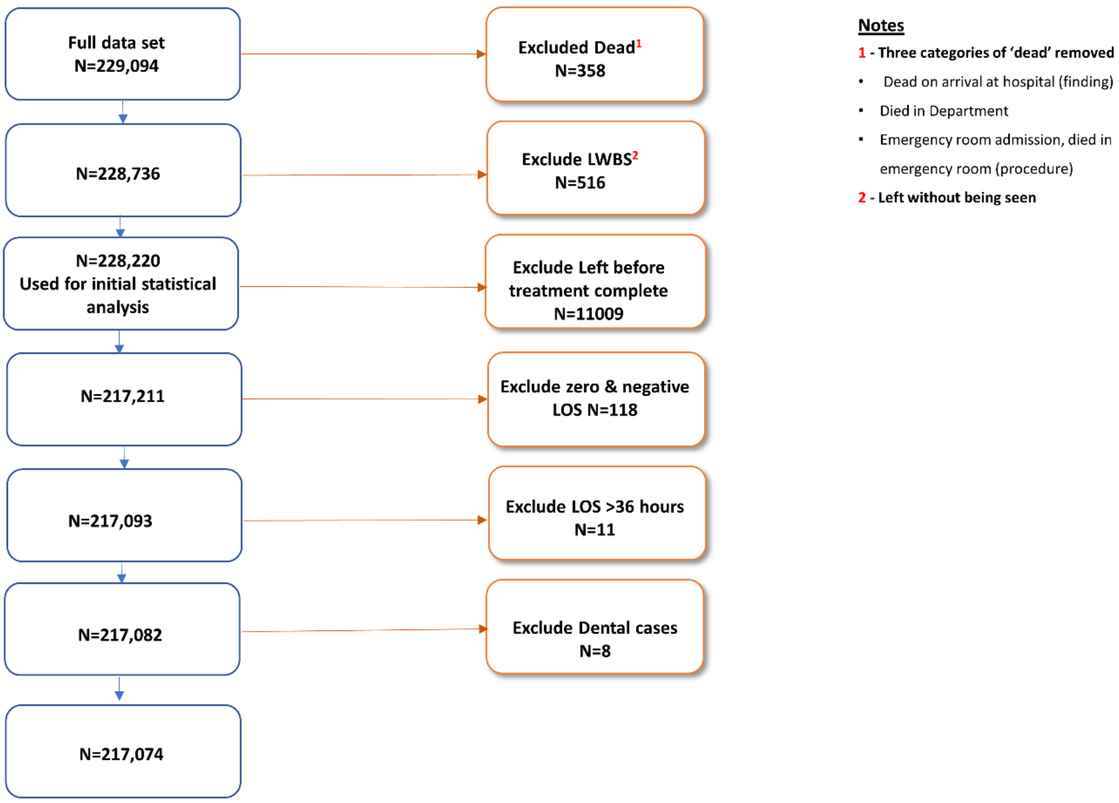


Figure 5.2 Exclusion criteria

A separate examination of the data on LWBS was done and showed results in line with what is recorded in literature regarding age groups and severity of the condition of patients who leave without being seen (Goodacre and Webster, 2005). This was to assess the existence of unusual trends that would require further investigations. Appendix E.3 illustrates the characteristics of these patients. Initially, descriptive statistical analysis was performed in Microsoft excel.

Anomalies in the data where LOS and other time differences were zero or negative resulted in a further 118 visits being excluded. Emergency medicine healthcare resource groups (EM-HRG) codes are used by the EDs used for reimbursements. 11 visits corresponding to EM-HRG code VB10Z were identified which represent dental emergencies and therefore excluded from the data as they were considered outside the scope of this study. EDs are generally not equipped to treat dental emergencies (Bassey et al., 2020) hence, considered an exclusion criterion in this study. Further information about EM-HRG codes is presented in Section 5.14. Box plots were used to help identify the skewness of the data and outliers. The box plots for LOS and boarding showed a few significant outliers. Following on from the boxplots, the LOS was capped at 36 hours (Ross et al., 2019) resulting in 8 visits falling outside this range. This represents a very small proportion of the sample leaving a final figure of 217, 074 visits across the two years. The LOS from these 8 visits were significantly higher than the remaining sample and would have skewed the results of the analysis if not removed.

5.4 Checking For Normality and Linearity

Histograms, scatter plots and QQ (quantile-quantile) plots were derived for the whole data set and also for each year. The test for normality was done using the Kolmogorov-Smirnov test as shown in Table 5.3 below which indicated that, the data were not normally distributed. The LOS, Arrival to Triage, Triage to Seen, Seen to Medical Decision (MD) and boarding times for the whole sample totalling 217074 had significant values of 0.000. A significant value (*Sig.*) less than .05 indicates deviation from normality (Field, 2009). As the data were not normally distributed, the LOS was transformed using the natural log. A histogram of the LOS before and after the log transformation is presented in Appendix E.4 and Appendix E.5 respectively.

Table 5.3 Tests of Normality

	Kolmogorov-Smirnov test		
Time-blocks	**Statistic**	**df**	**Sig.**
Arrival to Triage	.298	217074	.000
Triage to Seen	.107	217074	.000
Seen to MD	.166	217074	.000
Boarding	.304	217074	.000
LOS	.213	217074	.000

5.5 Comparison of National, Regional and Study Site Data

The study's data were compared to the national (England) and regional data to ascertain the trends in the number of attendances each hour versus the average LOS for that hour. Data for 2016-2017 and 2017-2018 have been presented for the national and regional data. These years have been compared to the 2017 and 2018 data from the study site. Figure 5.3 below shows similar trends in the data from the study site compared to the national and regional data. The graphs illustrate an inverse relationship between demand i.e., the number of patients attending ED each hour and the average LOS for each hour across the day. This is displayed in minutes. The dataset, therefore, reflects similar trends as the national and regional datasets with respect to the variables of interest.

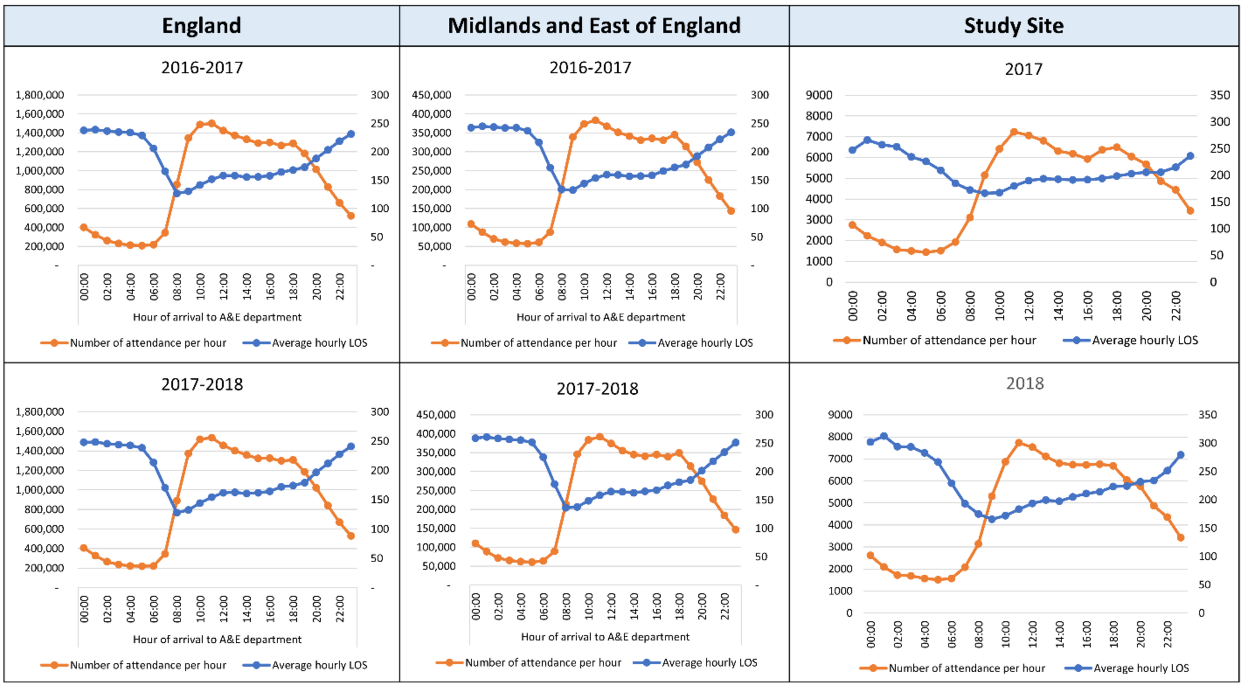


Figure 5.3 Inverse relationship graphs compared with national and regional data

Source: Author

5.6 The Need for a Model to Predict Emergency Department Length of Stay

Due to the volatile nature of ED arrivals, they are difficult to forecast or manage. However, several researchers have used statistical tools to predict ED LOS and the likelihood of breaching the 4HQI (Bobrovitz et al., 2017, Manolitzas and Stylianou, 2018, Becker et al., 2019, Ross et al., 2019, Suriyawongpaisal et al., 2019, Curiati et al., 2020, Sivayoham et al., 2020). Resources are limited due to restricted budgets (Brady et al., 2017) therefore the ability of a developed model to predict a patient's LOS can be useful to policymakers and ED administrators in planning and improving the care process as well as ensuring adequate staffing is available (Chaou et al., 2017).

A brief review of literature on different statistical methods used by researchers in ED patient flow was conducted to ascertain commonly used statistical methods to guide the data analysis. It revealed that Kusumawati et al (2019), conducted a study to determine significant factors that affect ED LOS in an Indonesian hospital to support the development of strategies to improve patient flow.

They used non-parametric tests Kruskal–Wallis test to analyse data that was not normally distributed. Their results showed that specialist consultation, Disposal status and acuity level related to an increase in ED LOS (Kusumawati et al., 2019). Becker (2019) used Spearman's correlation to determine the association between ED LOS, hospital LOS and that of the study groups. Categorical variables were estimated using the Chi-square test (Becker et al., 2019). Manolitzas and Stylianou (2018) examined the increased waiting time in a Greek ED during a period of economic crisis. They used linear regression to assess the effect of several variables on patient LOS and used multivariable logistic regression to determine the factors that lead to delays in the time patients spend in ED. They log-transformed the dependent variable LOS to normalise it as it was positively skewed (Manolitzas and Stylianou, 2018). They found that, the delay in the total patient time the patient spent in ED was influenced the patient's triage type which is either green or amber; the type of care the patient required i.e., orthopaedic, surgical, etc.; and the time of arrival to ED whether it was during regular working hours or out of hours. Their recommendation was for the Greek Department of Health to set a waiting time limit to support healthcare improvement (Manolitzas and Stylianou, 2018).

In addition, Bobrovitz et al (2017) identified factors that impact the probability of breaching the 4HQI which are the patient's age, the source of ED referral, types of investigation and the hour, day and month of arrival. The Chi-square test was also used in identifying the difference between the patients who breached and those who did not (Bobrovitz et al., 2017). They discovered that those who were most likely to breach were older patients who arrived at night, arrived on a Monday, came through self-referral and had multiple investigation types (Bobrovitz et al., 2017). Curiati et al (2020) used logistic regression to identify factors that can predict prolonged ED LOS and hospital admission in older adults. They assessed collinearity between the variables by calculating the variance inflation factors (VIF) and found arrival after-hours and the need for pathology and imaging as the predictors which had the highest effect on the patients' LOS (Curiati et al., 2020). Ross et al (2019) modelled patient flow in a busy ED using multivariable logistic regression to model breach. They discovered relationships between LOS and capacity, demand and process indicators to improve ED performance (Ross et al., 2019). Kocher et al (2012) also used VIF to test collinearity and used a generalized linear model (GLM). They discovered a significant association between testing and treatment with prolonged ED LOS (Kocher et al., 2012). Sweeny et al (2020) used logistic regression to identify factors that lead to long LOS for patients who are 65 years and older. They also assessed collinearity using VIF (Sweeny et al., 2020). They found that the factors with the highest predictive association to long LOS as after-hours arrival, less urgent Australasian triage Scale (ATS) and imaging and pathological investigations (Sweeny et al., 2020).

The next objective in the data processing was to develop and validate an accurate model to predict breaching or no breaching of the 4HQI using logistic regression (LR) with respect to the 22 independent variables listed in Table 5.2. These variables are being informed by the literature review conducted and the RAD process modelling. The review also revealed LR as a commonly used methodology for modelling breach/no breach when examining patient waiting times.

5.7 Coding of Variables

From the 22 variables used in the initial analysis, 16 variables directly related to the patient's LOS were chosen and further analysed for a final selection for the remaining statistical analysis as shown in Figure 5.4 below.

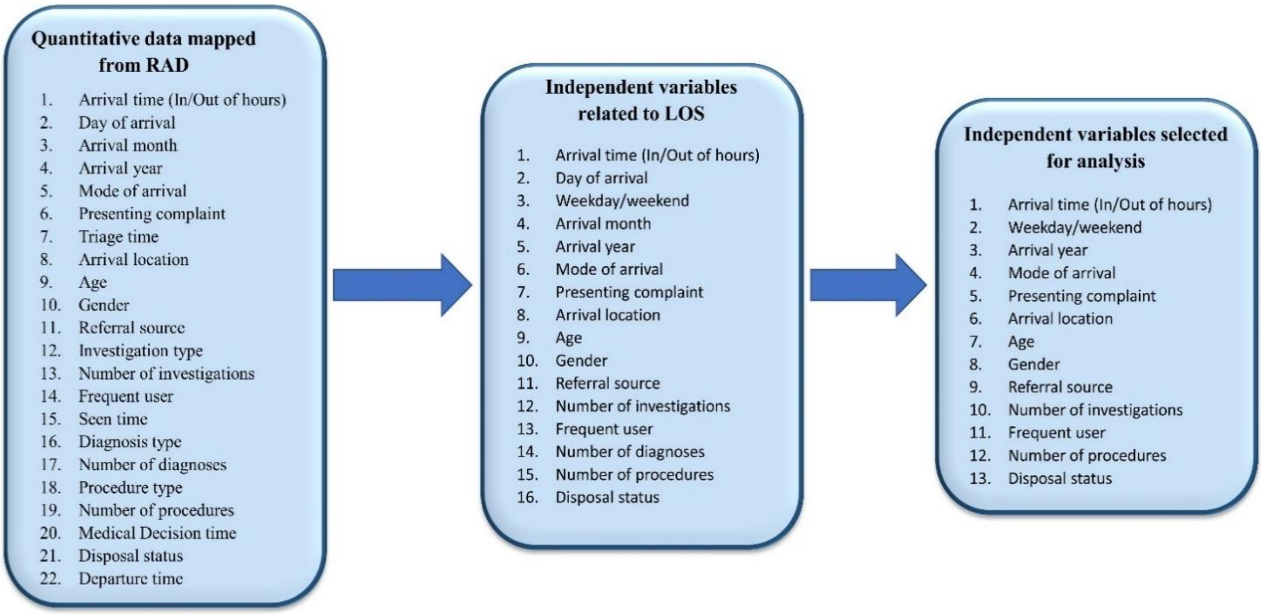


Figure 5.4 Variable selection for statistical analysis

Altogether 13 variables were selected based on their statistical significance determined by their Wald value (see Appendix E.6) and literature. For instance, gender and referral source were initially excluded for statistical reasons but included based on practical significance and extant literature that supports their inclusion. Most of the literature reviewed included these two variables (Brady et al., 2017, Kusumawati et al., 2019, Ross et al., 2019, Suriyawongpaisal et al., 2019). These 13 variables as shown in Figure 5.4 above are age, frequent user (i.e., frequent ED attendance); gender, mode of arrival, referral source; arrival location, disposal status (i.e., admitted or discharged), number of investigations, number of procedures, arrival time (i.e., in hours or out of hours), year of arrival; presenting complaint and day of arrival (i.e., weekday or weekend). The data were transformed and coded for loading and analysis. The 13 variables, when broken down into individual groups produce 39 variables. It was then modelled using logistic regression (breach) and a generalized linear model (length of stay in minutes). A description of the variables is provided below followed by the table for the univariate and bivariate analysis. In addition to predicting breach or no breach using LR and the exact time of a patient's LOS using GLM, it was important to understand decisions made along the patient journey. The decision tree which is a decision support tool commonly used in operational research was used to identify homogenous groups of patients who breach the 4HQI. It has been used by other researchers in modelling decisions related to ED patients (Feng et al., 2019, Gul and Celik, 2020, Rahman et al., 2020).

5.7.1 Age

The exact age of the patient was not provided by the hospital to preserve anonymity therefore age was provided in 5-year groups from 17 years to 81 years and then 82 years to 101 years as one group. This resulted in 14 separate age groups which were further combined to create 4 groups as shown in Table 5.6 below.

5.7.2 Gender

Four categories of gender were provided with a few patients having a gender identification of U and X. These two were combined into one group with male and female as the remaining two groups.

5.7.3 Frequent User

Different studies have defined ED frequent attendance differently. This ranges from between three to seventeen visits per year (Locker et al., 2007, Krieg et al., 2016). Four or more visits seem to be a common definition (Locker et al., 2007, Krieg et al., 2016, Dufour et al., 2019). This research chose to use five or more visits in twelve months. The causes of frequent ED attendance are multifactorial (Locker et al., 2007) and denote a failure in the system hence, forming a variable of interest for this study.

5.7.4 Mode of Arrival

This was grouped as follows: 0 represents Emergency Medical Service EMS (999, 999 with medical escort, ambulance and helicopter) and 1 for all other modes of arrival (Non-EMS).

5.7.5 Referral Source

The sources of referral were grouped into two main categories and coded as follows: 0 represents all non-self-referral categories which include GP, Healthcare provider and many others totalling 33 individual categories. 1- represents self, self-referral and work as referral sources.

5.7.6 Arrival Location

This refers to the main units in the department where patients are seen according to the severity of their condition. These are 0-GP, 1-Minors (See & Treat), 2- Majors, and 3- Resuscitation.

5.7.7 Disposal Status

This refers to the disposition decision of whether the patient is discharged or admitted with 0 representing discharged and 1 representing admitted.

5.7.8 Number Of Investigations

The number of investigations ranged from 0 where no investigation was undertaken to a maximum of three investigations which was the maximum the hospital was willing to provide.

The investigations were further classified into five main groups based on the type of investigation. Information about the five groups and the tests that are classified under each group is provided in Table 5.4 below. A patient who had one, two or three investigations could be from a combination of any of the five classifications below.

Table 5.4 Investigation code and interpretation

Code	Investigation group	Types of tests
1.	Vital signs & observations	ECG, BP, bedside echo, Peak expiratory flow measurement,
2.	Laboratory tests & POCT	haematology, blood matching, biochemistry, urine chemistry, histology, clotting, immunological blood tests, cardiac enzyme, toxicology, blood culture, serology, bacteriology
3.	Simple imaging	X-ray plain film
4.	Complex imaging	CT scan, ultrasound, MRI (magnetic resonance imaging)
5.	All Other	Visual, other

5.7.9 Number of Procedures

The number of procedures ranged from 0 where no procedures were undertaken to a maximum of 3 procedures which was the maximum the hospital was willing to provide.

5.7.10 Arrival Time

The time of arrival of the patients was coded as out of hours (0) from 6:00 pm to 8:00 am and regular/ in hours (1) from 8:00 am to 6:00 pm.

5.7.11 Year of Arrival

This was coded as 0 for 2017 and 1 for 2018. The data were from 1st January 2017 to 31st December 2018, spanning 48 months.

5.7.12 Presenting Complaint

There were several descriptions of presenting complaints provided so these were grouped to arrive at 6 main categories as listed below by grouping some of the specialties together. Information about the six groups and the broad categories of presenting complaints that are classified under the group is provided in Table 5.5 below.

Table 5.5 Codes for presenting complaints and interpretation

Code	Presenting complaint
1	Airway / breathing/Circulation / chest
2	Environmental/General / minor / admin
3	Gastrointestinal
4	Head and neck/Neurological /Eye
5	Trauma / musculoskeletal
6	All others

5.7.13 Day of Arrival

The initial analysis using histograms did not reveal much difference in the trends for the different days of the week though attendance on Mondays was slightly higher than on the other days as confirmed in other studies (Wargon et al., 2010, Brady et al., 2017). Since the ED, as well as the hospital, have a reduction in support services during weekends compared to weekdays (Higginson and Boyle, 2018), it was deemed more useful to group the days as weekends and weekdays with 0 representing weekdays and 1 for weekends.

5.8 Preliminary Analyses: Descriptive

Table 5.6 below provides the summary statistics based on the whole sample (N=217074). In the study, 19.29% (N=41886) had breached the 4HQI. Next, a baseline comparative analysis was conducted between those who had breached the 4HQI with those who had not, using Pearson's Chi-squared test (X^2) for categorical variables and Kruskal-Wallis (H statistics) for the continuous variables (LOS). The non-parametric test, Kruskal-Wallis, was preferred over the one-way ANOVA (Analysis of Variance) due to the non-normality of the distribution. Pearson's chi-squared test and Kruskal-Wallis are both considered distribution-free tests (Stewart, 2016). The median was used instead of the mean or mode since it is a better measure of the central tendency for skewed data. It is not affected by the spread of the distribution compared to the other two (Field, 2009). Due to the size of the data (Bobrovitz et al., 2017), a p-value less than 0.01 was considered statistically significant.

Table 5.6 Summary statistics of independent variables against 4-hour breach and length of stay

Variable name and level	4-hour breach								Length of Stay		
	No (N=175188)		Yes (N=41886)		Total (N=217074)		Chi-Square	P value	Median	H Statistic	P value
	N	%	N	%	N	%	--	--	--	--	--
Age (years)							11153.933	<0.001	--	19272.8	<0.001
17-31	57653	32.9	7382	17.6	65035	30	--	--	160	--	--
32-51	52808	30.1	8908	21.3	61716	28.4	--	--	171	--	--
52-71	37048	21.1	10247	24.5	47295	21.8	--	--	195	--	--
72-101	27679	15.8	15349	36.6	43028	19.8	--	--	231	--	--
Frequent user							1161.11	<0.001	--	2071.95	<0.001
No	159033	90.8	35663	85.1	194697	89.7	--	--	183		
Yes	16155	9.2	6223	14.9	22378	10.3	--	--	214		
Gender							54.539	<0.001	--	139.075	<0.001
Others	119	0.1	8	0	127	0.1	--	--	150	--	--
Female	91502	52.2	22614	54	114116	52.6	--	--	188	--	--
Male	83567	47.7	19264	46	102832	47.4	--	--	183	--	--
Mode of arrival							18537.306	<0.001	--	31777.1	<0.001
EMS	50328	28.7	26882	64.2	77211	35.6	--	--	229	--	--
Non-EMS	124860	71.3	15004	35.8	139864	64.4	--	--	160	--	--
Referral source							39.295	<0.001	--	152.025	<0.001
All others	36988	21.1	9429	22.5	46417	21.4	--	--	192	--	--
Self	138200	78.9	32457	77.5	170658	78.6	--	--	184	--	--
Arrival location							27518.483	<0.001	--	48983.4	<0.001
GP	7822	4.5	176	0.4	7998	3.7	--	--	125	--	--
Minors (See &Treat)	103652	59.2	7962	19	111614	51.4	--	--	151	--	--
Majors	54930	31.4	27277	65.1	82207	37.9	--	--	227	--	--
Resus	8784	5	6471	15.4	15255	7	--	--	237	--	--
Disposal status							21281.77	<0.001	--	41751.1	<0.001
Discharged	123333	70.4	13443	32.1	136777	63	--	--	156	--	--
Admitted	51855	29.6	28443	67.9	80298	37	--	--	232	--	--

Table 5.6 Summary statistics of independent variables against 4-hour breach and length of stay (cont'd)

Variable name and level	4-hour breach								Length of Stay		
	No (N=175188)		Yes (N=41886)		Total (N=217074)		Chi-Square	P value	Median	H Statistic	P value
	N	%	N	%	N	%	--	--	--	--	--
Number of Investigation							16553.81	<0.001	--	36809.1	<0.001
0	63647	36.3	5988	14.3	69636	32.1	--	--	147	--	--
1	52552	30	8698	20.8	61250	28.2	--	--	170	--	--
2	21365	12.2	6238	14.9	27603	12.7	--	--	199	--	--
3	37624	21.5	20962	50	58586	27	--	--	232	--	--
Number of procedures							4985.861	<0.001	--	9357.62	<0.001
0	17757	10.1	3187	7.6	20944	9.6	--	--	166	--	--
1	66350	37.9	11042	26.4	77393	35.7	--	--	170	--	--
2	50870	29	11212	26.8	62082	28.6	--	--	183	--	--
3	40211	23	16445	39.3	56656	26.1	--	--	217	--	--
Arrival time							3096.865	<0.001	--	5287.01	<0.001
Out of hours -6:00pm to 8:00am	69019	39.4	22765	54.3	91785	42.3	--	--	202	--	--
Regular hours/In hours -8am to 6pm	106169	60.6	19121	45.7	125290	57.7		--	173	--	--
Year of arrival							335.922	--	--	646.945	<0.001
2017	87575	50	18851	45	106426	49		--	181	--	--
2018	87613	50	23035	55	110649	51		--	190	--	--
Presenting complaint							4941.299	<0.001	--	11441.4	<0.001
Airway / breathing/Circulation / chest	29787	17	9831	23.5	39619	18.3	--	--	207	--	--
Environmental/General / minor / admin	22498	12.8	8823	21.1	31321	14.4	--	--	213	--	--
Gastrointestinal	17964	10.3	5422	12.9	23386	10.8	--	--	206	--	--
Head and neck/Neurological /Eye	17273	9.9	4214	10.1	21487	9.9	--	--	190	--	--
Trauma / musculoskeletal	61299	35	8791	21	70090	32.3	--	--	159	--	--
All others	26367	15.1	4805	11.5	31172	14.4	--	--	173		
Day of arrival							5.438	<0.020	--	56.863	<0.001
Weekday	127313	72.7	30676	73.2	157990	72.8	--	--	185	--	--
Weekend	47875	27.3	11210	26.8	59085	27.2	--	--	189	--	--

In Table 5.6 presented above, the null hypothesis H_0 is that there are no differences in means for the various groups of independent variables. It can be seen based on the Chi-Square at $p<0.001$ and the H statistics of variables that age, frequent users, gender, mode of arrival, referral source, arrival location, disposal status, number of investigations, number of procedures, arrival time, year of arrival, presenting complaint, day of arrival, were all identified as statistically significant determinants for LOS and hence, breach of the 4HQI.

5.9 Logistic Regression Analysis

Assuming a non-linear relationship (non-parametric data set), the study used binary logistic regression estimates (breach or no breach) to model the relationship between LOS and its determinants. The resulting model can be useful for making predictions. The process began with ensuring that all the assumptions governing this method of analysis had been met (Field, 2009, Tabachnick and Fidell, 2014).

5.9.1 Assumptions of logistic regression

1. Binary Nature of Dependent Variable: Counting the unique outcomes of the dependent variable, there are only two, which are breach (1) of the 4HQI or no breach (0). This assumption is therefore met.

2. Independent Observations: A scatter plot of residuals (order of observation) against time shows a random pattern (see graph in Appendix E.7) indicating independence of observations.

3. Multicollinearity of Independent Variables: Logistic regression is sensitive to high correlation between the independent variables (Pallant, 2016) therefore multicollinearity was assessed using the variance inflation factor which indicates the collinearity between the independent variables and the dependent variable (Dodge, 2008). There is no fixed rule on interpreting but is generally accepted that a VIF of 1 implies no correlation, a VIF more than 5 but less than 10, indicates there is moderate correlation and a VIF greater than 10 shows a high correlation and a cause for concern (Field, 2009, Pallant, 2016). The rule of thumb is that VIF should be less than 3 (Kutner et al., 2004). The VIF for the independent variables shown in Table 5.7 are all under 2, hence there is no severe multicollinearity within the dataset.

Table 5.7 Variance inflation factor of independent variables

Independent variables	Collinearity Statistics VIF
Age	1.257
Frequent user	1.033
Gender	1.006
Mode of arrival	1.710
Referral source	1.057
Arrival location	1.971
Disposal status	1.583
Number of investigations	1.486
Number of procedures	1.134
Arrival time	1.051
Year of arrival	1.029
Presenting Complaint	1.233
Day of arrival	1.013

4. Extreme Outliers: The box plot in Figure 5.5 below indicates that there are no extreme outliers. It should be noted that all outliers were removed as described in Section 5.3 where the LOS was capped at 36 hours (Ross et al., 2019). This was to prevent the outliers from skewing the results.

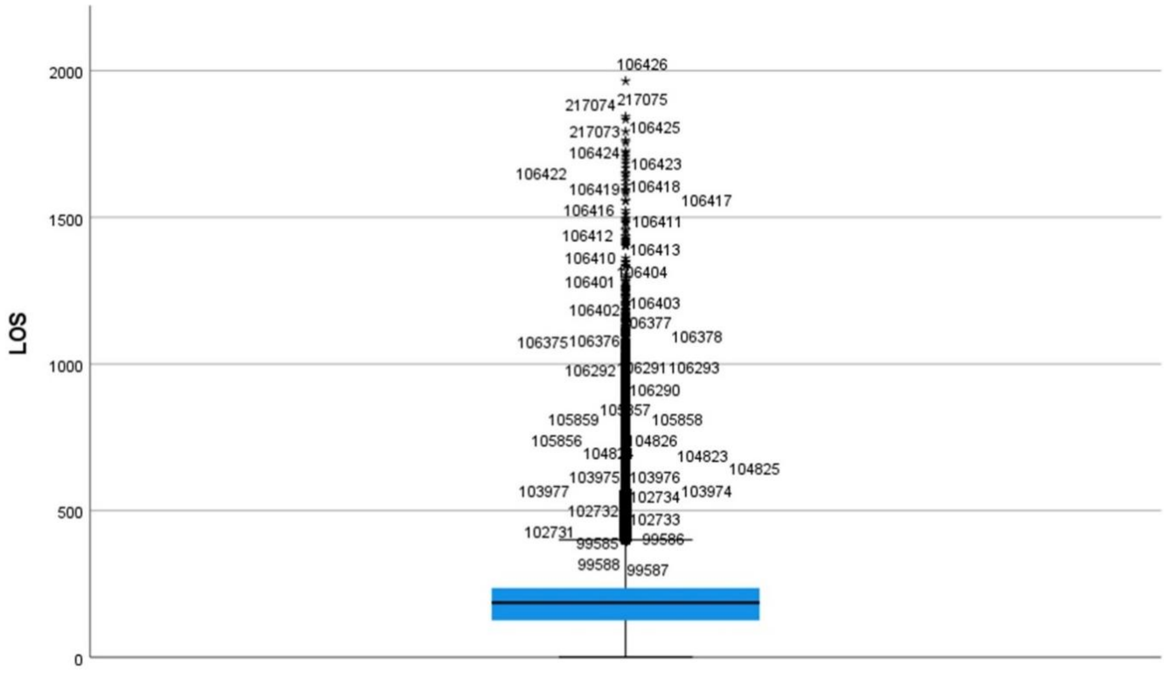


Figure 5.5 Box plot of length of stay

5. Linearity of the log odds of the data: In logistic regression, the dependent variable is categorical therefore the assumption of a linear relationship between it and the independent variable is violated (Field, 2009). Therefore, the assumption is to check the linear relationship between the independent variables and the log odds or logit of the dependent variable (length of stay). However, all the independent variables are categorical, none is continuous therefore this assumption is not violated.

6. Sufficiency of Sample Size: The sample size is large enough to draw valid conclusions from the fitted logistic regression model. Some authors recommend a 10 to 1 ratio of cases to independent variables (Nunnally, 1978), others recommend a minimum sample size of 300 (Tabachnick and Fidell, 2014) or 500 (Bujang et al., 2018) with another rule of 50 as the event per variable (EPV) resulting in the formula n= 100 +50i where 'i' is the number of independent variables in the sample. This formula produces 100 + 50 (13) = 750. Hence, since the sample size is 217074 > 750, the sample is sufficient for the analysis.

Based on the above information, the data set satisfies the logistic regression assumptions and is thus adequate for logistic regression analysis.

5.9.2 The Logistic Regression Model

Whether a patient breached or not at four hours was modelled using logistic regression. The 13 independent variables which were further split into 39 individual variables as listed in Section 5.7 were included in the model. The following variables were redundant in the model since they were used as references; non- frequent user, referral source (self referral), arrival location (GP), disposal status (discharged), number of procedure (0), number of investigation (0), day of arrival (weekend), group age 4 (72-101 years), arrival time (out of hours), year of arrival (2017), mode of arrival (non-EMS), gender (others), and presenting complaints (all others).

The dependent variable, length of stay, is regressed on the determinants of length of stay.

The derived model is given as:

$$
\log \frac{* b}{1 - * b} = Constant + \beta_{0,1}(Frequent\ user) + \tilde{\mathrm{N}}_{0,1}(Referral\ source)
+ X_{0,1,2,3}(Arrival\ location) + \mathrm{Ą}_{0,1}(Disposal\ status)
+ Z_{0,1,2,3}(Number\ of\ procedures) + \phi_{0,1,2,3}(Number\ of\ investigations)
+ \mathrm{Ķ}_{0,1}\ (Day\ of Arrival) + \mu_{1,2,3,4}(Age) + \mathrm{Ŗ}_{0,1}(Arrival\ time)
+ \hat{\mathrm{W}}_{0,1}(Year\ of arrival) + \mathrm{Ņ}_{0,1}(Mode\ of\ arrival) + \rho_{0,1,2}(Gender)
+ \psi_{1,2,3,4,5,6}\ (Presenting\ Complaint)
$$

5.9.2.1 Model Description Based on Data

Table 5.8 below shows the variables in the equation with the B, SE, degrees of freedom (df), the significance of each variable, the exponential B (Exp B) and the 95% confidence interval for each of the Exp B is explained as follows (Pallant, 2016): the B values are used to calculate the probability of a number falling in or outside a specified category. They are the estimated coefficients with SE representing standard error. The value can be positive or negative to indicate the direction of the association where a positive value shows that an increase in the independent value will result in an increase in the probability of an event occurring. The negative however shows that an increase in the independent variable will result in a decrease in the probability of an event occurring. The Exp B values are the odd ratios for the independent variables and give the predicted change in odds for a unit change in the predictor variable. The Wald value gives the importance of each of the independent values in predicting the dependent value.

Based on the values from the table, the model description is given as:

$$
\log \frac{*}{1 - * b} = -0.080 - 0.173(Frequent\ user_1) + 0.59(Referral\ source_0)
+ X_{1,2,3}(Arrival\ location) - 0.735(Disposal\ status_1)
+ Z_{1,2,3}(Number\ of\ procedures) + \phi_{1,2,3}(Number\ of\ investigations)
+ 0.082\ (Day\ of Arrival_0) + \mu_{1,2,3}(Age) + 0.597(Arrival\ time_1)
- 0.214(Year\ of arrival_1) + 0.277(Mode\ of\ arrival_0) + \rho_{1,2}(Gender)
+ \psi_{1,2,3,4,5}\ (Presenting\ Complaint)
$$

Table 5.8 Logistic Regression Model showing variables in the equation

Variables in the Equation								
							95% C.I.for EXP(B)	
	B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Frequent user (Yes)	-.173	.018	92.890	1	.000	.841	.812	.871
Referral source (All others)	.059	.015	15.341	1	.000	1.060	1.030	1.092
Arrival location			4027.701	3	.000			
Arrival location (Minors)	-1.977	.081	597.801	1	.000	.139	.118	.162
Arrival location (Majors)	-1.081	.026	1749.709	1	.000	.339	.322	.357
Arrival location (Resus)*	-.001	.020	.005	1	.946	.999	.960	1.039
Disposal status (Admitted)	-.735	.015	2449.129	1	.000	.479	.466	.494
Number of procedures			284.693	3	.000			
Number of procedures (1)	-.128	.025	26.813	1	.000	.880	.838	.924
Number of procedures (2)	-.273	.016	283.900	1	.000	.761	.738	.786
Number of procedures (3)	-.131	.016	67.351	1	.000	.877	.850	.905
Number of investigations			1263.851	3	.000			
Number of investigations (1)	-.668	.020	1170.560	1	.000	.513	.493	.533
Number of investigations (2)	-.323	.017	368.602	1	.000	.724	.700	.748
Number of investigations (3)	-.093	.019	24.790	1	.000	.911	.878	.945
Day of arrival (Weekday)	.082	.014	35.442	1	.000	1.085	1.056	1.115
Age			903.154	3	.000			
Age (17-31)	-.533	.019	782.646	1	.000	.587	.565	.609
Age (32-51)	-.418	.018	554.538	1	.000	.658	.636	.681
Age (52-71)	-.242	.017	205.165	1	.000	.785	.759	.811
Arrival time (In hours)	.597	.012	2278.337	1	.000	1.816	1.772	1.861
Year of arrival (2018)	-.214	.012	292.134	1	.000	.808	.788	.828
Mode of arrival (EMS)	.277	.015	321.937	1	.000	1.319	1.280	1.359
Gender			32.288	2	.000			
Gender (Female)*	-.265	.378	.491	1	.484	.767	.366	1.610
Gender (Male)	.069	.012	31.651	1	.000	1.071	1.046	1.097
Presenting Complaints			485.597	5	.000			
Presenting Complaints (Airway /Breathing/Circulation / Chest)	-.321	.022	203.228	1	.000	.726	.694	.758
Presenting Complaints (Environmental/General /Minor / Admin)	.076	.023	10.645	1	.001	1.079	1.031	1.129
Presenting Complaints (Gastrointestinal)	-.128	.025	26.560	1	.000	.880	.838	.924
Presenting Complaints* (Head and Neck/Neurological /Eye	-.033	.026	1.606	1	.205	.967	.919	1.018
Presenting Complaints (Trauma / Musculoskeletal)	-.085	.022	14.928	1	.000	.918	.879	.959
Constant	-.080	.039	4.228	1	.040	.923		
Model	--	--	40857.05	26	0.000	--	--	--

5.9.3 Analysis of the Model

This study analysed the effect of the determinants of length of stay as it relates to breach or no breach of the 4HQI using logistic regression. The results from the LR will be useful in understanding processes that need to be targeted in addressing decision-making along the patient flow. This was to enhance the lessons learnt from the RADs and to support the solutions suggested in addressing them, thereby ensuring patients meet waiting time expectations.

As shown in Table 5.8, the logistic regression model is statistically significant, X^2 = 40857.05, df (26) P < 0.001. This indicates that the overall model equation is significant in predicting breach or no breach of length of stay with respect to the determinants. The derived model can explain the variations in LOS from 17.2% to 27.4% (Cox & Snell R^2 =0.172 and Nagelkerke R^2 =0.274). The percentage of variation in the length of stay caused by the determinants increases as they are introduced into the model as a means of improving the model's predictive ability using the forward stepwise method (see Appendix E.8). The model coefficients are significant at P < 0.000 at different df for each independent variable.

The Hosmer-Lemeshow (HL) test is one of the most widely used tests to assess the goodness-of-fit of a model and also to check its calibration with a result of P<0.05 denoting that the model does not have an adequate fit (Pallant, 2016, Fortis et al., 2018). The calibration is an important measure of the model's accuracy where a statistically significant result implies that the model does not calibrate perfectly. This test, however, is sensitive to large sample sizes (Kramer and Zimmerman, 2007, Fortis et al., 2018). The model may have a good fit but for samples greater than 50,000, there is a 100% probability of the model showing statistical significance even though the same model performs well with a sample size of 5000 (Kramer and Zimmerman, 2007, Fortis et al., 2018). Due to the data sensitivity of this test, a randomly selected sample size of 1000 was used to check the true accuracy of the model which yielded $p < 0.21$ indicating a goodness fit of the model although for the entire data set, the p < 0.000 (indicating significance). This indicates that the data under consideration fits the model. See Appendix E.9 for the HL test results.

5.9.4 Sensitivity And Specificity Analysis

Furthermore, the overall percentage accuracy of the model is 81% (see Table 5.9 below). 95.3% of patients who did not breach the 4HQI are correctly predicted by the model to have not breached. Furthermore, 21.4% of patients who breached are correctly predicted by the model.

Of all the cases predicted for no breaches of length of stay, 83.5% are correctly predicted ((166872/199810) *100) i.e., the negative predictive value. The number 199,810 was derived from adding 166,872 and 32938 from the No breach column in Table 5.9 below. Considering all cases predicting breach of length of stay, 51.8% are correctly predicted ((8948/17264) *100) i.e., the positive predictive value. 17,264 was derived from adding 8316 and 8948.

Table 5.9 Logistic regression Model test classification

	Observed		Predicted		
			QI_Violation		Percentage Correct
			No breach	Breach	
Step 13	QI_Violation	No breach	166872	8316	95.3
		Breach	32938	8948	21.4
	Overall Percentage				81.0
a. The cut value is .500					

5.9.5 Model Parameter Analyses

Given the model specification, the model is highly significant (*p = <0.01*) with the exception of gender (Female), arrival location (Resus) and presenting complaints (Head and neck/Neurological /Eye). These three do not add significantly to the model as compared to the other determinant variables. In testing the derived model, the data were divided into two using the pareto rule of 80/20 where it is believed that 80% of effects are derived from 20% of causes ((Naidenov and Prof, 2014)). This rule is often used in statistics for splitting data (Lever et al., 2016, Mathew, 2019, Mengiste et al., 2021). The results of this split are shown in Table 5.10 below. A random sample of 80% of cases (N=217074) was selected and run using the logistic regression model giving 81% of the overall classification of the selected cases and unselected cases correctly predicted which is an indication of a good fit model. Also, 93.3% of those who did not breach and 21.5% of those who breached were correctly predicted by the model.

Table 5.10 Testing the model using pareto rule

Observed			Predicted					
			Selected Cases[b]			Unselected Cases[c]		
			QI_Violation		Percentage Correct	QI_Violation		Percentage Correct
			No breach	Breach		No breach	Breach	
Step 13	QI_Violation	No breach	133476	6542	95.3	33483	1687	95.2
		Breach	26350	7130	21.3	6597	1809	21.5
	Overall Percentage				81.0			81.0
a. The cut value is .500								
b. Selected cases Approximately 80% of the cases (SAMPLE) EQ 1								
c. Unselected cases Approximately 80% of the cases (SAMPLE) NE 1								

In conclusion, the logistic regression test was performed to determine the effect of the determinants of length of stay on the likelihood of a patient breaching the 4HQI. Results were statistically significant X^2 (26) = 40857.05, $P < 0.01$ as the model explains 27.4% (Nagelkerke R^2) of the variation in the length of stay and correctly classifies 81% of cases, thus the model is a good fit.

5.9.6 Predicting Breach or No Breach

Further analysis involved measuring the importance of each independent variable by calculating its $\chi 2$ /df ratio (Ross et al., 2019). This was used to rank the importance of each variable in terms of their contribution in the model relative to all the other variables as shown in Table 5.11 below. The variable ranked 1 (Disposal status = Admitted) is contributing the most to the model compared to the variable ranked 26 (Arrival location = Resus) which is contributing the least.

The coefficients of the model parameters were analysed and the odds ratio Exp (B) was interpreted to determine whether there is a breach or no breach of the 4HQI with respect to a unit change in each parameter, holding all others constant. It should be noted that there is a 95 per cent confidence interval for each Exp (B) displayed as shown in Table 5.8. The effect of each variable to breach or not breach was also determined using the parameter coefficient as described in detail in Table 5.11 below.

Table 5.11 Analyses of the Model for Predicting Breach or No breach

Variables in the Equation	B	Wald	Rank	Exp (B)	Model Parameter Coefficients Analyses	Analyses of Exp (B) - Odds Ratio
Disposal status (Admitted)	-0.735	2449.13	1	0.479	Having Disposal status (admitted), versus Disposal status (discharge) decreases the log odds by 0.735. The negative coefficient shows that the disposal status (admitted), with reference to disposal status (discharge), reduces the likelihood of a breach. Comparing the variable to other determinants, the variable is the 1st important contributor in the model.	The odd ratio is Exp. (B) = 0.479. This means that disposal status (admitted) is less likely to breach with reference to discharged requirements, having allowed all the other determinants in the model.
Arrival time (In hours)	0.597	2278.34	2	1.816	Arrival time (in hours) versus arrival time (out of hours) increases the log odds by 0.597. The positive coefficient suggests that the arrival time (in hours, increases the likelihood of breach with respect to arrival time (out of hours). Comparing the variable to other determinants, it is the 2nd important contributor in the model.	The odd ratio is Exp. (B) = 1.816 This means that a patient who arrives during in (regular) hours is more likely to breach the length of stay compared to arrival during out of hours, having all the other determinants in the model.
Arrival location (Majors)	-1.081	1749.71	3	0.339	Using arrival location Majors versus location GP decreases the log odds by 1.081. The negative coefficient shows that the arrival location Majors with reference to GP reduces the likelihood of breaching. Comparing the variable to other determinants, the variable is the 3rd important contributor in the model.	The odd ratio is Exp. (B) = 0.339. The shows that a patient whose arrival location is Majors is less likely to breach with reference to arrival location GP, having allowed all the other determinants in the model.

Table 5.11 Analyses of the Model for Predicting Breach or No breach (cont'd)

Variables in the Equation	B	Wald	Rank	Exp (B)	Model Parameter Coefficients Analyses	Analyses of Exp (B) - Odds Ratio
Number of investigations (1)	-0.668	1170.56	4	0.513	Having number of investigation (1) versus number of investigation (0) decreases the log odds by 0.668. The negative coefficient means the likelihood of breach will be reduced with respect to 1 investigation compared to no investigation. Comparing the variable to other determinants, it is the 4th most important contributor in the model.	The odd ratio is Exp. (B) = 0.513. This means that a patient with 1 investigation is <u>less</u> likely to breach in reference to no investigation, having all the other determinants in the model.
Age (17-31)	-0.533	782.65	5	0.587	A patient in group age (17-31) as against group age (72-101), decreases the log odds by 0.533. The negative coefficient means the likelihood of breach will be reduced for age (17-31) with respect e to group age (72-101). Comparing the variable to other determinants, it is the 5th important contributor in the model.	The odd ratio is Exp. (B) = 0.587 This means that a patient in age group category 17- 31 years is <u>less</u> likely to breach the length of stay in reference to age group category 72-101 years, having all the other determinants in the model.
Arrival location (See & Treat)	-1.977	597.8	6	0.139	Using arrival location See & Treat versus location GP, decreases the log odds of length of stay by 1.977. The negative coefficient shows that the arrival location See & Treat decreases the likelihood of breach with respect to GP. Comparing the variable to other determinants, the variable is the 6th important contributor in the model.	The odd ratio is Exp. (B) = 0.139. This shows that a patient whose arrival location is See & Treat is <u>less</u> likely to breach with reference to arrival location GP, having allowed all the other determinants in the model.

Table 5.11 Analyses of the Model for Predicting Breach or No breach (cont'd)

Variables in the Equation	B	Wald	Rank	Exp (B)	Model Parameter Coefficients Analyses	Analyses of Exp (B) - Odds Ratio
Age (32-51)	-0.418	554.54	7	0.658	A patient in age group (32-51) as against age group (72-101) decreases the log odds by 0.418. The negative coefficient implies the likelihood of breach will be reduced for age (32-51) with respect to group age (72-101). Comparing the variable to other determinants, it is the 7th important contributor in the model.	The odd ratio is Exp. (B) = 0.658. This means that a patient in age group category 32-51 is less likely to breach the length of stay with reference to age group category 72-101 years, having all the other determinants in the model.
Number of investigations (2)	-0.323	368.6	8	0.724	Having number of investigation (2) versus 0 decreases the log odds of the length of stay by 0.323. The negative coefficient means the likelihood of breach will be reduced with respect to 2 investigations compared to no investigation. Comparing the variable to other determinants, it is the 8th most important contributor in the model.	The odd ratio is Exp. (B) = 0.724. This means that a patient with 2 investigation is less likely to breach the length of stay with reference to no investigation (0), having all the other determinants in the model.
Mode of arrival (EMS)	0.277	321.94	9	1.319	Mode of arrival (EMS) versus mode of arrival (non-EMS) increases the log odds by 0.277. The positive coefficient indicates EMS arrival increases the likelihood of breach compared to non-EMS. Comparing the variable to other determinants, it is the 9th most important contributor in the model.	The odd ratio is Exp. (B) = 1.319 This means that a patient who arrived with EMS is more likely to breach compared to non-EMS arrival, having all the other determinants in the model.

Table 5.11 Analyses of the Model for Predicting Breach or No breach (cont'd)

Variables in the Equation	B	Wald	Rank	Exp (B)	Model Parameter Coefficients Analyses	Analyses of Exp (B) - Odds Ratio
Year of arrival (2018)	-0.214	292.13	10	0.808	Year of arrival (2018) as against year (2017) decreases the log odds by 0.214. The negative coefficient implies that the likelihood of breach will be reduced for year of arrival (2018) compared to year of arrival (2017). Comparing the variable to other determinants, it is the 10th important contributor in the model.	The odd ratio is Exp. (B) = 0.808 This means that a patient who arrived in 2018 is less likely to breach compared to 2017, having all the other determinants in the model.
Number of procedures (2)	-0.273	283.9	11	0.761	Having number of procedure (2) versus number of procedure (0), decreases the log odds of the length of stay by 0.273. The negative coefficient means the likelihood of breach will be reduced with respect to 2 procedures compared to no procedure. Comparing the variable to other determinants, it is the 11th most important contributor in the model.	The odd ratio is Exp. (B) = 0.761. This means that a patient with 2 procedures is less likely to breach in reference to no procedure, having allowed all the other determinants in the model.
Age (52-71)	-0.242	205.17	12	0.785	A patient in age group (52-71) as against age group (72-101). decreases the log odds of the length of stay by 0.242. The negative coefficient implies that the likelihood of breach will be reduced for age (52-71) with respect to group age (72-101). Comparing the variable to other determinants, it is the 12th most important contributor in the model.	The odd ratio is Exp. (B) = 0.785 This means that a patient in age group 52-71 years is less likely to breach in reference to age group category 72-101 years, having all the other determinants in the model.

Table 5.11 Analyses of the Model for Predicting Breach or No breach (cont'd)

Variables in the Equation	B	Wald	Rank	Exp (B)	Model Parameter Coefficients Analyses	Analyses of Exp (B) - Odds Ratio
Presenting Complaint (Airway / breathing/Circulation / chest)	-0.321	203.23	13	0.726	Presenting complaint (Airway /Breathing/Circulation / Chest) relative to presenting complaint (all others) decreases the log odds of the length of stay by 0.31. The negative coefficient means that presenting complaint (Airway /Breathing/Circulation /Chest) compared to complaint (all others) reduces the likelihood of breach. Comparing the variable to other determinants, it is the variable is the 13th important contributor in the model.	The odd ratio is Exp. (B) = 0.726 This means that presenting complaint (Airway/Breathing/Circulation/ Chest) is less likely to breach compared to presenting complaint (all others) having all the other determinants in the model.
Frequent user (Yes)	-0.173	92.89	14	0.841	Using frequent user relative to non-frequent user decreases the log odds of breach by 0.173. The negative coefficient suggests a decrease in the likelihood of a breach for a frequent user compared to non-frequent user. Comparing the variable to other determinants, this variable is the 14th important determinant in the model.	The odd ratio is Exp. (B) = 0.841. This means that a frequent user patient is less likely to breach the 4HQI than a non-frequent user patient, having allowed all the other determinants in the model.
Number of procedures (3)	-0.131	67.35	15	0.877	Having number of procedure (3) versus number of procedure (0), decreases the log odds of by 0.131. The negative coefficient means mean the likelihood of breach will be reduced with respect to 3 procedures compared to no procedure. Comparing the variable to other determinants, it is the 15th most important contributor in the model.	The odd ratio is Exp. (B) = 0.877. This means that a patient with 3 procedures is less likely to breach in reference to procedure (0), having all the other determinants in the model.

Table 5.11 Analyses of the Model for Predicting Breach or No breach (cont'd)

Variables in the Equation	B	Wald	Rank	Exp (B)	Model Parameter Coefficients Analyses	Analyses of Exp (B) - Odds Ratio
Day of arrival (Weekday)	0.082	35.44	16	1.085	Using day of arrival (weekday) versus day of arrival (weekend) increases the log odds by 0.082. The positive coefficient suggests that the day of arrival (weekday), increases the likelihood of breach with respect to arrival at weekend. Comparing the variable to other determinants, it is the 16th most important contributor in the model.	The odd ratio is Exp. (B) = 1.085. This means that a patient who arrives on a weekday is more likely to breach in reference to an arrival on a weekend, having all the other determinants in the model.
Gender (Male)	0.069	31.65	17	1.071	However, a patient in gender (male) versus gender (others) decreases log odds by 0.069. This means that gender (male) compared to gender (others) increases the log odds of length of stay. Comparing the variable to other determinants, it is the 17th most important contributor in the model.	The odd ratio is Exp. (B) = 1.071 This means that a male patient is more likely to breach the 4HQI compared to other gender patients, having all the other determinants in the model.
Number of procedures (1)	-0.128	26.81	18	0.880	Using number of procedure (1) in reference to the number of procedure (0), decreases the log odds by 0.128. The negative coefficient means mean the likelihood of breach will be reduced with respect to number of procedure (1) compared to no procedure. Comparing the variable to other determinants, the variable is the 18th most important contributor in the model.	The odd ratio is Exp. (B) = 0.880. This means that a patient with number of procedure (1) is less likely to breach with reference to no procedure (0), having all the other determinants.

Table 5.11 Analyses of the Model for Predicting Breach or No breach (cont'd)

Variables in the Equation	B	Wald	Rank	Exp (B)	Model Parameter Coefficients Analyses	Analyses of Exp (B) - Odds Ratio
Presenting Complaint (Gastrointestinal)	-0.128	26.81	19	0.880	Presenting complaints (Gastrointestinal) versus presenting complaints (all others), decreases the log odds by 0.128. The negative coefficient means that presenting complaint (Gastrointestinal) compared to presenting complaint (all others), reduces the likelihood of breach. Comparing the variable to other determinants, it is the 19th most important contributor the model.	The odd ratio is Exp. (B) = 0.880. This means that presenting complaint (Gastrointestinal) is <u>less</u> likely to breach compared to presenting complaint (all others), having all the other determinants in the model.
Number of investigations (3)	-0.093	24.79	20	0.911	Having number of investigation (3) versus 0 decreases the log odds by 0.093. The negative coefficient means that the likelihood of breach will be reduced with respect to 3 investigations compared to no investigation. Comparing the variable to other determinants, it is the 20th most important contributor in the model.	The odd ratio is Exp. (B) = 0.911. This means that a patient with 3 investigations is <u>less</u> likely to breach in reference to no investigation, having all the other determinants in the model.
Referral source (All others)	0.059	15.34	21	1.06	Use of referral source (all others) compared to self- referred increases the log odds of breach by 0.59. The positive coefficient indicates an increase in the likelihood of the breach of self-referral with respect to the other referral source. Comparing the variable to other determinants, this variable is the 21st most important determinant in the model.	The odd ratio is Exp. (B) = 1.06. This means that a patient who arrives based on other referral sources is <u>more</u> likely to breach than self- referred, having allowed all the other determinants in the model.

Table 5.11 Analyses of the Model for Predicting Breach or No breach (cont'd)

Variables in the Equation	B	Wald	Rank	Exp (B)	Model Parameter Coefficients Analyses	Analyses of Exp (B) - Odds Ratio
Presenting Complaint (Trauma /Musculoskeletal)	-0.085	14.93	22	0.918	Presenting complaints (Trauma /Musculoskeletal) versus presenting complaints (all others) decreases the log odds by 0.085. The negative coefficient means that presenting complaint (Trauma /Musculoskeletal) compared to complaint (all others) reduces the likelihood of breach. Comparing the variable to other determinants, it is the 22nd most important contributor in the model.	The odd ratio is Exp. (B) = 0.918. This means that presenting complaint (Trauma /Musculoskeletal) is <u>less</u> likely to breach the length of stay compared to presenting complaint (all others), having all the other determinants in the model.
Presenting Complaint (Environmental/General / minor / admin)	0.076	10.65	23	1.079	Presenting complaints (Environmental/General /Minor /Admin) with reference to complaint (all others) increases the log odds by 0.076. The negative coefficient means that presenting complaint (Environmental/General /Minor /Admin) compared to complaint (all others) increases the likelihood of breach. Comparing the variable to other determinants, it is the 23rd most important contributor in the model.	The odd ratio is Exp. (B) = 1.079 This means that presenting complaint (Environmental/General/Minor/Admin) is <u>more</u> likely to breach compared to presenting complaint (all others), having all the other determinants in the model.
Presenting Complaint (Head and Neck/Neurological /Eye)	-0.033	1.61	24	0.967	Presenting complaints (Head and Neck/Neurological /Eye) versus presenting complaints (all others) decreases the log odds by 0.033. The negative coefficient means that presenting complaint (Head and Neck/Neurological /Eye) compared to presenting complaint (all others) reduces the likelihood of breach. However, presenting complaints 4 coefficient is not significant in the model (p = 0.205 > 0.05). Comparing the variable to other determinants, it is the 24th most important contributor in the model.	The odd ratio is Exp. (B) =0.967 This means that presenting complaint (Head and Neck/Neurological /Eye) is <u>less</u> likely to breach compared to presenting complaint (all others), having all the other determinants in the model.

Table 5.11 Analyses of the Model for Predicting Breach or No breach (cont'd)

Variables in the Equation	B	Wald	Rank	Exp (B)	Model Parameter Coefficients Analyses	Analyses of Exp (B) - Odds Ratio
Gender (Female)	-0.265	0.49	25	0.767	A patient in gender (female) versus gender (others) decreases log odds of length of stay by 0.265. This means that gender (female) compared to gender (others) decreases the likelihood of breach. However, gender (1)'s coefficient is not significant in the model (p = 0.484 > 0.05). Comparing the variable to other determinants, the variable is the 25th most important contributor in the model.	The odd ratio is Exp. (B) = 0.767 This means that a female patient is less likely to breach the length of stay compared to other gender patients, having all the other determinants in the model.
Arrival location (Resus)	-0.001	0.01	26	0.999	Using arrival location Resus versus location GP (0) decreases the log odds by 1.081. The negative coefficient shows that the arrival location Resus with reference to GP reduces the likelihood of breaching. Comparing the variable to other determinants, the variable is the 3rd important contributor in the model.	The odd ratio is Exp. (B) = 0.999. This indicates that a patient who arrives at Resus is less likely to breach the length of stay than arriving at GP, having allowed all the other determinants in the model.

The ranking provided in the table above is useful in knowing the variable contributing the most to the model. The top five based on ranking were disposal status of admitted, time of arrival of in hours, arrival location of Majors, number of investigations of 1, and age group 1 (17-21 years). Furthermore, some of the odds ratio interpretation such as a patient who arrived with EMS being more likely to breach compared to Non-EMS arrival and patient in the 72-101 age group being more likely to breach compared to the other age group is in line with literature (Ross et al., 2019). However, other interpretation of the odds ratios need to be approached with caution as it might be statistically correct but not in line with practice and literature. For example, according to the odds ratio interpretation, a patient with 3 procedures is 0.877 more likely to breach in reference to one who had no procedure. This means that the patient with 3 procedures is less likely to breach in comparison to the patient with no procedure. An alternative interpretation is that a patient with no procedure is (1/0.877) = 1.14 more likely to breach the length of stay in reference to a patient with 3 procedures. Similarly, a patient with 3 investigations with an odds ratio of 0.911is less likely to breach in reference to no investigation which also means that a patient with no investigation is (1/0.911) = 1.10 more likely to breach in reference to a patient with 3 investigations. It was noted that the odds ratio for the age groups increase from the lower age group to the higher one. Also, the odds ratio increases from 1 investigation to 2 and subsequently to 3. However, in practice, procedures and investigations consume time therefore patients who have undergone 3 of these will most likely have a longer LOS and therefore breach compared to those who have had none. Improvement suggestions made based on statistical results must consider clinical interpretation and evidence from literature to support its application in practice.

5.10 Generalized Linear Model Analysis

The LR analysis provided a prediction of breach or no breach. Further analysis using generalized linear model was necessary to predict the number of minutes the patient stayed whether they breached or not. The improvement process that commenced from the RAD analysis of bottleneck solutions, will be suitably implemented in combination with a prediction of the patient LOS. The GLM which is becoming an industry standard for measuring the effect of variables on an observed object (Anderson et al., 2007) was used to model the length of stay. As a generalized form of a linear model, it does not require the assumptions of the classical linear model to be met (Anderson et al., 2007). The process of developing the model began with ensuring that the assumptions of GLM as outlined by McCullagh and Nelder (McCullagh and Nelder, 1989) and Anderson (Anderson et al., 2007) were met.

5.10.1 Assumptions of Generalized Linear Model

The data must be independent and uncorrelated. This assumption had already been met as part of the logistic regression assumptions in Section 5.9.1. Unlike in the case of linear regression, the dependent variable Y is not required to be normally distributed but must be from an exponential family of distributions such as Normal, Binomial, Poisson, or Multinomial. To satisfy this assumption, the length of stay, which was not normally distributed, was log-transformed using the natural log to normalise it as detailed in the next section. Moreover, the variance is not required to be constant and therefore can vary with the mean of the distribution hence homogeneity of variance is not needed. It is also assumed that the effect of the independent variable on the dependent variable is additive. If this assumption is not met, the independent variables have to be transformed however, all the independent variables are categorical therefore this assumption is not violated.

5.10.2 The Generalized Linear Model

Once the assumptions had been met, the model was developed using the natural log-transformed LOS to allow prediction based on the independent variables.

Where In (LOS) = Ω

$$
\begin{aligned}
\Omega = 5.664 + {} & \beta_0(Frequent\ user) + \text{Ñ}_1(Referral\ source) + X_{0,1,2}(Arrival\ location) \\
& + \text{Ą}_0(Disposal\ status) + Z_{0,1,2}(Number\ of\ procedures) \\
& + \phi_{0,1,2}(Number\ of\ investigations) + \text{Ķ}_1(Day\ of\ Arrival) + \mu_{1,2,3}(Age) \\
& + \text{Ŗ}_0(Time\ of\ arrival) + \hat{\text{W}}_0(Year\ of arrival) + \text{Ɲ}_1(Mode\ of arrival) \\
& + \rho_{0,1}(Gender) + \psi_{1,2,3,4,5}\ (Presenting\ Complaint)
\end{aligned}
$$

The length of stay can be predicted using the above model and the coefficient of the independent variables in the table. The full result of the analysis is presented in Appendix E.10. A condensed version showing the models in the equation, coefficients, significance, and interpretation of the coefficient is presented in Table 5.12 below. The goodness of fit and tests of model effects are presented in Appendix E.11 and Appendix E.12 respectively.

As the dependent variable was log-transformed, back transformation is necessary to ensure an accurate interpretation of results as the unit of measurement has changed (Lee, 2020). For example, a comparison of arithmetic means changes to that of geometric means after log transformation hence back-transformation in the form of exponentiation is required (Field, 2009, Lee, 2020). In the case of the natural log, the natural exponential function must be used (Lee, 2020). Therefore for every increase in the independent variable Y, the dependent variable increases by (Exp (X))-1)*100 (Lee, 2020). The coefficients are therefore transformed for easy interpretation in Table 5.12.

5.10.3 Analysis and Interpretation of Coefficients

The model parameters are presented in Table 5.12 below. The transformed coefficient provides an indication of an increase (if the coefficient is positive) or a decrease (if the coefficient is negative) of the LOS for the individual variables. The redundant variables indicated in the table were used as references in the model.

Table 5.12 Model parameters, ranking and interpretation

Variables in the equation	Model Parameter Coefficients	Sig.	Interpretation/Analyses Exp (coefficient) - 1) *100	Rank (Wald (X2) / df)
[Number of investigations=0]	-0.261	.000	-22.97%	1
[Disposal status=Discharged]	-0.213	.000	-19.18%	2
[Arrival time=Out of hours]	0.158	.000	17.12%	3
[Age=17-31]	-0.159	.000	-14.70%	4
[Age=32-51]	-0.136	.000	-12.72%	5
[Number of investigations=1]	-0.126	.000	-11.84%	6
[Number of procedures=1]	-0.1	.000	-9.52%	7
[Arrival location=See & Treat]	-0.182	.000	-16.64%	8
[Number of procedures=0]	-0.136	.000	-12.72%	9
[Arrival location=GP]	-0.216	.000	-19.43%	10
[Mode of arrival=EMS]	0.079	.000	8.22%	11
[Age=52-71]	-0.084	.000	-8.06%	12
[Year of arrival=2017]	-0.053	.000	-5.16%	13
[Presenting Complaint= Airway / Breathing/Circulation / Chest]	-0.077	.000	-7.41%	14
[Number of procedures=2]	-0.049	.000	-4.78%	15
[Number of investigations=2]	-0.057	.000	-5.54%	16
[Presenting Complaint= Trauma / Musculoskeletal]	-0.047	.000	-4.59%	17
[Frequent user=No]	-0.045	.000	-4.40%	18
[Arrival location=Majors]	0.052	.000	5.34%	19
[Gender=Female]	0.017	.000	1.71%	20
[Presenting Complaint= Head and neck/Neurological /Eye]	0.019	.000	1.92%	21
[Presenting Complaint= Gastrointestinal]	-0.015	0.001	-1.49%	22
[Day of arrival=Weekday]	-0.008	0.001	-0.80%	23
[Referral source=All others]	0.008	0.003	0.80%	24
[Presenting Complaint= Environmental/General / Minor / Admin]	0.008	0.063	0.80%	25
[Gender=Others]	-0.062	0.169	-6.01%	26

To highlight some of the interpretation of the model parameters, it can be noted that in terms of age, patients who are 17-31 have the lowest LOS compared to the others. In reference to arrival location Resus, arrival locations GP and See &Treat decrease the LOS however, arrival location Majors, increases the LOS confirming that indeed, Majors is the unit which needs to be the centre of ED improvement initiatives. The percentage by which the LOS decreases for the number of procedures reduces from 0, 1 and 2 procedures consecutively. This shows that the higher the number of procedures, the longer the LOS. A similar trend is noticed for number of investigations. This derived model can be useful in estimating LOS.

5.11 Application of Derived Models in Predicting Waiting Times

The LR and GLM analysis resulted in models that can be applied in at least two areas with respect to the ED. First, the LR model can help predict whether or not a patient will breach waiting time expectations in the ED. Additionally, the GLM can also be used to estimate ED LOS for given groups of patients. They can be used by ED managers and policymakers to analyse the patient flow as factors that are significantly associated with a long ED LOS have been identified. Looking at the variables that emerged as top predictors for breach and LOS, it can be seen that the number of investigations, disposal status, arrival time, arrival location and age are of great importance. These variables need to be taken into consideration as part of resource planning and patient flow improvement initiatives. Statistical prediction is not without defects and as stated in Section 5.9.6 and must be interpreted with caution.

Uncertainties exist about patient-related information in the ED. Some information about the patient is available pre-hospital if they arrived by ambulance and for all others, information is collected along the patient journey in ED. Hence, some of the variables used in developing these two models will not be known at the time of patient arrival. Variables such as number of investigations, number of procedures and disposal status, will be known at the end of the patient's treatment in ED. Consequently, a decision was developed to further analyse the data using only variables known at the time of presentation. This will provide ED staff with a tool to predict the likelihood of a patient breaching or not at arrival based on the independent variables available at that stage. This prediction will serve as a guide throughout the patient journey and can be linked to the RAD mapping to monitor the patient flow to support waiting time expectations.

5.12 Decision Tree

A decision tree (DT) is an operational research tool for decision analysis by classifying cases or predicting dependent variables based on independent variables (Gul and Celik, 2020). It is a machine learning technique based on data mining and has been used for analysing complex problems such as ED crowding (Feng et al., 2019, Rahman et al., 2020). It is made up of nodes and leaves with logical rules guiding the path from the root node to the leaves as it branches out (Rahman et al., 2020). The tree-like structure enhances easy reading and interpretation of decision tree analysis by ED staff (Feng et al., 2019). As a non-parametric learning algorithm which can be applied to both regression and classification problems of EDs, the DT is suitable for non-linear data and is easy to visualise and interpret (Gul and Celik, 2020, Jain and Chatterjee, 2020). It is useful in investigating and understanding clinical decision support (Feng et al., 2019) and has been used successfully to predict ED patients' LOS (Gul and Celik, 2020). Rahman et al (2020) used it to analyse data with 33 independent variables including presenting problems variable, having 200 different attributes which were all deemed to be important and therefore not reclassified. Including a larger number of attributes and permutations has the advantage of producing results which provide a better understanding of complex problems such as those in healthcare (Podgorelec et al., 2002, Handelman et al., 2018).

The IBM SPSS software was used in applying the Quick, Unbiased, Efficient Statistical Tree (QUEST) growing method of decision tree with an option of tree pruning. The QUEST method was selected because it is a fast method and provides the binary classification (Saini et al., 2017) required for analysing breach or no breach. Moreover, it reduces the tendency to produce more splits as in the case of the other methods (Saini et al., 2017). The other methods were used initially but produced too many nodes and leaves, making interpretation difficult. The QUEST method provided an adequate number of nodes and terminal nodes to generate useful information about homogenous groups of patients with a prediction of breach or no breach.

It was identified that 3 out of the 13 independent variables used for the LR and GLM analysis can be classified as modifiable by the ED. This classification was made by the author in assessing the factors that EDs had control over. The remaining 10 will be classified as non-modifiable. The modifiable factors are number of procedures, number of investigations and disposal status. These factors are within the control of the ED and their values have an impact on the patient's LOS as has been shown in the LR and GLM analysis. The modifiable factors provide avenues for exploring solutions for addressing bottlenecks which will be further explored in Chapter 6. The non-modifiable factors are age, gender, presenting complaint, arrival time, arrival location, mode of arrival, referral source, frequent user, year of arrival and day of arrival. These 10 independent variables will be available to the ED when the patient arrives, and registers therefore selected for the DT model. Consequently, the other 3 variables will not be known at that stage. The DT model can help to quickly group patients according to their age, gender, presenting complaint, arrival time, arrival location, mode of arrival, referral source, frequent user, year of arrival and day of arrival with QI violation as the dependent variable determining breach or no breach. The DT model can therefore be included in the Triage process.

The DT analysis showed that all the variables that were selected for the model were statistically significant at $p<0.01$. The tree showed arrival location as the root node with the highest Chi-square value. This means that the arrival location was identified as the strongest predictor of whether a patient breaches or not with Resus and Majors emerging higher than Minors and GP which became a terminal node. The next variable was age with age group 72-101 having a higher likelihood of breach than the remaining four age groups. This was followed by arrival time (in and out of hours) with in-hours being a terminal node and out of hours having a stronger likelihood. The mode of arrival was next showing EMS arrival as being higher and finally presenting complaints in that order of predicting ability. Presenting complaints groups 4 (Head and Neck/Neurological/Eye), 5 (Trauma/Musculoskeletal) and 6 (all others) emerged with a higher likelihood of breach than the remaining three 1 (Airway/Breathing/Circulation/Chest), 2 (Environmental) and 3 (Gastrointestinal). Frequent user and gender were included in the model but not shown on the tree indicating a low predictive ability. Referral source, year of arrival and weekend/ weekday were not included i.e., not selected by the DT programme to build the model. These variables were not considered strong predictors.

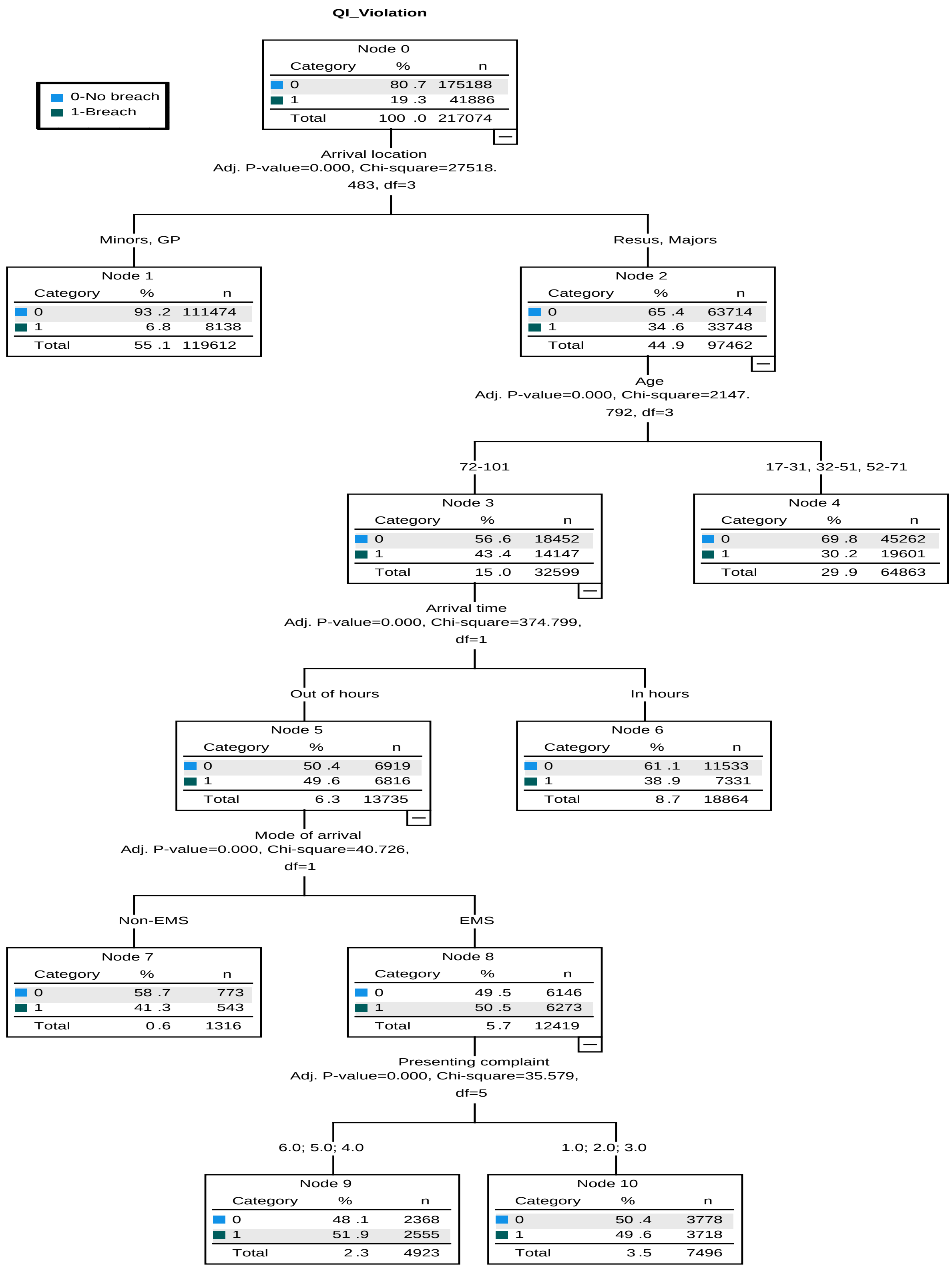


Figure 5.6 Decision tree for QI violation

Table 5.13 Tree table with variable parameters

Node	No breach		Breach		Total		Predicted Category	Parent Node	Primary Independent Variable			
	N	Percent	N	Percent	N	Percent	--	--	Variable	Sig.	Chi-Square	df
0	175188	80.7%	41886	19.3%	217074	100.0%	0	--	--	--	--	--
1	111474	93.2%	8138	6.8%	119612	55.1%	0	0	Arrival location	.000	27518.48	3
2	63714	65.4%	33748	34.6%	97462	44.9%	0	0	Arrival location	.000	27518.48	3
3	18452	56.6%	14147	43.4%	32599	15.0%	0	2	Age	.000	2147.61	3
4	45262	69.8%	19601	30.2%	64863	29.9%	0	2	Age	.000	2147.61	3
5	6919	50.4%	6816	49.6%	13735	6.3%	0	3	Arrival time	.000	374.79	1
6	11533	61.1%	7331	38.9%	18864	8.7%	0	3	Arrival time	.000	374.79	1
7	773	58.7%	543	41.3%	1316	0.6%	0	5	Mode of arrival	.000	40.73	1
8	6146	49.5%	6273	50.5%	12419	5.7%	1	5	Mode of arrival	.000	40.73	1
9	2368	48.1%	2555	51.9%	4923	2.3%	1	8	Presenting Complaint	.000	35.58	5
10	3778	50.4%	3718	49.6%	7496	3.5%	0	8	Presenting Complaint	.000	35.58	5

As shown in Figure 5.6 the resulting tree had a tree depth of 5 layers with 11 nodes and 6 terminal nodes. The numbers and percentages corresponding to the breach and no breach for each of the nodes and terminal nodes are presented in Table 5.13 together with details of the predicted category, parent node, the statistical significance, the Chi-square, and degrees of freedom.

It can be deduced from the decision tree that patients seen in Majors or Resus, 72 years or above, who arrived out of hours by EMS mode of arrival have the highest likelihood of breach. Those with presenting complaint categories 4 (Head and Neck/Neurological/Eye), 5 (Trauma/Musculoskeletal) and 6 (all others) have a slightly higher likelihood than the remaining three presenting complaints; 1 (Airway/Breathing/Circulation/Chest), 2 (Environmental) and 3 (Gastrointestinal). It can be seen from Table 5.14 below that the overall accuracy of the model's predictive ability was 80.80% as per the classification table, which is an indication of a good fit.

Table 5.14 Classification table for the decision tree

Classification			
	Predicted		
Observed	No- breach	Breach	Percent Correct
No- breach	172820	2368	98.6%
Breach	39331	2555	6.1%
Overall Percentage	97.7%	2.3%	80.8%
Growing Method: QUEST Dependent Variable: QI_Violation			

5.13 A Focus on Majors

The total number of visits corresponding to each of the arrival locations, GP, Minors, Majors and Resus is used to calculate the corresponding percentage of breach with the results as 0.0811, 3.6679.12.5651 and 2.6810 respectively. The RAD process mapping revealed Majors as a bottleneck problem spot hence a decision was made to focus on Majors for further analysis instead of the whole data set as per the following explanation. Minors saw the highest number of patients, 51.4% (N=111614) and those with the most life-threatening conditions were seen in Resus 7% (N=15255) of the whole sample (N=217074). However, the percentage of breach of the 4HQI in these two areas were 19% and 15.4% respectively. On the other hand, Majors made up 37.9% (N=82207) of attendances yet accounted for 65.1% of the 4HQI breaches making it an area of concern. Resus and Minors are therefore not the areas of concern in this context though both consume resources which would have otherwise potentially been available to use for Majors patients. Table 5.15 shows the rate of the 4HQI violation associated with the different arrival locations.

Table 5.15 Percentage of breach per arrival location

Arrival location	**Percentage proportion of violation**	
Overall	(41886/217074) *100	19.2957
GP	(176/41886) *19.2957	0.0811
See and Treat	(7962/41886) *19.2957	3.6679
Majors	(27277/41886) *19.2957	12.5651
Resus	(6471/41886) *19.2957	2.9810

5.14 The Complexity of Patients in Majors

Majors see complex patients; this is supported by EM-HRG codes in this study. Furthermore, Majors receive patients from both EMS and Non-EMS arrival. The Streaming and Triage RAD presented in Chapter 4, Fig 4.5 showed multiple entry points in the unit, signifying the complexness of care. The EM-HRG codes extracted from the Majors unit in this data set are consistent with the expected presentations. Table 5.16 below provides details about the codes, the category of investigation and treatment that it corresponds to and the type of emergency department that applies. The amount of resource consumed is highest for VB01Z and reduces as the list goes down with VB11Z consuming the least. The codes are obtained from a combination of the categories of investigations and treatments that were undertaken. For example, a patient with HRG code VB02Z would have undergone a category 3 investigation such as computed tomography (CT) and a category 4 treatment such as a lumbar puncture (Higginson and Guly, 2007).

Table 5.16 EM-HRG codes for A&E prices 2017/2018

		Tariff (£)	
HRG code	**HRG name**	**Type 1 and 2 Departments**	**Type 3 Departments**
VB01Z	Emergency Medicine, Any Investigation with Category 5 Treatment	322	63
VB02Z	Emergency Medicine, Category 3 Investigation with Category 4 Treatment	293	63
VB03Z	Emergency Medicine, Category 3 Investigation with Category 1-3 Treatment	212	63
VB04Z	Emergency Medicine, Category 2 Investigation with Category 4 Treatment	192	63
VB05Z	Emergency Medicine, Category 2 Investigation with Category 3 Treatment	161	63
VB06Z	Emergency Medicine, Category 1 Investigation with Category 3-4 Treatment	113	63
VB07Z	Emergency Medicine, Category 2 Investigation with Category 2 Treatment	141	63
VB08Z	Emergency Medicine, Category 2 Investigation with Category 1 Treatment	130	63
VB09Z	Emergency Medicine, Category 1 Investigation with Category 1-2 Treatment	91	63
VB10Z	Emergency Medicine, Dental Care	82	63
VB11Z	Emergency Medicine, No Investigation with No Significant Treatment	63	63
VB99Z	Emergency Medicine, Patient Dead on Arrival	91	63

Source: NHS, 2017

The EM-HRG codes for Majors patients are shown in Table 5.17 below. This table shows the count and corresponding percentages for EM-HRG codes for all Majors patients and those who breached. It can be seen that EM-HRG codes VB003, VB04, VB07, VB08, VB09, and VB011 are the most common codes. This demonstrates how this unit sees patients with complex and varying needs and therefore needs to be an area of focus for improving ED patient flow.

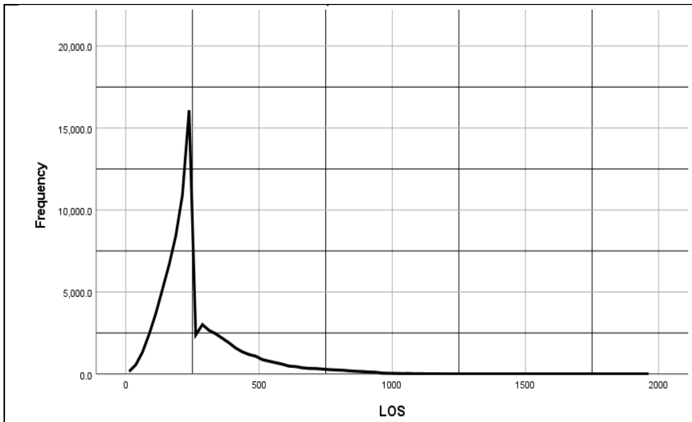
Table 5.17 EM-HRG codes for Majors

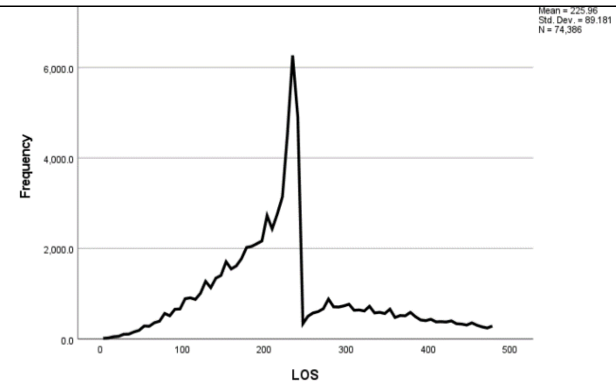
All Majors Patients		**Patients breaching 4HQI in Majors**	
(N=82,207)		**(N=27,277)**	
EM-HRG codes	**Counts (%)**	**EM-HRG codes**	**Counts (%)**
VB01Z	21 (0.03)	VB01Z	8 (0.03)
VB02Z	1741 (2.12)	VB02Z	1027 (3.77)
VB03Z	8368 (10.18)	VB03Z	4058 (14.88)
VB04Z	11084 (13.48)	VB04Z	4868 (17.85)
VB05Z	2092 (2.54)	VB05Z	778 (2.85)
VB06Z	3712 (4.52)	VB06Z	1238 (4.54)
VB07Z	16548 (20.13)	VB07Z	6116 (22.42)
VB08Z	14928 (18.16)	VB08Z	4331 (15.88)
VB09Z	14580 (17.74)	VB09Z	2976 (10.91)
VB011Z	9056 (11.02)	VB011Z	1852 (6.79)
Missing codes	77 (0.09)	Missing codes	25 (0.09)
Total	82207 (100)	Total	27277 (100)

Source: Author

5.15 Three Time-blocks

The length of stay though being an important metric for measuring the performance of the ED must be interpreted with caution. Using the 4HQI in isolation could be misleading as it does not reveal the underlying trends in the performance. For instance, two hospitals with similar LOS performance may have completely different patient admission and discharge patterns when looked at closely (Eatock et al., 2017). Hospitals tend to make a decision on admission or discharge when approaching the 4-hour point which explains the peak in activities about 20 minutes to the end of the four hours as noted by other researchers (Mason et al., 2012, Eatock et al., 2017, Swancutt et al., 2017). In particular, patients are more likely to be admitted in the last 20 minutes of the 4HQI or after the indicator than in the preceding 3 hours and 39 minutes (Mason et al., 2012). This phenomenon is also evident in the dataset where in Figure 5.7 below of the LOS graph of all Majors patients and for Majors patients who stayed for 24 hours or less, there is a peak just before 240 minutes.





LOS for Majors patients	LOS for Majors patients who stayed for 24 hours or less

Figure 5.7 LOS of Majors patients and Majors violators showing peak before 240 minutes

The total length of stay in ED is measured from arrival to departure. It is therefore recommended by the author that the LOS should be analysed as three time-blocks i.e., Time-block 1. Arrival to Seen, Time-block 2. Seen to MD and Time-block 3. MD to departure. The purpose is to reduce this phenomenon from occurring just before the 240 minutes with a sudden increase in admissions. Such a change in focus can help move patients swiftly along the journey rather than simply focusing on the final LOS. Whether a fixed time such as 4HQI is in use or a new mean threshold, the patient's journey must be monitored thoroughly to ensure a steady admission and discharge of patients throughout and not just before a specific time. Individual EDs can set local targets for monitoring these time blocks. An example is a recommendation of one hour from arrival to seeing a clinician which has been shown to result in a higher probability of the patient leaving the ED in less than 4 hours (Gill et al., 2018). Usually, admitted patients have a longer LOS than discharged patients (Brick et al., 2014, Sweeny et al., 2020) as was the case in this study. Appendix E.13 shows that the mean LOS for admitted patients was 275.85 minutes (ST DEV 158.727) and 167.73 minutes (ST DEV 99.365) for discharged patients for the overall dataset. Additionally, for QI violators, the mean LOS was 436.57 minutes (ST DEV 162.192) for admitted patients and 376.64 minutes (ST DEV 151.595) for discharged patients. Moreover, boarding and LOS, in general, are longer during out-of-hours (Sweeny et al., 2020) because there are fewer discharges and therefore fewer beds available.

A review of the three time-blocks revealed different trends for the overall data, for those who breached and those who did not. Table 5.18 below shows the minimum and maximum values. Range, mean, percentage of LOS, standard deviation (ST DEV) and variance values of arrival to Seen, Seen to Medical Decision, boarding and LOS for the whole data set (N=217074), for patients who did not breach (N= 175188) and those who breached. As shown in Table 5.18, Arrival to Seen accounted for over 40.99% of the overall data set, 48.14% for those who did not breach and 29.70% for those who breached. The patients who breached the 4HQI seem to have spent more time (38.69%) in the last time block (boarding) compared to those who did not which was only 14.95%. Viewing the patient journey in these time-blocks can help ensure all patients progress through all three in a timely manner. The approximated mean values of Arrival to Seen of 85 minutes, Seen to Medical Decision of 72 minutes, and boarding of 50 minutes can be used as a guide when monitoring patients' LOS in each of the time-block since it ensures that patients are seen under 240 minutes as the overall LOS.

Table 5.18 Descriptive Statistics of time-blocks

Descriptive Statistics of Time-blocks for Overall Dataset								
Time-Blocks	N	Range	Minimum	Maximum	Mean	% of LOS	Std. Deviation	Variance
Arrival to seen	217074	1206	0	1206	85.15	40.99%	60.955	3715.459
Seen to MD	217074	1751	0	1751	72.40	34.86%	74.628	5569.297
Boarding	217074	1635	0	1635	50.18	24.16%	97.785	9561.940
LOS	217074	1964	1	1965	207.72	100.00%	135.149	18265.374
Valid N	217074							
Descriptive Statistics of Time-blocks for patients who did not Breach the 4HQI								
Time-Blocks	N	Range	Minimum	Maximum	Mean	% of LOS	Std. Deviation	Variance
Arrival to seen	175188	240	0	240	75.87	48.14%	47.392	2245.972
Seen to MD	175188	239	0	239	58.18	36.91%	43.539	1895.617
Boarding	175188	233	0	233	23.56	14.95%	37.173	1381.844
LOS	175188	239	1	240	157.61	100.00%	58.266	3394.886
Valid N	175188							
Descriptive Statistics of Time-blocks for patients who Breached the 4HQI								
Time-Blocks	N	Range	Minimum	Maximum	Mean	% of LOS	Std. Deviation	Variance
Arrival to seen	41886	1206	0	1206	123.96	29.70%	89.414	7994.944
Seen to MD	41886	1751	0	1751	131.89	31.60%	128.646	16549.713
Boarding	41886	1635	0	1635	161.48	38.69%	168.598	28425.183
LOS	41886	1724	241	1965	417.33	100.00%	161.311	26021.246
Valid N	41886							

5.16 Duration of Stay of Admitted Patients

An analysis examining patient admission data were conducted to assess the duration of admitted patients. The results from the analysis revealed that nearly 66% of patients admitted to the hospital stayed for three days. Table 5.19 provides a count on the number of days with nearly 30% staying for less than one day i.e., under 24 hours. The number of patients who stayed for one day was 21.19%, 9.00% stayed for two days and 6.15% stayed for three days. The question that arises is, whether these patients were admitted to avoid breaching, or whether more time was needed for investigations indicating a lack of information. As previously stated in Section 1.6, the lack of information to process patients timely, the lack of a decision-maker and the lack of timely decision-making create bottlenecks which affect ED waiting times.

Table 5.19 Duration of stay in day for admitted patients

Duration of stay in days	Count of Duration of stay	% Count of Duration of stay
0	22964	29.64%
1	16420	21.19%
2	6973	9.00%
3	4762	6.15%
	51119	65.98%

The number of admitted patients who stay for 24 hours or less, peaks between 2 and 3 hours as shown in Figure 5.8 below. This shows that some of the patients needed more time for specialist input and tests for safe discharge. For this reason, addressing these two, bottleneck A (awaiting specialty input) and bottleneck B (test outside ED), will result in a reduction in the number of patients needing beds and handover. Consequently, addressing bottleneck D (bed search) and bottleneck E (handover to admitting ward) indirectly.

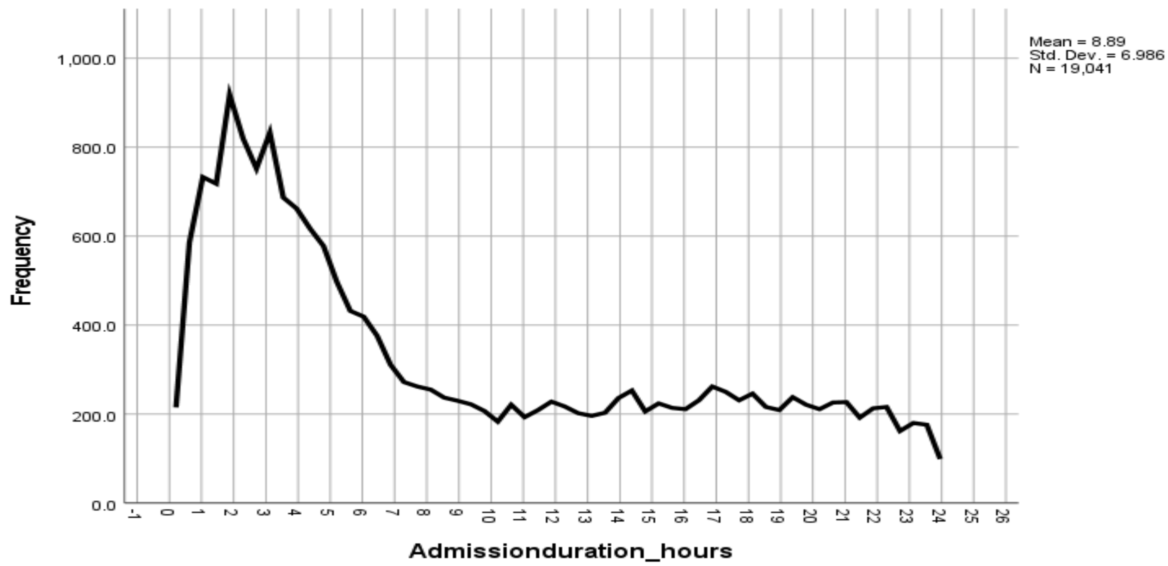


Figure 5.8 Simple line graph of admission duration in hours

The Logistic regression model, generalized linear model and decision tree provided models for predicting breach and length of stay. Furthermore, the analysis of length of stay presented in Section 5.15 resulted in a recommendation of monitoring LOS as three time-blocks. This together with the evaluation of the duration of stay of admitted patients reveal that the ED could benefit from a system that supports regular monitoring of patients along the journey. Process modelling using RAD could be integrated into such a system to map out the patient pathway as part of the monitoring process. This led to the conception of an alert system which is further explained in the next section.

5.17 Alert System for monitoring length of stay.

The utilisation of alert systems to support decision-making has been shown to have benefits in various applications in the emergency department (Shetty et al., 2021, Dutta et al., 2022). For instance, Kim et al (2012) implemented a 2-4-8 project where alerts were transmitted 2 and 4 hours after a patient had been seen if a medical decision had not yet been made. Another alert was sent out 8 hours after a medical decision to admit had been made if the patient was still waiting. This resulted in a reduction in the median length of stay for patients who received consultations.

Their study demonstrated that sending out alerts to inform decision-makers about patient delays could reduce the length of stay. Cho et al (2011), implemented a computerised consultation management system which sent out alerts 3 hours after consultation if a treatment plan was not in place and 6 hours afterwards if a medical decision of admission or discharge had not been registered. The system led to a reduction in length of stay for ED patients (Cho et al., 2011). Decision support systems have also been integrated into electronic medical records for hospital-wide usage (Van Dort et al., 2021).

The alert system being proposed in this study is to support decision-making and monitoring of patients in the ED. Specifically, it could support decisions regarding patient disposition to be made early in the process pending review of investigation results and outcome of treatment (Burke et al., 2017). This can be used as a form of predicting disposition (i.e., bringing decision-making forward). Also, beds can be requested in advance while awaiting review and acceptance by the specialty (Burke et al., 2017). In this study, the alert system has been named ED Patient Alert System (EDPas) and can be potentially integrated into the electronic patient record system, taking into consideration, compatibility, data security and confidentiality of data systems.

5.17.1 Context Diagrams

A context diagram is seen as an important first step in developing a business process model for a manual or computerised system. It shows the system in the context of its environment (Dennis et al., 2012). The main stages of a system development life cycle can be divided into four parts namely, planning, analysis, design and implementation as shown in the Figure 5.9 below (Dennis et al., 2012).

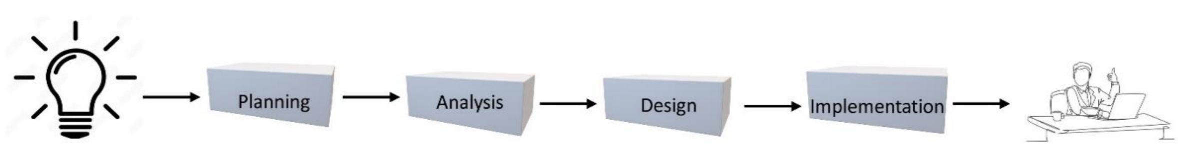


Figure 5.9 The system development life cycle

Source: Adapted from (Dennis et al., 2012)

For planning, analysing, designing, and implementing an alert system, the context diagram in Figure 5.10 below is proposed. Each box has been labelled with arrows indicating the direction of information flow. The system is looking at how patient identification (ID) together with arrival time and patient demographic information and independent variables (IV), can be fed into the system to help predict the timelines of the patient journey. This can be utilised to support patients during their stay in ED and also support the monitoring of the waiting time QI. Once a patient arrives (1), their details can be fed into the system to predict their likelihood of breach, or no breach based on the decision tree (2) and logistic regression (3) models. Their LOS can also be predicted using the generalized linear model (4). A combination of pre-hospital/PRF, CAS card information and RAD modelling (5) can help bring decision-making forward to predict the patient disposition. Information collected at various stages of the patient journey can be fed into the system (6) to provide feedback and improve the prediction and monitoring the patient waiting times.

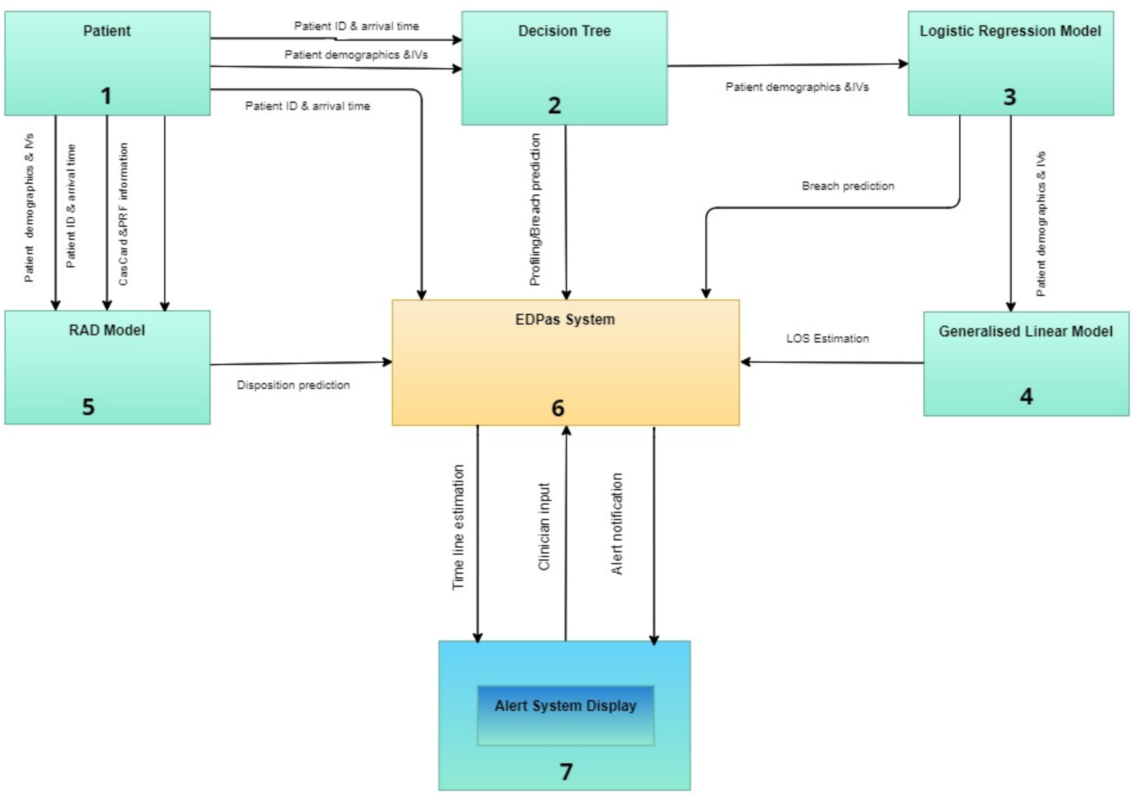


Figure 5.10 Alert system context diagram

Source: Author

If a patient is still waiting to be triaged after a period when they were meant to be seen, the system can send alerts to notify staff that the patient is still waiting to be triaged. The three time-blocks presented in Section 5:15 can be incorporated into the ongoing monitoring of the patient. The use of a visual dashboard for monitoring alerts is recommended (Van Dort et al., 2021) therefore, this system will have a display (6) as shown in Figure 5.10.

A framework of the alert system is presented here since its design, implementation and analysis will require further exploration which remains currently beyond the scope of this dissertation. The analysis, further design and implementation of this system will be addressed in future works.

5.17.2 Quality of Data for the Alert System

The patient demographics and independent variables (IV) known at the time of arrival can be entered into the system to generate a prediction of the QI violation status. These are age, gender, presenting complaints, frequent user, referral source, mode of arrival, arrival location, weekday/weekend arrival, arrival time (in and out of hours) and year of arrival. The other three IVs, disposal status, number of investigations and procedure will not be known as the time of presentation and hence excluded from the model.

In addition to the above initial information, further details about the patient journey can be entered into the system to amend the predicted time and improve the accuracy of the prediction as the patient travels through the ED. This additional information includes all the time stamps as well as investigations and procedures that were performed. These are triage time, seen time, medical decision time, departure time, investigations, diagnosis, procedures, and specialty input requirements.

The time between requests for tests and when results are available can help to better manage these processes and also, the time between specialty referral to when the specialty doctor arrives in the ED. This is not essential for the functioning of the alert system but can help enhance it. Some of the variables are available on the PRF for ambulance arrivals and on the CAS Card for all patients.

5.17.3 Cost-benefit Analysis of an Alert System

According to Dennis et al 2012, the costs and benefits of developing a system can be broken down into four main categories, these are development costs (one-time cost incurred in creating the system), operational costs (ongoing cost required to operate the system), tangible benefits (revenue or cost savings) and intangibles (cost and benefits) (Dennis et al., 2012). In the table below, the cost and benefit of having the alert system have been outlined. Scenarios considered are for no alert system, an alert system developed, integrating with an existing system and maintaining the system. Also, what happens when there are too many alerts, too few or inaccurate alerts? These have associated costs and benefits that need to be carefully reviewed as part of future work in developing the system.

Table 5.20 Cost-benefit of an alert system

Scenarios	Cost	Benefit
No alert system	Panic admission or discharge close to 4 hours	No implementation or running cost
Alert system developed	Development cost IT resources required to develop the system	Regular alert through the patient journey Better management of QI
Integrate with existing electronic patient record system	Development cost IT recourses Systems must be compatible	Tracks individual patients Alerts are specific to that patient All information required to monitor the patient is in one place
Maintaining system	Operational cost in keeping system running and updated	System is kept updated
Too many alerts	Important alerts could be buried under other non-important ones System integrity will diminish System could be overwhelmed	Important alert points will not be missed
Too few alerts	Important alert points could be missed if no alert is sent when one is required System integrity will diminish	System will not be overwhelmed
Accuracy of alert (type 1/type2)	Inaccurate alerts will affect utilisation and reliance on the system	Accurate alerts will yield the benefits as intended and boost the utilisation and integrity of the system

Source: Author

5.18 Conclusion

The process of finding solutions to address bottlenecks identified in Chapter 4 underscored the requirement to understand decisions taken along the patient journey. This led to interrogating anonymised RCHD. Logistic regression, generalized linear model and decision tree methods were applied to generate models to predict breach or no breach of the 4HQI and LOS. Specifically, the LR model can predict breach or no breach, the GLM model can predict the LOS and the DT model can be used on arrival to also predict breach or no breached based on the variables known at that stage. Guided by the insights from the procedural knowledge information modelling (Chapter 4), further analysis focused on the Majors unit to gain a better understanding of the reasons behind this unit being the most crowded unit and its contribution to the ED's waiting time performance. An alert system was proposed to support the monitoring of patient flow. It combines the benefits of the RAD and the statistical models in predicting the patient pathway and disposition decision, for those arriving in Majors to ensure they meet waiting time expectations.

Furthermore, an analysis was conducted to look at the LOS which revealed that the patient journey will benefit from being divided into three time-blocks rather than monitored as one continuous time. The data were interrogated further by bringing in lessons from the process modelling and integrating the two which will be done in the next chapter; Chapter 6.

Chapter 6

Integration of Process Modelling and Data Analysis

This chapter provides an integration of the qualitative side of the study (i.e., the process modelling to develop the systems model using role activity diagrams) with the quantitative side (i.e., the data analysis). First of all, the data is examined to confirm the existence of bottlenecks and an approximate percentage of their representation is calculated. Next, further analysis was conducted to select groups of patients to test out the improvement suggestions in the simulation environment using discrete event simulation.

6.1 Introduction

The routinely collected data were crosschecked against the bottlenecks to ascertain trends that confirm their existence following the processing of patients through the Majors unit of the ED. A description of the data analysis is detailed in the next section.

The five bottlenecks that were identified from the Majors RAD were:

1. Bottleneck A- Awaiting specialty input
2. Bottleneck B- Test outside ED
3. Bottleneck C- Awaiting transportation
4. Bottleneck D- Bed search
5. Bottleneck E- Handover to admitting ward

6.2 Identification of Bottlenecks from The Quantitative Data

Table 6.1 below shows the descriptive statistics for the full data set covering the 2 years which was a total of 217074 patient visits, of these 82,207 comprised of Majors visits with Majors patients having violated the 4HQI a total of 27,277 times. All the times displayed are in minutes (mins). The time blocks shown in the table are Arrival to Triage, Triage to Seen, Seen to Medical Decision

(MD) and Medical Decision to departure, also referred to as boarding. Even though the idea of the three time-blocks was proposed in the previous chapter, the information presented in Table 6.1 is based on the original four time-blocks. Arrival to Triage and Triage to Seen were combined to form time-block 1 as described in Section 4.11 to match the three time-block proposal. Time-block 1 and the remaining two time-blocks, Seen to Medical Decision and boarding are also illustrated in Figure 6.1 below. A review of Table 6.1 shows that Arrival to Triage for the three data sets is similar with 11.84 minutes, 10.67 minutes and 13.50 minutes for the full data, Majors and Majors violators respectively. However, Triage to Seen is significantly higher for Majors violators at 114.87 minutes compared to the other two. Similarly, Seen to MD of 136.99 minutes and boarding was 167.47 minutes for the Majors violators. The mean LOS for the full dataset was 207.72 minutes which was lower than 4 hours i.e., 240 minutes. However, for Majors only, this was 266.46 minutes and for Majors violators, it was 432.83 minutes. Therefore, LOS for violators was significantly higher than Majors only and the full dataset. Further analysis focused mainly on Majors patients and violators to explore trends and opportunities for improvements.

Table 6.1 Descriptive statistics for the full dataset, Majors and Majors violators

Descriptive Statistics					
Full Dataset					
Time blocks	Number of patient visits	Minimum (mins)	Maximum (mins)	Mean (mins)	Std. Deviation
Arrival to triage	217074	0	1125	11.84	22.384
Triage to Seen	217074	0	1167	73.30	59.068
Seen to MD	217074	0	1751	72.40	74.628
Boarding	217074	0	1635	50.18	97.785
LOS	217074	1	1965	207.72	135.149
Time blocks	**All Majors**				
Arrival to triage	82207	0	965	10.67	21.984
Triage to Seen	82207	0	1167	81.31	64.535
Seen to MD	82207	0	1751	93.67	92.033
Boarding	82207	0	1340	80.82	119.101
LOS	82207	1	1965	266.46	158.554
Time blocks	**Majors Violators Only**				
Arrival to triage	27277	0	965	13.50	29.982
Triage to Seen	27277	0	1167	114.87	82.636
Seen to MD	27277	0	1751	136.99	135.001
Boarding	27277	0	1340	167.47	167.160
LOS	27277	241	1965	432.83	170.799

Figure 6.1 shows that Seen to Medical Decision and boarding were the two main time-blocks that were seen to be problematic due to the occurrence of bottlenecks. Two of the bottlenecks (specialty input and test outside ED) occurred between Seen and Medical Decision and three bottlenecks (awaiting transportation, bed search and handover to admitting ward) occurred between Medical Decision and departure. This is illustrated in Figure 6.1 with test outside the department represented with a broken line as explained in Section 4.11. This bottleneck could also occur between Triage and Seen.

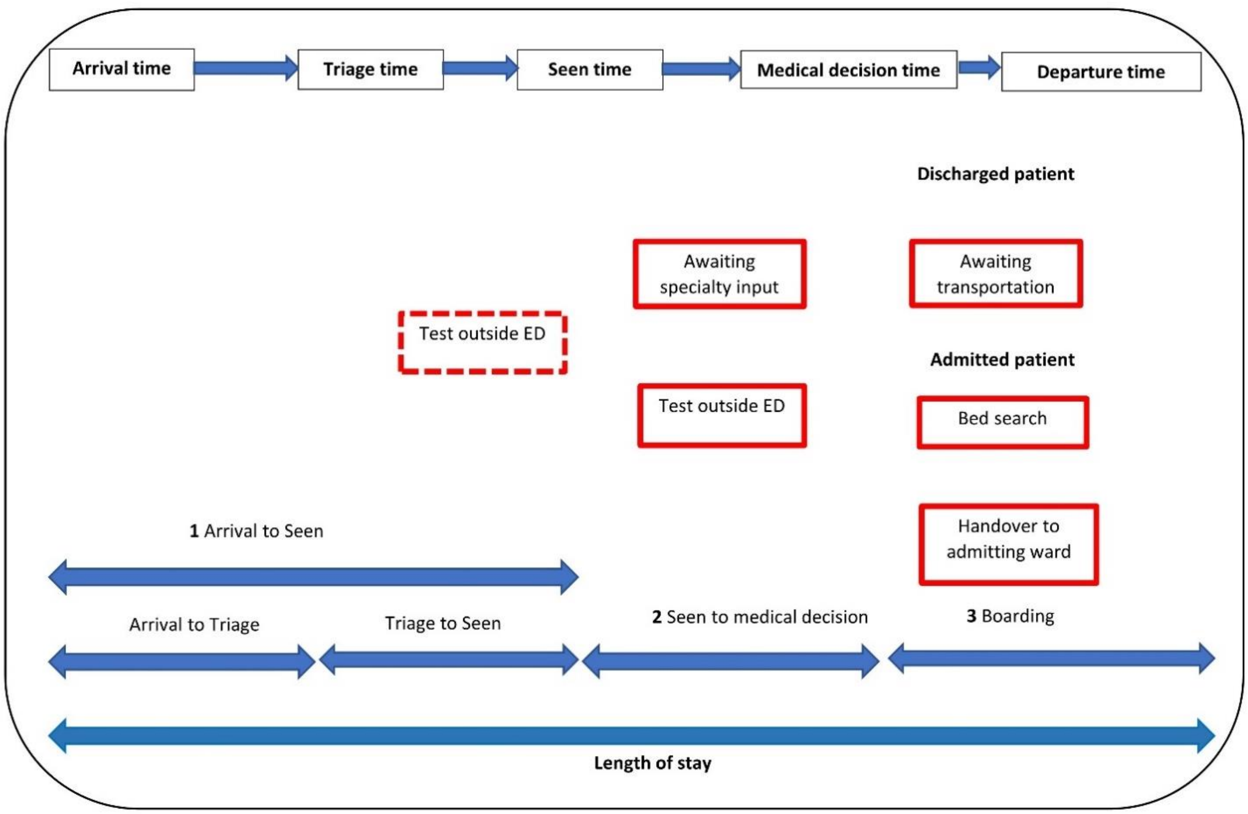


Figure 6.1 Majors unit bottlenecks illustrated against time-blocks

Source: Author

6.2.1 Evidence of Bottlenecks in the data

The time blocks from Arrival to Departure were analysed to yield evidence within the data which were matched with the five bottlenecks.

As reported in literature patients undergoing multiple investigations tend to have a higher LOS (Bobrovitz et al., 2017, Chaou et al., 2017, Suriyawongpaisal et al., 2019). Further analysis of the number of investigations was conducted for the whole dataset, Majors patients and Majors violators only as shown in Table 6.2 below. These revealed that for the whole dataset, the majority of the patients (83%) who had no investigations done were discharged, this shows potentially low acuity patients. Only 17% of patients were admitted without any investigations. This ratio changes for Majors patients and Majors violators. For Majors violators, more patients i.e., 54.8% were discharged without investigation as compared to 45.2% who were admitted. A higher percentage of discharged patients had 3 investigations among the violators (36.3%) compared to the whole dataset where only 11.7% were discharged after 3 investigations.

Table 6.2 Counts and percentages of all patients, Majors Patients and Majors Violators

Disposal Status	**Discharged**			**Admitted**		
	Count	**Row N %**	**Column N %**	**Count**	**Row N %**	**Column N %**
Number of investigations	**All patients**					
0	57780	83.0%	42.2%	11856	17.0%	14.8%
1	45919	75.0%	33.6%	15331	25.0%	19.1%
2	17083	61.9%	12.5%	10520	38.1%	13.1%
3	15995	27.3%	11.7%	42591	72.7%	53.0%
Number of investigations	**All Majors**					
0	10149	67.8%	29.7%	4829	32.2%	10.0%
1	9135	50.4%	26.8%	9001	49.6%	18.7%
2	5707	46.3%	16.7%	6631	53.7%	13.8%
3	9155	24.9%	26.8%	27600	75.1%	57.4%
Number of investigations	**Major violators**					
0	1809	54.8%	22.7%	1491	45.2%	7.7%
1	1910	35.6%	24.0%	3457	64.4%	17.9%
2	1348	32.6%	16.9%	2782	67.4%	14.4%
3	2887	19.9%	36.3%	11593	80.1%	60.0%

For all patients, the column percentage shows that discharged patients have fewer tests done than admitted patients with 42.2% having no investigation and 11.7% having three completed. However, for Majors violators, 36.3% of the discharged patients had three investigations whereas 22.7% had none. Also, 60% of admitted patients from the Majors violators dataset had three investigations and only 7.7% had none.

In the case of discharged patients, those who stayed in the department beyond 30 minutes were most likely waiting for transportation. Another possibility for the delay that was considered was medication to take out (TTOs). Ambulatory patients can go to the pharmacy to collect prescriptions therefore, the patients who were likely to wait for this to be done on their behalf were those who were also waiting for transportation.

Bed search and handover delay may apply to all admitted patients who stayed in the ED beyond a threshold of 60 minutes. It is known from literature that admitted patients board longer than discharged patients (Brick et al., 2014, Brady et al., 2017, Kusumawati et al., 2019). The data analysis shows a mean time of 216.58 minutes (Appendix F.1). On the other hand, discharged patients usually do not 'board' (this term is being used to describe the time from Medical Decision to departure though mainly used when referring to admitted patients) for long hence the short mean discharge time for the period. However, for some patients i.e., those who violated the 4HQI possibly due to waiting for transport, they waited for an average of 48.15 minutes before departure (Appendix F.1).

Additional analysis was performed to ascertain whether 'problematic' patients could be identified by the presenting complaint, but the results did not show a significant proportion of a particular group standing out from the others.

The mode of arrival was also looked at more closely. Table 6.3 below shows the number and corresponding percentages for EMS and Non-EMS arrival for all Majors patients which comprised a sample of 82,207 visits and for violators only who were 27,277 in total. Table 6.3 shows that 65.3% of Majors patients and 72.3% of Majors violators arrived by EMS. This higher percentage of patients who arrived by EMS compared to the Non-EMS arrival is an indication that pre-hospital information collected on the PRF was available for a significant proportion of the patients. The suggestions discussed in Section 4.11.1 will apply to these patients.

Table 6.3 Mode of arrival for Majors and Majors violators

Mode of arrival (All Majors- 82, 207)			**Mode of arrival (Majors violators- 27, 277)**		
	N	**%**		**N**	**%**
EMS	53653	65.3	EMS	19723	72.3
Non-EMS	28554	34.7	Non-EMS	7554	27.7

6.3 Percentage Representation of Each Bottleneck in The Data

In order to identify how the bottlenecks impacted the patient's journey for those who violated, additional analysis was conducted for each bottleneck as detailed below. Data selection filters in SPSS were used in extracting the data for each bottleneck from the full data set. An explanation for each of the filters is provided in the subsequent sub-sections.

6.3.1 Awaiting Specialty Input

The dataset did not specify which patients received specialty input therefore this had to be inferred from the data. ED doctors at this Type 1 ED do not admit directly into specialty wards hence specialty input is required for every admission except medical patients admitted to the clinical decisions unit and surgical patients admitted for assessment on the surgical assessment unit. The following characteristics were used to extract patients who were most likely to receive specialty input:

- Seen in Majors
- Admitted
- Violated the 4HQI
- Long Seen to Medical Decision (over 60 minutes)

The patients were grouped into Seen to MD of 30 minutes intervals with group 1 as 0 to 30 minutes, group 2 as 31 minutes to 60 minutes, group 3 as 61 minutes to 1 to 90 minutes and so on. The filter was therefore set to Seen to MD>2 to represent over 60 minutes. The explanation for the filter used to extract these patients has been provided above. The filters used to extract these patients were:

[Arrival location = 2 & Disposal status = 1 & QI_Violation = 1 & Seen to MD >2]

Furthermore, patients admitted into CDU and surgical assessment unit were excluded from the data since these patients did not require specialty input. This left 3770 patients who were direct admissions to inpatient units which works out to be 13.82% of the 27,277 Majors violators (Table 6.1). This percentage could be higher since some discharged patients may have required specialty input as well for safe discharge. However, these patients were not considered due to the difficulty in identifying them.

6.3.2 Test Outside Emergency Department

All the patients who were seen in Majors and violated the 4HQI were extracted from the data using the filters:

[Arrival location = 2 & QI_Violation = 1]

The patients were further divided based on the number of investigations as shown in Table 6.4 below. A total of 3300 patients which equates to 12.1% of Majors violators had no investigation and were therefore excluded from this bottleneck.

Table 6.4 Number and percentage of investigations and percentage for Majors violators

Number of Investigations	Number of Patient Visits	Percentage
0	3300	12.1%
1	5367	19.7%
2	4130	15.1%
3	14480	53.1%

For the remaining 23,977(87.9%), 5367 (19.7%) of Majors violators had one investigation, 4130 (15.1%) had two investigations and 14480 (53.1%) had three investigations. Further details about the types of investigations are shown in Table 6.5 below.

Table 6.5 Numbers of investigation types for Majors Violators

Order of Investigation	Type of investigation	Count	Column N %
Investigation 1	Vital signs & observations	2970	12.4%
	Laboratory tests & POCT	6774	28.3%
	Simple imaging	10471	43.7%
	Complex imaging	3755	15.7%
	All Other	7	0.0%
	Total	**23977**	
Investigation 2	Vital signs & observations	3714	20.0%
	Laboratory tests & POCT	10993	59.1%
	Simple imaging	2944	15.8%
	Complex imaging	940	5.1%
	All Other	19	0.1%
	Total	**18610**	
Investigation 3	Vital signs & observations	1738	12.0%
	Laboratory tests & POCT	11109	76.7%
	Simple imaging	1211	8.4%
	Complex imaging	379	2.6%
	All Other	43	0.3%
	Total	**14480**	

Data for up to three investigations were provided by the hospital where applicable. This means that for patients who had one investigation, this was recorded as investigation 1. Those who had two investigations had data for investigations 1 and 2. Similarly, patients who had three investigations had investigations 1, 2 and 3 completed. Taking into consideration investigation 1 alone, a total of 14226 patients had completed simple and complex imaging. This equates to 59.33% of the total of patients who had investigation 1 completed (23,977) and 52.15% of Majors violators. When considering investigation 2, there was a total of 3884 simple and complex imaging tests equating to 14.24% of Majors violators. Finally, for investigation 3, a total of 1590 simple and complex imaging was undertaken also equating to 5.83% of Majors violators. As discussed in Section 4.11.1, the use of pre-hospital ultrasound has been shown to be promising however, that is only one test out of the complex imaging group since it includes MRI and CT scans. The use of pre-hospital information to reduce the need for repeat testing will be very relevant to blood tests though the percentage representation cannot be quantified. It was difficult to ascertain from the data which of the blood tests were undertaken in the laboratory or as POCT therefore these figures were excluded from the percentages above. However, Table 6.5 shows that these figures were quite high with 6774 for investigation 1, 10,993 whereas for investigation 2 and 11,109 for investigation 3. The service agreement between the ED and the laboratory is to limit the turnaround time for blood test results to two hours which indicates that without such an agreement in place, it can take longer for blood test results to be received.

6.3.3 Awaiting Transportation

Table 6.6 shows that 34146 (41.5%) of Majors patients were discharged compared to 48061 (58.5%) who were admitted. Even though the number of discharged patients is less than admitted patients, the discharged category still represents a significant proportion of the patients. It will therefore be beneficial to address this bottleneck which relates to discharged patients. Staff have to continue to care for these patients who are still in the department. Measures to ensure they leave the department in a timely manner will help to offload the department leading to a smoother flow. A smoother flow of discharged patients out of the ED will also enhance patient safety due to the negative impact of crowding in ED (Chang et al., 2018, Higginson and Boyle, 2018).

Table 6.6 Admitted versus discharged patients

Majors	**Disposal status**	**Frequency**	**Percentage**
	Discharged	34146	41.5
	Admitted	48061	58.5
	Total	82207	100.0

Out of the total number who were discharged, 7954 patients had violated the QI as shown in Table 6.7 below.

Table 6.7 QI violation for Majors patients against Disposal status

QI Violation	Disposal status	Frequency	Percentage
No breach	Discharged	26192	47.7
	Admitted	28738	52.3
	Total	54930	100.0
Breach	Discharged	7954	29.2
	Admitted	19323	70.8
	Total	27277	100.0

For the Majors patients, 29.2% (N=7954) had violated the 4HQI and of these, 2775 had stayed for more than 30 minutes after the medical decision to discharge. Hence, an inference is being made that, these patients could not leave the ED after being discharged due to transportation requirements. This equates to 10.17% of the total number of Majors patients who violated i.e. (2775/27277) *100.

The filters used to extract these patients were:

[Arrival location= 2 & QI_Violation = 1 & Disposal status = 0 & Boarding > 30]

6.3.4 Bed Search

Admitted and boarding over 60 minutes=15956 patients who make up 58.50% of Majors patients who violated.

The filters used to extract these patients were:

[Arrival location = 2 & QI_Violation = 1 & Disposal status = 1& Boarding > 60]

6.3.5 Handover

It was not possible to establish from the data how many of the admitted patients had delays caused by the handover process. Since handover is an integral part of admission, it was assumed that every admitted patient had to go through this process. Bottlenecks D and E were therefore considered together.

The bottlenecks are not mutually exclusive therefore the percentages do not add up to 100.

For Majors patients who violated, each bottleneck equates to the following percentage of patients:

- Awaiting specialty input 13.82%
- Test outside ED 52.15%
- Awaiting transport 10.17%
- Bed search and handover 58.50% (over 60 minutes)

The improvement suggestions presented in the preceding sub-sections for awaiting specialty input, test outside ED and awaiting transport bottlenecks will be tested using Discrete Event Simulation modelling in the next section.

6.4 Role Activity Diagram Preceding Discrete Event Simulation Methodology

Discrete event simulation modelling was used in testing the improvement suggestions presented in the sections above. The process involved comparing the RAD of the Majors unit with the data available and producing a condensed version of the patient flow for developing the DES model. The processes extracted from the RAD were presented in Figure 5.2 in Chapter 5. The RAD processes were mapped indirectly to the DES model as illustrated in Figure 6.2 below via a condensed RAD-informed flowchart.

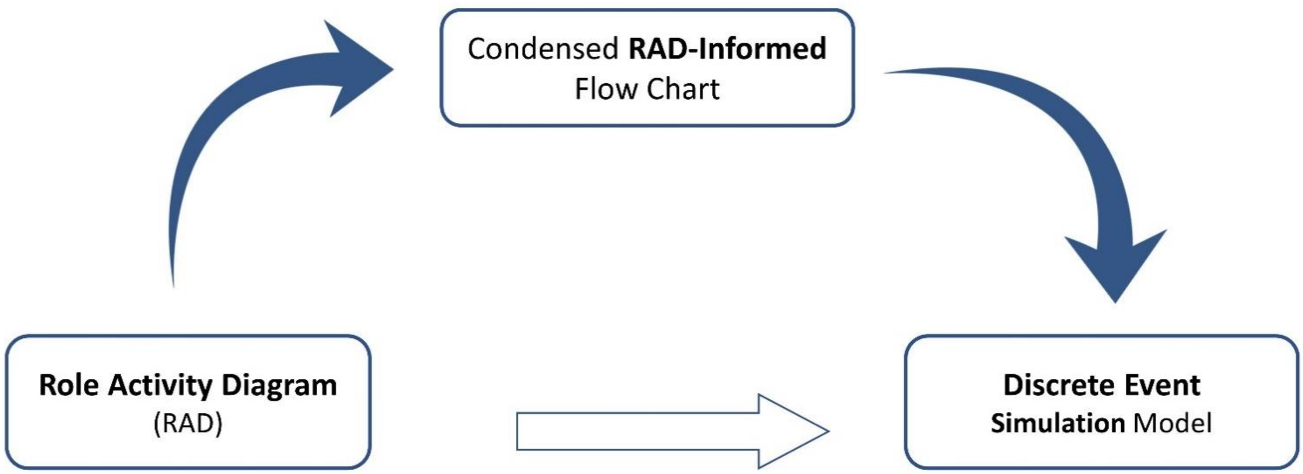


Figure 6.2 Indirect mapping of RAD to DES model

Source: Author

The attributes of the flowchart were developed through careful mapping of processes in both the Majors RAD (Chapter 5, Figure 4.4) and the Streaming and Triage RAD (Appendix D.2). As illustrated in Table 6.8 below, the corresponding process names and the mapping of RAD concepts to Simul8 DES objects are described in the comment's column. Subsequently, the flowchart process names which also correspond to the DES process names are displayed with the flowchart symbol. This information was used to construct the condensed flowchart presented later in Figure 6.3.

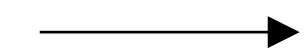
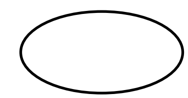
It should be noted that the DES elements for other software might be different. Non-tangible resources such as electronic patient reports were considered outside the scope of this study and therefore not modelled. Similarly, non-patient activities such as answering the telephone, liaising with potters, reporting broken equipment to the relevant department, and contacting IT were not modelled.

Table 6.8 RAD concepts mapped to DES objects in Simul8

Item Number	RAD Process Number (Fig 4.4 EMS arrival)	RAD Process Number (Fig 4.5 Non- EMS arrival)	RAD Process Name	RAD Concepts	Simul8 DES Objects	Comments	Process Name (Flowchart & DES Model)	Flowchart Symbol
1	N/A	N/A	N/A	N/A	Clock	RADs are static models and therefore do not have a clock indicating time. This is unique to DES	N/A	N/A
2	Receptionist ED Coordinator Paramedic Patient Majors lead Staff nurse HCA Doctor Site/Dept Bed coordinator	Streaming nurse Receptionist Patient Triage nurse ECT Doctor	N/A	Role	Resource and work item	In modelling the Majors unit, the role represents the healthcare professionals who interact with the patients from arrival into the unit until discharged or admitted. Roles are important resources in DES modelling as they are vital to the flow moving swiftly by also activating other resources as work items move through activities and queues. The patient is also modelled as a role in the RAD to show how they interact with other roles. However, in the DES model, the patient is a work item, and the roles are mapped as resources required to execute activities. The patient is central to the flow, moving from one process to the other as work items.	N/A	N/A

Source: Author

Table 6.8 RAD concepts mapped to DES objects in Simul8 (cont'd)

Item Number	**RAD Process Number (Fig 4.4 EMS arrival)**	**RAD Process Number (Fig 4.5 Non- EMS arrival)**	**RAD Process Name**	**RAD Concepts**	**Simul8 DES Objects**	**Comments**	**Process Name (Flowchart & DES Model)**	**Flowchart Symbol**
3	N/A	N/A	N/A	Connector	Routing arrow	In DES, the activities are connected to each other with routing arrows which show the direction in which the work items move. RAD does not have directional arrows of flow however, concepts such as activities and interaction are joined by connectors.	N/A	Arrow 
4	N/A	N/A	N/A	N/A	Queue	In RAD, two activities can be connected to each other. However, in DES, activities are separated by queues where work items wait to move to the next activity or for resources to become available.	N/A	N/A
5	P1	N/A	Patients arrives in an ambulance	Trigger	Start point (EMS arrival)	A trigger point indicates the start of a thread of activities, similar to Start point which is where work items enter a simulation process. There can be more than one trigger point in an RAD and similarly, more than one start point in a simulation model.	EMS Arrival	Terminal 
6	N/A	P1	Patients arrives in ED	Trigger	Start point (Non-EMS arrival)	Same as above	Non-EMS Arrival	Same as above

Source: Author

Table 6.8 RAD concepts mapped to DES objects in Simul8 (cont'd)

Item Number	RAD Process Number (Fig 4.4 EMS arrival)	RAD Process Number (Fig 4.5 Non- EMS arrival)	RAD Process Name	RAD Concepts	Simul8 DES Objects	Comments	Process Name (Flowchart & DES Model)	Flowchart Symbol
7	P2	N/A	Handover by Paramedic	Interaction	Activity followed by a queue	In RADs, roles collaborate through interactions to perform activities however, DES does not differentiate between activities undertaken by one resource from that undertaken through collaboration between several resources. Interactions in RAD are therefore mapped to activities and queues.	EMS Handover	Process 
8	P3	N/A	Patients Registered (CAS Card completed)	Interaction	Same as above	Same as above	Registration	Same as above
9	N/A	P4	Registered at Reception (CAS Card completed)	Interaction	Same as above	Same as above	Registration	Same as above
10	N/A	P13	Initial Assessment	Interaction	Same as above	Same as above	Triage	Same as above
11	P31	N/A	Tests and treatment information given	Interaction	Same as above	Same as above	Initial treatment	Same as above
12	P11 - P12	N/A	Discussing, and completing assessments and tests	Interaction	Same as above	Same as above	Part of the Initial assessment process	Same as above

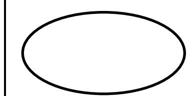
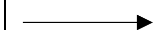
Source: Author

Table 6.8 RAD concepts mapped to DES objects in Simul8 (cont'd)

Item Number	RAD Process Number (Fig 4.4 EMS arrival)	RAD Process Number (Fig 4.5 Non- EMS arrival)	RAD Process Name	RAD Concepts	Simul8 DES Objects	Comments	Process Name (Flowchart & DES Model)	Flowchart Symbol
13	P45	N/A	Medical Decision	Interaction	Activity	Activities in RAD can be mapped directly to activities in DES which represents a place where work items are acted upon. Work items get released once the activity is complete therefore the activity durations have an impact on flow.	Medical Decision	Process 
14	P10	N/A	Listing assessments and tests	Activity	Same as above	Same as above	Initial Assessment	Same as above
15	P46	N/A	Admit (Yes/No)	Case Refinement	Activity	There is no direct mapping from case refinement in RAD to DES. However, at each activity, a routing-out option can be used to make decisions on how the work item moves to the next stage. The routing-out can be based on options such as percentages, priority or labels. In this case (P46), this was modelled as part of the medical decision process.	Medical Decision	Same as above
16	P20	N/A	Patient examined, assessment and test results analysed	Part refinement	Activity, routing arrows and queue	Part refinement in RAD which represents parallel processes can be mapped to DES using a series of activities, queues and routing arrows to replicate the simultaneous activities undertaken. The activities can be modelled with different durations and queues modelled with different capacities as required.	Seen	Same as above

Source: Author

Table 6.8 RAD concepts mapped to DES objects in Simul8 (cont'd)

Item Number	RAD Process Number (Fig 4.4 EMS arrival)	RAD Process Number (Fig 4.5 Non- EMS arrival)	RAD Process Name	RAD Concepts	Simul8 DES Objects	Comments	Process Name (Flowchart & DES Model)	Flowchart Symbol
17	P18	N/A	Patient examined, assessment and test results analysed	Part refinement	Activity, routing arrows and queue	DES objects do not indicate the state therefore these can be modelled as part of an activity, in this case Triage.	Triage	Same as above
18	P26/P51/P55	N/A	Stop (after patient leave ED) Transportation requirement (inferred from data)	Stop	End point	The stop symbol marks the end of a process in RAD. This could be the entire RAD process or a subprocess. Similarly, a DES model can have more than one end point.	Discharged	Terminal 
19	P73	N/A	Stop (after patient leave ED)	Stop	End point	Same as above	Admitted	Same as above
20	Between P28/P29	N/A	Specialist arrived? Yes/No	Loop	Routing arrow	The loops in RAD which are used to indicate processes that repeat themselves can be achieved in DES using routing arrows.	Specialist referral	Arrow 
21	P37	N/A	Test Performed	Loop	Routing arrow	DES does not have encapsulated processes; however, these can be modelled in DES by creating sub-models which can be embedded into the main model. This was deemed outside the scope of this research as the encapsulated process in the RAD was not analysed as a sub-process. Process P37 was therefore modelled as an activity.	Test	Process 

Source: Author

The methodology described above of indirect RAD to DES mapping was used because the information required for direct mapping of all the 73 processes captured in the Majors RAD to DES is difficult to obtain. This information is not normally captured in the patient electronic record system. Moreover, collecting this manually for this study would have limited the practical application of the methodology in busy EDs.

Additionally, current commercially available software does not support the direct importation of RAD data into the simulation environment. This can only be achieved through manual intervention (Shukla et al., 2015) which requires the user to have programming skills. This was deemed to generate another barrier to the practical application of that methodology by ED staff who may not possess the programming skills required for such an implementation. In this part of the study, DES is being used to solve the problems identified using RAD. Without the RAD, the bottlenecks would not have been identified in the first place. The flowcharts would not have revealed them. The RADs are therefore being used to complement the benefits of using DES. The RADs developed in Chapter 4 to capture the systems knowledge to help define it and identify bottlenecks have uncovered more than other traditional processing modelling techniques normally used to precede DES model generation as discussed in Section 2.7.1.

6.5 Building a Discrete Event Simulation Model

A discrete event simulation model was built using Simul8 software from Simul8 Corporation. The main elements required to build a simulation model are:

1. **Work items**

   These are items that will be processed through the system that is being simulated which in this study is the emergency department. In this model, the work items are the patients moving through the Majors unit.

2. **Activities**

   These are points along the process where work items have actions performed on them. Activities require time for execution and associated resources. The duration of each activity referred to as 'activity duration' must be specified as part of the model-building process. In this model, activities take place at various stages along the patient flow.

3. **Start point**

   This is where work items enter the simulation process for the first time. There can be more than one Start point. In the case of this model, the start point represents the two entry points for patients arriving at the Majors unit which are via EMS (ambulance conveyance) Non-EMS (self-presenting). At start points, the rate at which work items enter the system must be specified. This is known as the inter-arrival rate. This can be done using a known distribution that fits how work items enter the simulation.

4. **Routing arrows**

These are used to connect activities in the simulation to show the logical flow of work items as illustrated in the initial flow chart in Figure 6.3. These arrows show how patients move from one activity to the other.

5. **Queue**

This is where work items wait until resources or activities required for the next process are available. In this model, this is where patients wait to move to the next activity. There are several instances along the patient journey where they wait for results or to be attended to. The queues can be specified as having a fixed capacity or shelf-life after which they expire. Once that capacity is met, the queue cannot accept any more work items. Fixed capacities were used for this model.

6. **Clock**

The clock shows the working hours of the simulation. This can be set to daytime and night-time or a 24-hour clock depending on the system being modelled. In the case of ED, as it is open 24 hours a day, the clock was set to run for 24 hours, 7 days a week.

7. **Resources**

These are the people, or items required to perform the various activities. This is referring to the clinical and medical staff in this model i.e., doctors, nurses, healthcare assistants and emergency care technicians who work in the ED. The resources have to be described in terms of the type and number required.

8. **End point**

This is where work items leave the process, marking the end of the simulation. For this model, this will be when the patient leaves ED following discharge or admission.

The development of the model started with converting the detailed RAD of the Majors unit into a condensed conceptual model which is represented by a flow chart illustrating the patient journey from arrival into Majors to departure as shown in Figure 6.3 below.

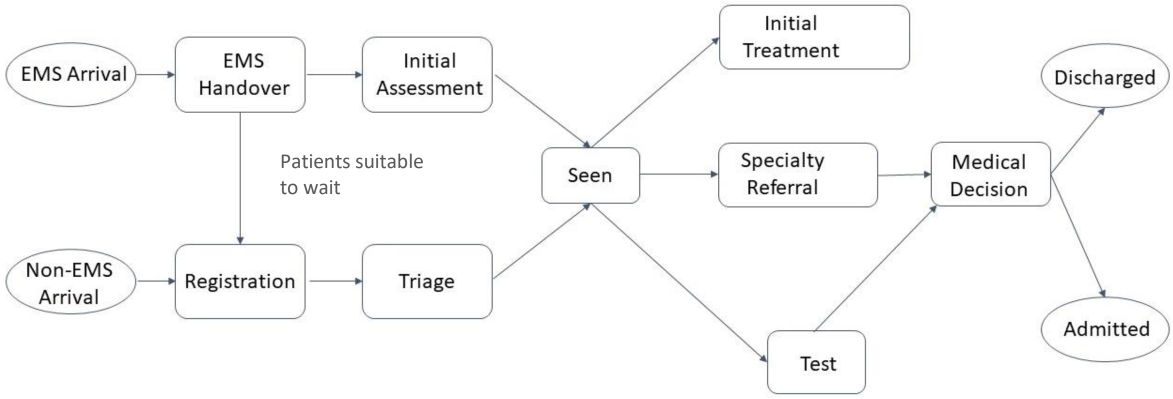


Figure 6.3 Condensed RAD informed flow chart

Source: Author

The model in Figure 6.3 shows the two entry routes into the ED for EMS arrival and Non-EMS arrival (i.e. self-presenting patients). A clinical handover takes place between the hospital staff, normally the ED coordinator and paramedics from the ambulance service. The coordinator makes a quick clinical assessment of the patient and sends them to the waiting area to register and wait to be triaged if they are suitable to wait. Patients who are accepted to be seen in Majors under initial tests and assessments following the clinical handover. This handover will include a handover to the Majors lead who coordinates the initial test and assessments required. After this step, the patient waits and is seen by a doctor for examination and assessment of initial test results. Similarly, Non-EMS arrivals and EMS arrivals who were sent to the waiting area are also seen by a doctor after undergoing triage. Patients can be referred to see a specialist if specialty input is required. The specialist may proceed to a medical decision or require additional tests to arrive at a decision. The patients who see an ED doctor may also have additional tests requested or be given initial treatment. Once a medical decision has been made, the patients are either discharged or admitted. A transfer to another department is also being processed as an admission.

6.6 Model Parameters

The model was further developed using input parameters derived from observation, subject matter experts and the hospital data which comprises the anonymised routinely collected data. Relevant information for the modelling was also derived from current literature. Table 6.9 below provides information about the input parameters and their source.

Table 6.9 DES Input parameter and source

Input Parameter \ Source	Hospital Data	Subject Matter Experts	Observation	Literature
Inter arrival time	✓			
Distribution type			✓	✓
Activity duration		✓	✓	
Queue capacity		✓	✓	
Resource type and quantity	✓			

The inter-arrival rate for EMS and Non-EMS arrival was specified using an exponential distribution which is a suitable distribution type for describing arrivals when describing complex systems such as ED with a random number of inputs (Chahal, 2010, Zhao et al., 2015) such as an emergency department. The input values were calculated using real ED data.

Inter-arrival rate = (1/arrival rate) * 60

Arrival rate = number of patients arriving per hour

The data shows that the arrival rate as presented in Table 6.10 below is 3.06 per hour for EMS and 1.86 for Non-EMS arrivals. This means that the arrival rate in minutes was (1/3.06) * 60 =19.61. Similarly, the inter-arrival rate for Non-EMS was (1/1.86) *100= 32.26.

Table 6.10 Hourly arrival rates for EMS and Non-EMS patients

Rate	EMS	Non-EMS
Arrivals per hour	3.06	1.86

The calculations above resulted in an inter-arrival rate of 19.61 minutes for EMS arrival and 32.26 for Non-EMS arrivals as shown in Table 6.11. This table also provides details of the remaining processes which were modelled using mostly triangular distributions (Chahal, 2010, Law, 2013, Weng et al., 2019) with the intervals for the processing times based on expert opinion and observation. Activity duration and queue capacities that were entered into the model were specified based on observations made in the ED and input from ED staff. The number of staff was specified on the staff rotas.

6.7 Discrete Event Simulation Inputs

The following parameters formed the input to the DES model:

- Inter arrival time
- Distribution type
- Activity duration
- Queue capacity
- Resource type and quantity

6.8 Discrete Event Simulation Outputs

The outputs for the model were:

- Time in the system (length of stay) and standard deviation

Table 6.11 Input parameters and distributions

Model input	**Distribution type**	**Minutes**
Start point- EMS arrival	Exponential	19.61
Start point- Non-EMS arrival	Exponential	32.26
EMS arrival-Handover	Rounded	5,30
Registration	Triangular	4,5,7
Triage	Average	5
Initial assessment	Triangular	5,10,15
Seen	Triangular	10,15,30
Test 1	Triangular	5,10,15
Test 2	Triangular	10,15,20
Test 2	Triangular	10,15,20
Initial treatment	Triangular	5,10,15
Specialist referral	Triangular	15,30,45
Medical Decision	Triangular	5,10,15
Discharged	Triangular	10,15,30
Admitted	Triangular	10,15,30

The processes outlined in the flow chart in Figure 6.3 and the input parameters and distributions as provided in Table 6.11 were used to develop the DES model of the Majors unit as shown in Figure 6.4 below.

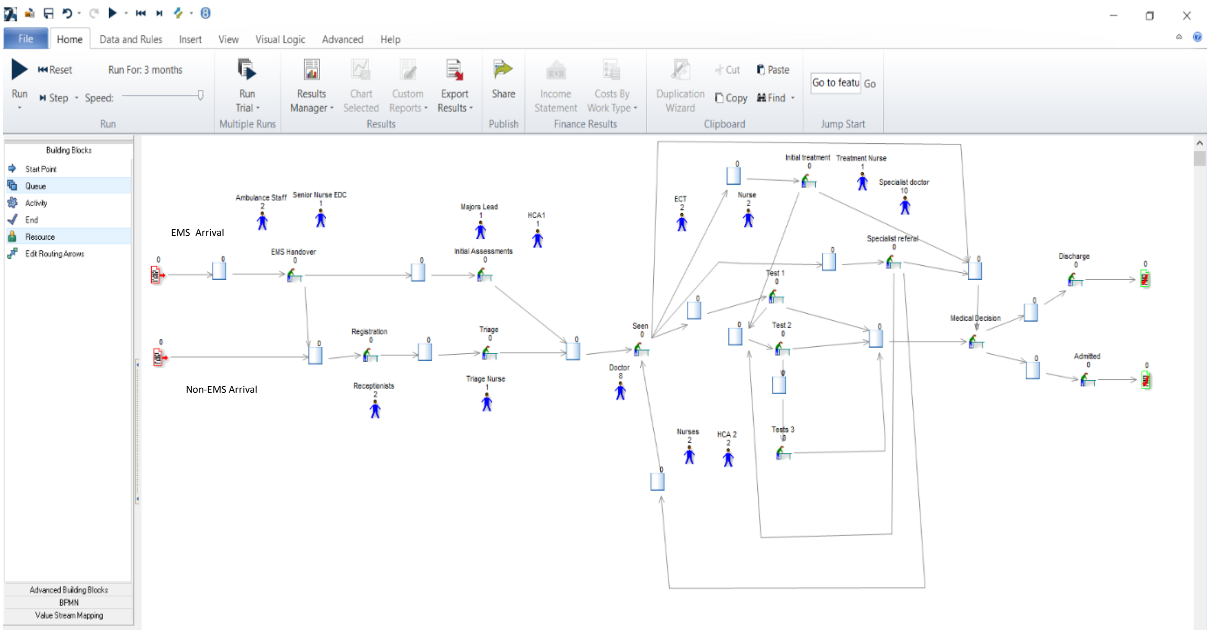


Figure 6.4 Screenshot of the DES model in Simul8

6.9 Warm-up Time

As recommended in the Simul8 user guide (Simul8, 2022), finding a suitable warm-up period is important for models representing systems that do not start empty (Karnon et al., 2012, Zhao et al., 2015). The result collection period is also important in achieving an accurate depiction of the real process. These two parameters were determined through a series of experiments as shown in the tables and figures below to arrive at 1 week (10080 minutes) for the warm-up period and 3 months for the results collection period.

First of all, Table 6.12 shows 20 different experiments that were conducted to compare the warm-up time in hours and minutes, to the output for discharged and admitted patients in terms of the time in the system which represents the mean LOS.

Table 6.12 Table of Warm-up time scenarios

Experiment number	Warm-up time		Discharged	Admitted
	Hour(s)	**Minutes**	**Time in system (Mean LOS)**	**Time in system (Mean LOS)**
1.	1 hour	60	130.36	155.99
2.	4 hours	240	129.54	154.67
3.	8 hours	480	125.03	156.52
4.	12 hours	720	139.29	160.35
5.	16 hours	960	153.03	173.49
6.	20 hours	1200	151.92	168.99
7.	24 hours	1440	151.67	150.78
8.	2 days	2880	143.28	184.74
9.	3 days	4320	154.09	222.58
10.	4 days	5760	149.32	128.27
11.	5 days	7200	172.25	213.28
12.	6 days	8640	130.79	214.94
13.	**7 days**	**10080**	**147.36**	**251.88**
14.	8 days	11520	278.71	399.29
15.	9 days	12960	277.69	436.09
16.	10 days	14400	145.9	177.23
17.	11 days	15840	237.38	301.31
18.	12 days	17280	343.67	385.02
19.	13 days	18720	287.44	460.46
20.	14 days	20160	167.34	203.34

The values derived from the table above were displayed in a graph as shown in Figure 6.5 below. The guidance for selecting a warm-up time is to chart the output in a graph as has been done and select a time just before the simulation moves from a relatively study state. It is assumed that the simulation is still warming up at this stage and starts behaving more realistically from this stage onwards (Simul8, 2022). Point number 13 on the graph was chosen which corresponds to 7 days or 10080 minutes as the warm-up period.

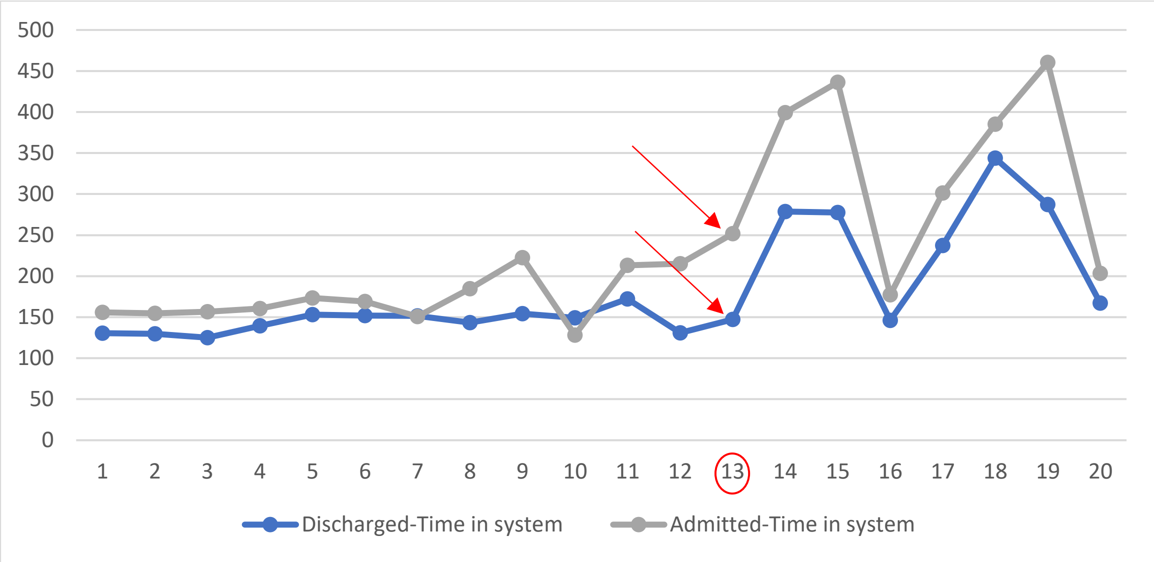


Figure 6.5 Figure of Warm-up time scenarios

6.10 Results Collection Period

Once the warm-up period was selected, another set of experiments was conducted to select the results collection period. The results for these 28 experiments are presented in Table 6.13 below. The table shows the number of runs in days and the resulting output of time in the system in minutes (i.e., mean LOS) for both discharged and admitted patients.

Table 6.13 Table of result collection period scenarios

Point number	Number of runs	Discharged	Admitted
		Time in system (Mean LOS)	Time in system (Mean LOS)
1.	1 day	147.36	251.88
2.	2 days	213.76	330.28
3.	3 days	236.43	368.88
4.	4 days	214.16	326.52
5.	5 days	218.5	321.26
6.	6 days	243.71	332.25
7.	7 days	250.29	351.96
8.	8 days	241.15	333.26
9.	9 days	242.02	321.33
10.	10 days	233.98	309.96
11.	11 days	227.9	298.16
12.	12 days	223.44	292.24
13.	13 days	217.33	280.74
14.	14 days	212.76	271.96
15.	4 weeks	214.17	326.52
16.	5 weeks	218.51	321.26
17.	6 weeks	243.72	332.25
18.	7 weeks	250.3	351.96
19.	8 weeks	241.16	333.26
20.	9 weeks	242.03	321.31
21.	10 weeks	234	309.93
22.	11 weeks	227.91	298.14
23.	**3 months**	**223.45**	**292.22**
24.	4 months	204.93	260.75
25.	5 months	201.27	253.92
26.	6 months	193.15	239.53
27.	1 year	193.49	249.77
28.	2 years	187.02	227.72

The information in Table 6.13 above is charted in the graph below, Figure 6.6. A similar procedure as was described for selecting the warm-up period was used in selecting the results collection period. Point 23 in the graph which corresponds to 3 months was selected. The graph was descending steadily before this point and starts to pick up again afterwards.

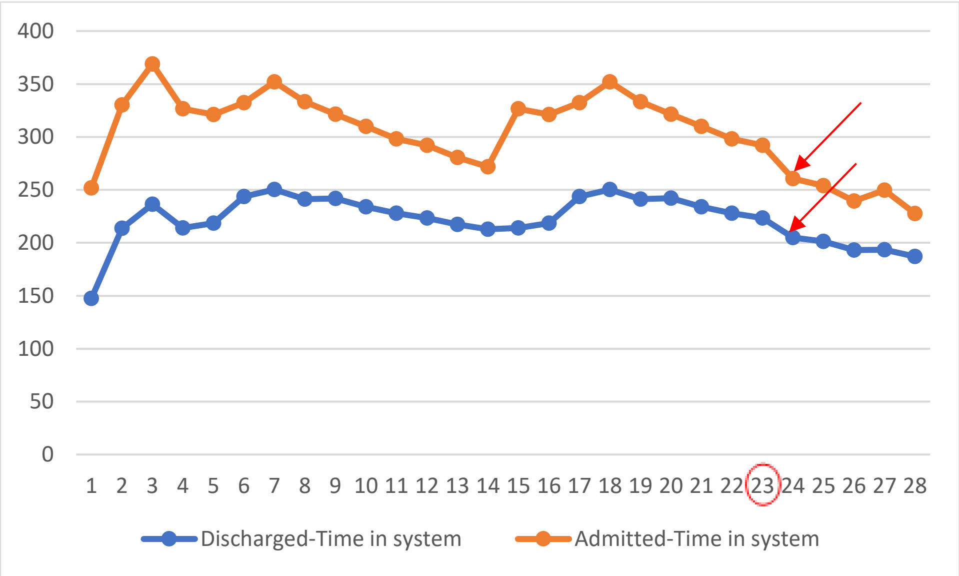


Figure 6.6 Figure of result collection period scenarios

After the warm-up and results collection periods were selected, the model was subjected to verification and validation processes. For verification, the run period was set to one day and the speed of the simulation was reduced. The patient entry was limited to one patient per entry route to observe how the patient moved through the system i.e., from one activity to the next through the queues. The model was behaving as intended which concluded the verification process. The validation process to examine how realistic the model is to the real ED was done by comparing the output of the simulation model to real data. The mean LOS and standard deviation (ST DEV) for discharged and admitted patients for both the real data and simulation model are presented in Table 6.14.

Table 6.14 Actual data against Simulated data

Disposal status	Real Data		Simulation model	
	Mean (LOS)	ST DEV	**Mean (LOS)**	ST DEV
Discharged Patients	223	137	223.45	114.79
Admitted Patients	297	165	292.22	147.42

The simulation was set using a warm-up period of 1 week as identified previously and a result collection period of three months. The average time in the system was also reviewed. The table below shows this comparison, with the mean LOS and the standard deviation (ST DEV) for discharge patients as 223 (ST DEV 137) in the real data and 223.24 (ST DEV 114.79) in the simulation model. Similarly, for admitted patients, the mean LOS was 297 (ST DEV 165) for the real data compared to the simulation model which was 292.22 (ST DEV 147.42).

It can be seen that the mean LOS from the simulation model is very similar to the real data for both discharged and admitted patients hence, confirming that the model is validated. This information is also presented in Figure 6.7 below showing a comparison of the LOS and ST DEV for admitted and discharged patients for both simulated and real data.

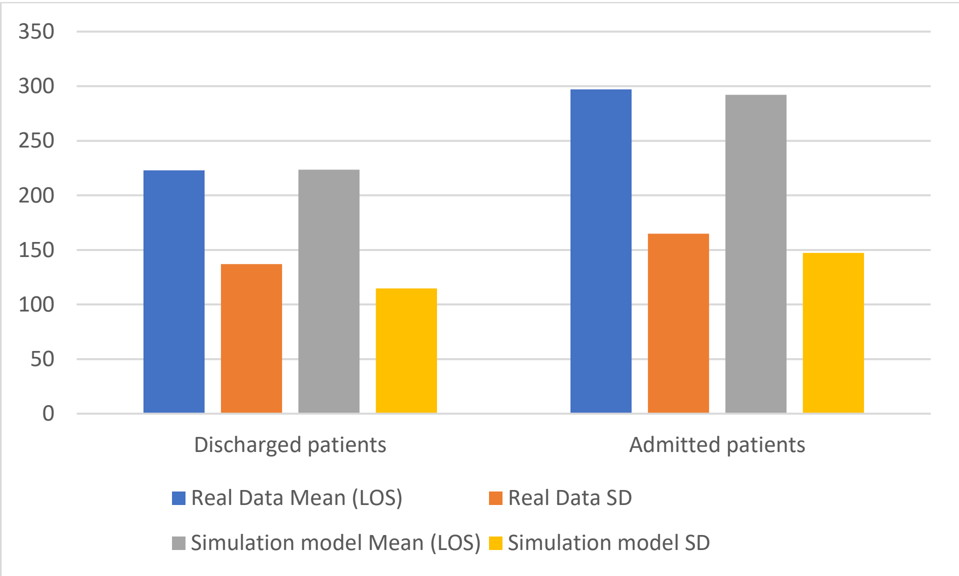


Figure 6.7 Comparison on LOS and ST DEV of real and simulated data

6.11 Bottleneck Analysis using a discrete event simulation model

Once the model was completed, the next step was to analyse how the bottlenecks could be addressed by focusing on three of the five bottlenecks: awaiting specialty input, test outside ED and awaiting transportation. The principles of LDA presented in Section 4.11 were applied to addressing bottlenecks A and C.

6.11.1 Bottleneck A- Awaiting Specialty input

This bottleneck is being prioritised because specialty input (SI) is required to reach a medical decision (Shin et al., 2018, Jung et al., 2020). A patient can be put in a different specialty bed but cannot be seen by a different specialist. Furthermore, the patient receiving the right specialty input on time can lead to quicker diagnosis, treatment, and medical decision on whether they will be admitted or discharged (Woods et al., 2008, Van der Veen et al., 2016). A consideration for addressing this bottleneck is to introduce an advanced nurse practitioner ACP in Triage. As stated in Section 4.11.2 the ACP at triage in the ED can help with requesting tests in advance and sending alerts for specialty input. The patient can be examined by an ED doctor by which time the test results should be available. The ED doctor can confirm if the specialty alert is required which will reduce the delay in the referral process for specialty input. Imaging requests for example have been reported to have been submitted between 2.4 hours to 2.8 hours after triage (Tse et al., 2016) which could be done earlier with an ACP in triage. Following agreements with the ED doctor, alerts for specialty input were sent.

As stated in Section 4.11.2 an Advanced Clinical Practitioner (ACP), can be positioned in triage to help reduce the bottleneck caused by specialty input. Having an ACP in triage can have a significant impact on the quality of care and improved efficiency resulting in reduced waiting times for patients in ED (Tucker and Bernard, 2015, Crouch and Brown, 2018, Fenwick et al., 2020, Kerr and Macaskill, 2020). More information about this role was provided in Section 4.11.2 followed by how the introduction of this role into triage was tested in the DES model as described in the following section.

6.11.1.1 Discrete Event Simulation Analysis of the Advance Clinical Practitioner in Triage

This recommendation was tested in DES using the developed model in Figure 6.4 by starting with a way of gauging how many patients the introduction of an ACP in triage will impact. All patients who are being triaged will be eligible to be seen by the ACP however, it is deemed that those with a lower acuity level would benefit from this. This is because high-acuity patients will most likely require specialty input even if they are seen by an ACP in triage. The EM-HRG though used for reimbursement provides an indication of the acuity level of the patients. It was deemed that the reimbursement codes VB08Z, VB09Z and VB011Z will be more suitable. As previously explained in Section 5.14, the amount of resource consumed is highest for VB01Z and reduces as the list goes down, with VB11Z consuming the least. VB08Z, VB09Z and VB011Z, therefore, represent low acuity and less complex cases. The breakdown of numbers and percentages for the codes was calculated for only those 3770 patients who were deemed to be affected by this bottleneck as previously explained in Section 6.3.1. From Table 6.15 below, the patients who are thought to have received specialty input have a wide range of EM-HRG codes from only 2 having VB01Z, through to 180 having VB11Z.

Table 6.15 Number of eligible patients for testing scenarios on specialty input

	Specialty Input Bottleneck Patients (QI violation only)	
EM-HRG Codes	**Count**	**Percentage**
VB01Z	2	0.05%
VB02Z	245	6.50%
VB03Z	1010	26.81%
VB04Z	508	13.49%
VB05Z	54	1.43%
VB06Z	121	3.21%
VB07Z	824	21.87%
VB08Z	544	14.44%
VB09Z	279	7.41%
VB11Z	180	4.78%
Grand Total	**3767***	**100.00%**
*EM-HRG codes were missing for 3 patients		

VB03Z has the highest count at 1010 representing 26.81% followed by VB07Z at 824 representing 21.87%. As a reminder, these reimbursement codes will not be known at the Triage stage however, it is being used in this study to provide an indication on how many patients could benefit from this initiative. In order to get a better idea of the number of patients who would benefit, it was deemed that focusing on only 3770 patients will be restricted.

Further analysis was conducted to determine how many Majors patients were admitted directly to the wards who had a Seen to MD greater than 60 minutes. This group of 9250 patients as shown in Table

6.16 below, therefore, included those who did not violate the QI as opposed to the 3770 who were strictly those who violated the QI.

Table 6.16 Number of eligible patients for testing scenarios on specialty input

EM-HRG Codes	**All Majors Direct Admission (Seen to MD>60)**	
	Count	**Percentage**
VB01Z	2	0.02%
VB02Z	397	4.29%
VB03Z	2166	23.42%
VB04Z	1023	11.06%
VB05Z	154	1.66%
VB06Z	296	3.20%
VB07Z	2118	22.90%
VB08Z	1691	18.28%
VB09Z	829	8.96%
VB11Z	574	6.21%
Grant Total	**9250**	**100.00%**

It was hypothesised that some of the patients who received specialty input and did not violate the QI, would still benefit from ACP in triage especially those with low acuity. A review of the EM-HRG codes for these patients also shows that only a few patients had codes VB01Z, VB02Z, VB05Z, and VB06Z. The highest group was VB03Z at 2166 (23.42%) followed by VB07Z and VB08Z at 2118 (22.90%) and 1691 (18.28%) respectively.

The DES scenarios were tested using this second group of 9250 patients since this will target a greater proportion of patients at triage. Medical and surgical patients have still been excluded from the testing. VB08Z, VB09Z and VB011Z add up to 3094 (33.45%) patients however, the scenarios were started at 1851 (20%) of this group of patients, then 2777 (30%), then 3701 (40%) and finally 4629 (50%). This therefore formed the basis for the DES input for testing scenarios as shown in Table 6.17 below.

Table 6.17 Number and percentage of patients to be seen by ACP and ED Dr

Scenario number	**Percentage of patients to be Seen by ACP and ED Dr**	**Number of patients to be Seen by ACP and ED Dr**
Scenario 1	20%	1850
Scenario 2	30%	2775
Scenario 3	40%	3700
Scenario 4	50%	4625

The 9250 patients used for the DES analysis, represent 11.25% of Majors patients (N=82,207). This figure was used to denote patients requiring specialty input. This number was reduced by the percentage that will be addressed by the ACP in triage in consultation with the ED doctor in each of the scenarios as shown in Table 6.18 below. Scenario 0 has 11.26% for specialty input and the remaining 88.74% to be seen by the ED doctor only. For scenario 1, 20% of the 9250 patients will be seen the ACP in Triage which works out to be 2.25% of the total number of Majors patients (N=82,207). The number of referrals is therefore reduced hypothetically to 9.01%. Scenarios 2 to 4 follow a similar logic with 50% of 9250 patients seen by the ACP and the other 50% referred for specialty input in Scenario 4.

Table 6.18 DES input for patients to be seen by ACP

Scenario number	**% Eligible patient to be Seen by ACP**	**% Specialist referral patients**	**% Seen by ACP**	**% Seen by ED Dr only (no referral)**
Scenario 0	0	11.26	N/A	88.74
Scenario 1	20	9.01	2.25	88.74
Scenario 2	30	7.88	3.38	88.74
Scenario 3	40	6.76	4.50	88.74
Scenario 4	50	5.63	5.63	88.74

The scenario testing involving the introduction of the ACP role yielded the output shown in Table 6.19 below. The time in the system which represents the mean LOS, reduced from 270.45 minutes (ST DEV 148.37) with all the 9250 patients being referred for specialty input to 253.09 minutes (ST DEV114.67) for scenario 1. It then reduced further for scenarios 2 through to 4. Scenario 4 had a mean LOS of 252.32 minutes (ST DEV 145.02). Scenario 3 where 40% of patients of eligible patients were seen by the ACP yielded the lowest mean LOS. This was 21.28 minutes difference from scenario 0. These minutes saved multiplied by the 40% of patients (N=3700) yields 78,736 minutes. Every minute saved is valuable as it all adds up to ensure a smooth flow and less crowded ED.

Table 6.19 DES output for introducing ACP at Triage

Scenario number	Mean (LOS) for admitted	ST DEV
Scenario 0	270.45	148.37
Scenario 1	253.09	114.67
Scenario 2	256.42	145.40
Scenario 3	249.17	138.32
Scenario 4	252.32	145.02

Similarly, Figure 6.8 below provides a diagrammatic representation of the figures presented in Table 6.19. It shows the mean LOS and ST DEV for admitted patients following the introduction of an ACP in triage.

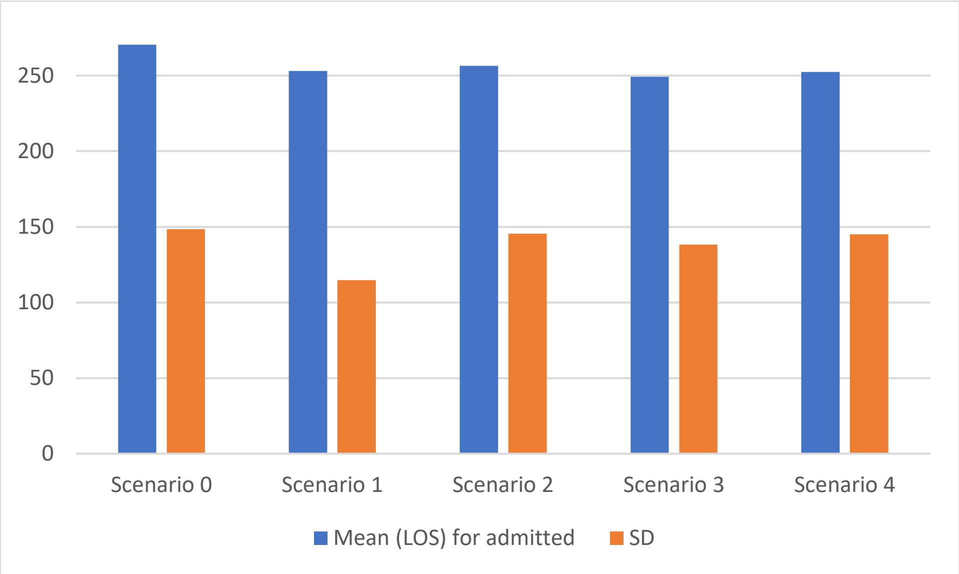


Figure 6.8 LOS output for introducing ACP at Triage

6.11.2 Bottleneck B- Test Outside Emergency Department

Tests i.e., investigations conducted help to reach a diagnosis for patients with those conducted outside the ED use up a considerable amount of time. This was identified as a bottleneck that affected a group of patients as presented in Section 6.3.2. The decision to select this bottleneck came from a review of the independent variables used for the logistic regression analysis and the generalized linear modelling which indicated that some of the variables are modifiable whilst others are not as previously stated in Section 5.12. In this study, non-modifiable variables were seen as patient demographic information as well as date and time of arrival. There were three modifiable factors which are number of procedures, number of investigations and decision to admit or discharge. The decision to admit or discharge is a medical decision and will therefore not be altered as a measure for reducing LOS. Admitted patients often have a longer LOS compared to discharged patients (Brick et al., 2014, Sweeny et al., 2020), however, a decision to admit should not be changed to discharge simply as a measure to reduce LOS. Equally important, a patient who is about to be discharged should not be admitted to avoid a long ED LOS if there are anticipated delays with the discharge process for example. The higher the number of procedures or investigations, the longer the patient's length of stay is however, the procedures are the treatments the patient is given based on their condition therefore this should not be altered to achieve a shorter LOS. Measures put in place to address this bottleneck, i.e., tests conducted outside the ED can help to speed up processes so that doctors can reach a medical decision in a timely manner for the patient to leave the ED swiftly. This bottleneck is not completely within the control of the ED however, as discussed earlier in Section 4.11.1, the use of precedence information can help reduce the number of investigations needed. Pre-hospital blood test results could be utilised to reduce delays caused by waiting for blood test results (Goodacre et al., 2011, Goyder et al., 2020). Similarly, pre-hospital ultrasound results, vital signs and observations in addition to cardiac health and ECG readings can all provide useful information to assist in diagnosing the patients (Delorenzo and Meadley, 2018, Roantree et al., 2021, Amissah and Lahiri, 2022). Nevertheless, medical and clinical staff will be expected to use their clinical judgement in requesting repeat tests when deemed clinically necessary to monitor patient deterioration.

6.11.2.1 DES Analysis of Reducing the Number of Tests

In order to address the test outside ED bottleneck, the impact of reducing the number of tests following the use of pre-hospital test results was analysed using DES. The number of tests were reduced from three tests to two and then one. The impact on the mean length of stay in the model for both discharged and admitted patients was measured as shown in Table 6.20 below.

Table 6.20 The impact of reducing the number of tests on LOS

Number of tests	**Discharged**		**Admitted**	
	Mean (LOS) mins	**ST DEV**	**Mean (LOS) mins**	**ST DEV**
3 tests	223.45	114.79	292.22	147.42
2 tests	214.09	114.37	280.52	143.71
1 test	194.52	109.03	256.99	138.25

The mean LOS for discharged patients who had three tests was 223.45 minutes (ST DEV 114.79) compared to two tests which was 214.09 minutes (ST DEV 114.37) and 194.52 minutes (ST DEV 109.03) for one test. The LOS difference between one test and three is 28.93 minutes. For admitted patients, the values are slightly higher though also reducing from three to two and then one test. For three tests, the mean LOS is 292.22 (ST DEV 147.42), for two tests it is 280.52 (ST DEV 143.71) and for one test the figures are 256.99 minutes (ST DEV 138.25) mean LOS. The LOS difference between one test and three is 35.23. It can be seen that the LOS can be reduced by reducing the number of tests which patients have to undertake. However, this must be approached with caution and clinical judgement applied in all cases in deciding on the tests that can be replaced by pre-ambulance results. Similarly, Figure 6.9 below provides a diagrammatic representation of the figures presented in Table 6.20. It shows the mean LOS and ST DEV for discharged and admitted patients as the number of tests are reduced from three, to two and then one.

Another important consideration in these scenario testing is the fact that information already available to the ED is being utilised more efficiently to bring decision-making forward and enhance a smooth flow.

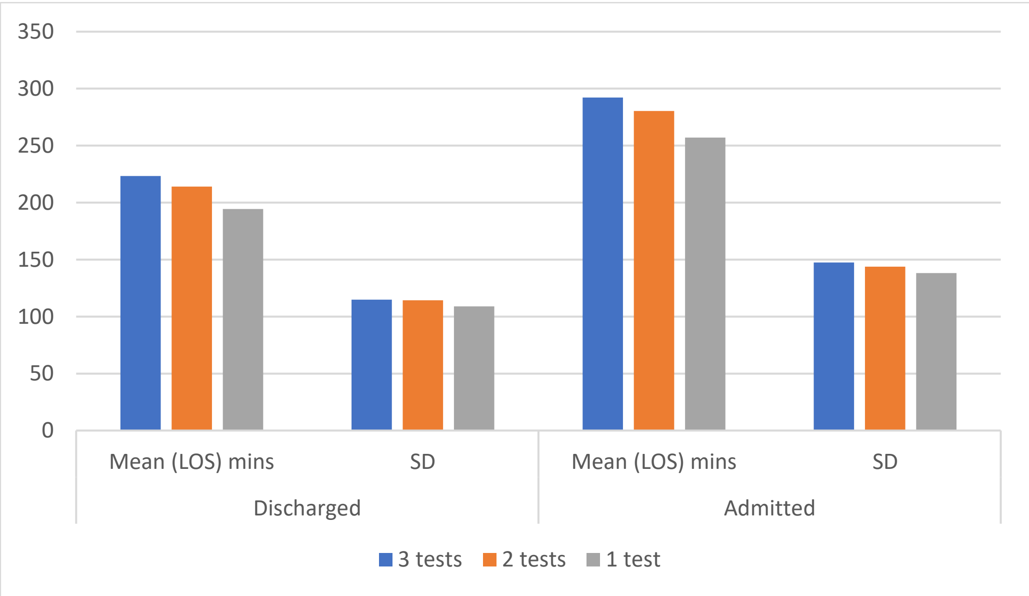


Figure 6.9 LOS output for reducing the number of tests

6.11.3 Bottleneck C- Awaiting Transportation

This study found a group of patients facing this bottleneck as identified in Section 6.3.3. The CAS Card has transportation information which can be collected at triage to assess if the patient will require transportation when discharged. Also, as stated in Section 4.11.3, this information can support the discharge team in better planning a patient's need for a care package so that the discharge team can be alerted in advance. This study hypothesises that such patients are also likely to require transport. The transportation bottleneck can be reduced with the use of a discharge lounge.

The analysis in Section 6.3.3 showed that 2775 patients, equating to 10.17% of Majors violated were likely to be awaiting transportation. However, all these patients will not be eligible to be sent to the discharge lounge. Further analysis was conducted to select the group of patients who could be sent to the discharge lounge.

Table 6.21 QI violation for Majors patients according to arrival time

	QI Violation			
Arrival time	**No breach**	**Breach**	**Row total**	**Column total**
Out of hours	24287 (62.1)	14820 (37.9)	39107 (100%)	39107 (47.6%)
In hours	30643 (71.1)	12457(28.9)	43100 (100%)	43100 (52.4%)
Total	54930 (66.8% of 82207)	27277 (33.2% of 82207)		82207 (100%)

A closer look at the Majors patients in Table 6.21 above shows that 33.2% of them violated the QI compared to the violation for the full data set which was 19.3% as shown in Table 6.22 below. The proportion who attended out of hours compared to in hours was close with 47.6% out of hours and the remaining 52.4% arriving in hours.

Table 6.22 QI violation for all patients

QI Violation	Frequency	Percentage
No breach	175188	80.7
Breach	41886	19.3
Total	217074	100.0

Further examination of the data showed that, 1157 of the 2775 (4.24% of 27277) patients who were possibly awaiting transport were discharged during the day i.e., in hours. See Appendix F.2

As shown in Appendix F.3 the average daily attendance for Majors is 112.61 therefore the average hourly attendance is 4.69 patients. The data shows that the 1157 patients spent a total of 146,318 minutes (2438.63 hours) in the ED after the decision to be discharged. Incoming demand does not stop therefore during this period, based on the hourly arrival rate, 11,437 (i.e., 2438.63x4.69) patients arrived in Majors who would have required attending to, yet ED staff were still looking after discharged patients who could not leave.

Therefore, addressing the transport issue did not only benefit the 1157 patients who stayed over 30 minutes but also included the 11,437 patients who arrived at the same time. The ED would have been crowded at the time which would have affected their likelihood of being seen and discharged on time. The impact of this bottleneck exceeds the 4.24% of Majors violators it constitutes. Furthermore, the use of the discharge lounge can be extended to all Majors patients discharged during the day who meet the eligibility criteria. This will be a proportion of the 16,264 patients who were discharged during the day as shown in Table 6.23 below. Some of the patients who did not violate the QI may still benefit from a quicker exit from ED after discharge if transport was required.

Table 6.23 QI violation for all patients

Arrival time	**Frequency**	**Percentage**
Out of hours	17882	52.4
In hours	16264	47.6
Total	34146	100.0

6.11.3.1 DES Analysis of the Use of a Discharge Lounge

The recommendation to utilise a discharge lounge for patients discharged from the ED during the day who require transport as suggested in Section 4.11.3 was tested in DES. The discharge lounge usage will speed up the departure of these patients so that ED staff can be freed up to attend to new patients. It will also free up space in ED. The discharge lounge currently operating at the study site is open from 8:00 am to 8:00 pm similar to others reported in the literature (Zainuddin and Balakrishnan, 2021) and utilised mainly by patients from the inpatient areas. This time range is also the same as in hours in this study. The eligibility criteria for discharge lounge usage are usually determined locally by the ED (Hernandez et al., 2014, Franklin et al., 2020). For the purposes of testing, the EM-HRG codes are being used once again to select low-acuity discharged patients from ED. These patients are less likely to require clinical care while waiting to go to their usual place of abode. They will be easier to manage in the proposed discharge lounge. The EM-HRG codes selected were VB08Z, VB09Z and VB011Z.

Focusing on simpler cases for the discharge lounge criteria and using the EM-HRG code presented in Table 6.24 as a guide, it can be seen that the last three groups make up over 60% of patients who could need transport.

Table 6.24 Number of eligible patients for testing scenarios

	All Majors in hours discharge	
EMHRG codes	**Count**	**Percentage**
VB01Z	5	0.03%
VB02Z	179	1.10%
VB03Z	1765	10.87%
VB04Z	533	3.28%
VB05Z	282	1.74%
VB06Z	724	4.46%
VB07Z	2022	12.46%
VB08Z	3252	20.03%
VB09Z	4766	29.36%
VB11Z	2705	16.66%
Grand Total	**16233***	**100.00%**
	*Total was 16264 but 31 were missing EM-HRG codes	

6.11.3.2 DES Input

Scenarios for testing were therefore set to 20%, 30%, 40% and 50% of patients discharged during the daytime (16264) as shown in Table 6.25.

Table 6.25 Patient percentages and numbers for discharge lounge users

Scenario number	**Patients eligible for discharge lounge**	**Number of patients eligible for discharge lounge**
Scenario 1	20%	3253
Scenario 2	30%	4879
Scenario 3	40%	6506
Scenario 4	50%	8132

The discharge process is a triangular distribution (10,15,30). In testing the discharge lounge scenarios, the DES model was modified to include a discharge lounge as a process leading to a third end point with an average processing time of 10 minutes as the time it will take to leave the department if there is no delay due to transportation. This value is based on observation and expert knowledge. The different scenarios were tested as shown in Table 6.26 below.

Table 6.26 DES input for testing discharge lounge scenarios

Scenario number	**% Eligible patient for discharge lounge usage**	**% Admitted**	**% Discharged home/usual place of abode**	**% Sent to Discharge lounge**
Scenario 0	0	58.5	41.5	Not in use
Scenario 1	20	58.5	37.55	3.95
Scenario 2	30	58.5	35.57	5.93
Scenario 3	40	58.5	33.59	7.91
Scenario 4	50	58.5	31.62	9.88

6.11.3.3 DES Output

Table 6.27 Mean LOS for discharged patients and discharge lounge users

Scenario number	**Discharged**		**Discharge lounge users**	
	Mean (LOS) mins	**ST DEV**	**Mean (LOS) mins**	**ST DEV**
Scenario 0	223.45	114.79	N/A	
Scenario 1	221.27	115.16	189.04	113.91
Scenario 2	221.89	115.01	191.32	106.98
Scenario 3	219.28	112.47	195.38	111.25
Scenario 4	219.92	110.82	197.39	108.06

Table 6.27 and Figure 6.10 shows that scenario one gives an average saving of 34.41 minutes per patient compared to no discharge lounge usage where the mean LOS was 223.45 (ST DEV 114.79) minutes as shown for scenario 0. This is significant as it could make a difference between breaching or not breaching. The mean LOS for the discharged patients leaving ED directly to their usual place

of abode is reducing by a small margin i.e., from 221.27 (ST DEV 115.16) minutes in scenario 1 to 219.92 (110.82) minutes in scenario 4. However, the mean LOS for those being sent to the discharge lounge is comparatively lower in all the scenarios. For scenario 1, the mean LOS is 189.04 (ST DEV 113.91) minutes through to scenario 4 where the mean LOS is 197.39 (ST DEV 108.06) minutes which is still lower than 223.45 minutes in scenario 0 with no discharge lounge in use. This confirms that introducing a discharge lounge will be beneficial though the cost of implementing and maintaining such a lounge has to be considered.

Overall, the analysis above shows how the use of the transport lounge can be beneficial to patients discharged during regular hours and in turn, result in a positive impact on new patients arriving.

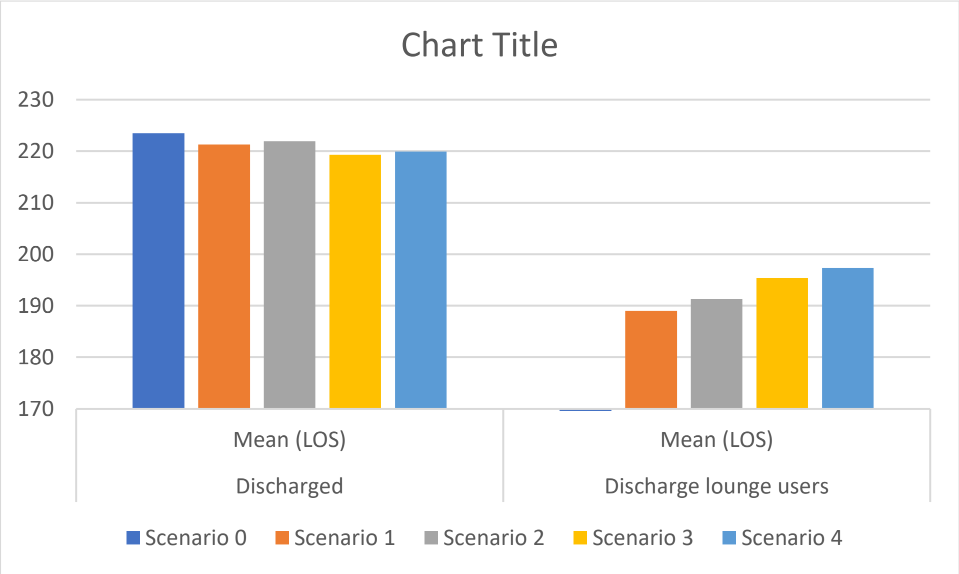


Figure 6.10 LOS output for testing discharge lounge usage

6.12 Conclusion

In this chapter, the lessons learnt from the systems modelling in Chapter 4 have been integrated with the data analysis in Chapter 5 to identify solutions for addressing three bottlenecks. These included an introduction of ACP in triage as a way of bringing processes forward in relation to the referral for specialty input, the use of precedence information to reduce repeat tests and the use of an ED discharge lounge for daytime discharges. These solutions have been tested in a simulation environment using a discrete event simulation model of the Majors unit. Different patient groups were used for the tests which resulted in reductions in the length of stay for different scenarios. Reducing the number of tests from three, to two and then one, showed a reduction in LOS. Similarly, the simulation showed a reduction in LOS for low-acuity patients who were seen by an

ACP in triage and for daytime discharges who were sent to a discharge lounge. Taken together, the results will have a positive impact on patient waiting times.

From the systematic review by Morley et al. (2018), it can be seen that a reduction in LOS of even a few minutes is regarded as beneficial. The studies reported various times of LOS reduction such as 6 minutes ((Copeland and Gray, 2015)), 10 minutes ((Quinn et al., 2007)), 14 minutes ((Han et al., 2010)), 32 minutes ((Begaz et al., 2017)and(Cha et al., 2015)), 34 minutes ((Burström et al., 2016)) and 36 minutes ((Holroyd et al., 2007)). Furthermore, addressing bottlenecks will lead to a smoother flow in ED which will also improve waiting time.

Chapter 7

Conclusions and Future Work

This chapter concludes the research by providing a summary of the main findings and research contributions presented in the thesis. It also presents details of the limitations and outlines recommendations for future work.

7.1 Introduction

Emergency department patient flow is being affected by bottlenecks which are impacting the department's ability to meet waiting time indicators. Taking an exploratory approach, this research utilised mixed methods with process modelling (qualitative) and analysis of routine data (quantitative) integration, to produce improvement suggestions for addressing bottlenecks. The suggestions were analysed using simulation.

This research was undertaken to understand and develop systematic context-specific methodologies for quality improvement and efficient system performance of the emergency department. This was to provide strategies to support ED waiting time by enhancing a smooth flow. The developed methodology is a dynamic model-driven methodology for ED processes. It serves as useful information for clinicians, managers, hospital administrators and policymakers on how to embark on quality improvement initiatives. The models developed in this research, though specific to the hospital data used, can be replicated in other EDs. This is the first study to model the Majors unit, the part of the emergency department that is associated with complex care and the likelihood of facing waiting time problems.

7.2 Summary of Research

Solutions targeted at improving ED flow and patient waiting times have had limited sustainability (Eldabi, 2009, Saghafian et al., 2015, Mohiuddin et al., 2017, Morley et al., 2018, Salmon et al., 2018) hence the problems remain. This research, therefore, looked at a systematic way of examining ED flow to address bottlenecks impacting flow and affecting patient waiting times.

To tackle these, the processes characterising patient flow in ED needed to be carefully examined to address inefficiencies and explore opportunities for improvements. Current techniques to examine flow have shortcomings due to their inability to model real systems and hence are reliant on simplistic models (Best et al., 2014, Hurwitz et al., 2014, Mohiuddin et al., 2017). In this study, obtaining granular information from the shop floor was shown to be an important first step when analysing complex systems such as an ED. A review of process mapping techniques revealed that RADs have the capability to model the level of granularity needed to explore complex systems (Ould, 1992, Odeh et al., 2002, Ould, 2007, Abu Rub et al., 2008, Zhao et al., 2009, Shukla et al., 2015). It is a systematic granular process mapping approach which provides a realistic picture of what is happening on the 'shop floor'. Hence, this technique was used in process mapping to gain an understanding of processes and derive systems knowledge of processes. Semi-structured interviews involving 21 clinicians were conducted in a level-1 ED of an NHS Acute Trust in the UK. The interviews provided information about activities undertaken by staff and interactions which have an impact on patient LOS and bottlenecks. This contributed to a better understanding of the complexities of patient care in such an activity-rich system and supported the development of RAD-based process mapping. From the interviews conducted and the RADs generated, the Majors unit was identified as the most crowded unit in the department. The Majors Unit in the ED sees complex patients as discussed in Section 5.13 as confirmed by the EM-HRG codes for patients seen in this unit. Moreover, this unit received both ambulance conveyance and self-presenting patients.

This is the first study to apply the RAD technique to model processes in an ED and specifically in the Majors unit. Modelling the processes of care through the application of the RAD technique helped with problem identification in the existing processes which is crucial with respect to ED waiting times. It showed several occasions where non-clinical factors such as awaiting the arrival of a specialty doctor, patients having tests outside the ED, discharged patients awaiting transportation and admitted patients awaiting beds and handover to inpatient ward all affected patient LOS. For instance, evidence suggests that patients requiring specialty input take time (Qureshi et al., 2010, Brick et al., 2014, Jung et al., 2020), especially in cases where there is difficulty in assigning the correct specialty or multiple specialty input is required (Brick et al., 2014). The specialist physicians have other responsibilities elsewhere in the hospital and may delay their response to the request. Similarly, some tests such as laboratory, x-ray and CT scans have to be conducted outside the ED (Paul and Lin, 2012, Khanna et al., 2017, Van Der Linden et al., 2017) as was also the case in this study's site and the patient has to wait for the results before being seen again by a physician for a decision to be made. Such tests conducted outside the department are not always within the control of ED staff. This also adds to the time it takes for physicians to arrive at a medical decision to admit or discharge. Transport arrangements by ED staff were also identified to be a time-consuming process leading to another bottleneck that then added to patients' overall stay in the department, a problem also noted in other studies (Brady et al., 2017, Tomar et al., 2019).

Quality improvements cannot be implemented without the use of data (Dormann et al., 2020). The lessons from the qualitative side of the study were integrated into the quantitative side through the analysis of anonymised routinely collected hospital data. This provided insight into the decisions which were taken along the patient journey. The data were analysed to derive models for predicting patient breaches using logistic regression and data tree methods. The length of stay was modelled using a generalized linear model.

Techniques currently used for addressing ED problems and improving waiting times were reviewed in Chapter 2. It was evident from the review that lean manufacturing is regarded as a state-of-the-art method (Abdelhadi, 2015, Dyas et al., 2015, Akmal et al., 2020, Souza et al., 2021) of which Value Stream Mapping seemed popular. However, VSM, which is commonly used in lean manufacturing projects for process mapping products (Holden, 2011, Akmal et al., 2020, Souza et al., 2021), does not provide as much granular information in comparison to RAD as was found through this study. Table 7.1 below shows how the three bottlenecks would have been modelled using VSM alongside the RAD mapping. It can be seen that RAD provides a more granular view of the bottlenecks. For instance, for bottleneck A illustrating awaiting specialty input, RAD can illustrate that repetitive process utilising the loop after P29. This looping process is not evidenced in the VSM equivalent. The red broken lines are being used to indicate the section of the process that repeats until the specialist arrives and the patient is seen. Furthermore, bottleneck B (test outside -P37), is an encapsulated process in RAD which is not a feature available in VSM and therefore modelled as processes. Similar to bottleneck A, bottleneck C also has a loop occurring at P53 where the patient continues to wait until transport becomes available. This is depicted using the loops unlike in the case of VSM. It is important that factors leading up to bottlenecks are examined carefully to prevent their occurrences altogether which the state-of-the-art does not allow. This study showed how RADs were useful for developing solutions to address bottlenecks. This was undertaken by exploring processes prior to the bottleneck to identify ways to prevent their occurrence or minimise their impact on LOS. A characteristic of VSM is defining processes as value added or non-value added, yet as discussed in Section 2.6.1.1, the definition of value, non-value added (waste) and customer in healthcare is not always understood. However, the depiction of the process in more detail to shed light on factors affecting process flows can help to see what is important to prevent waiting time problems.

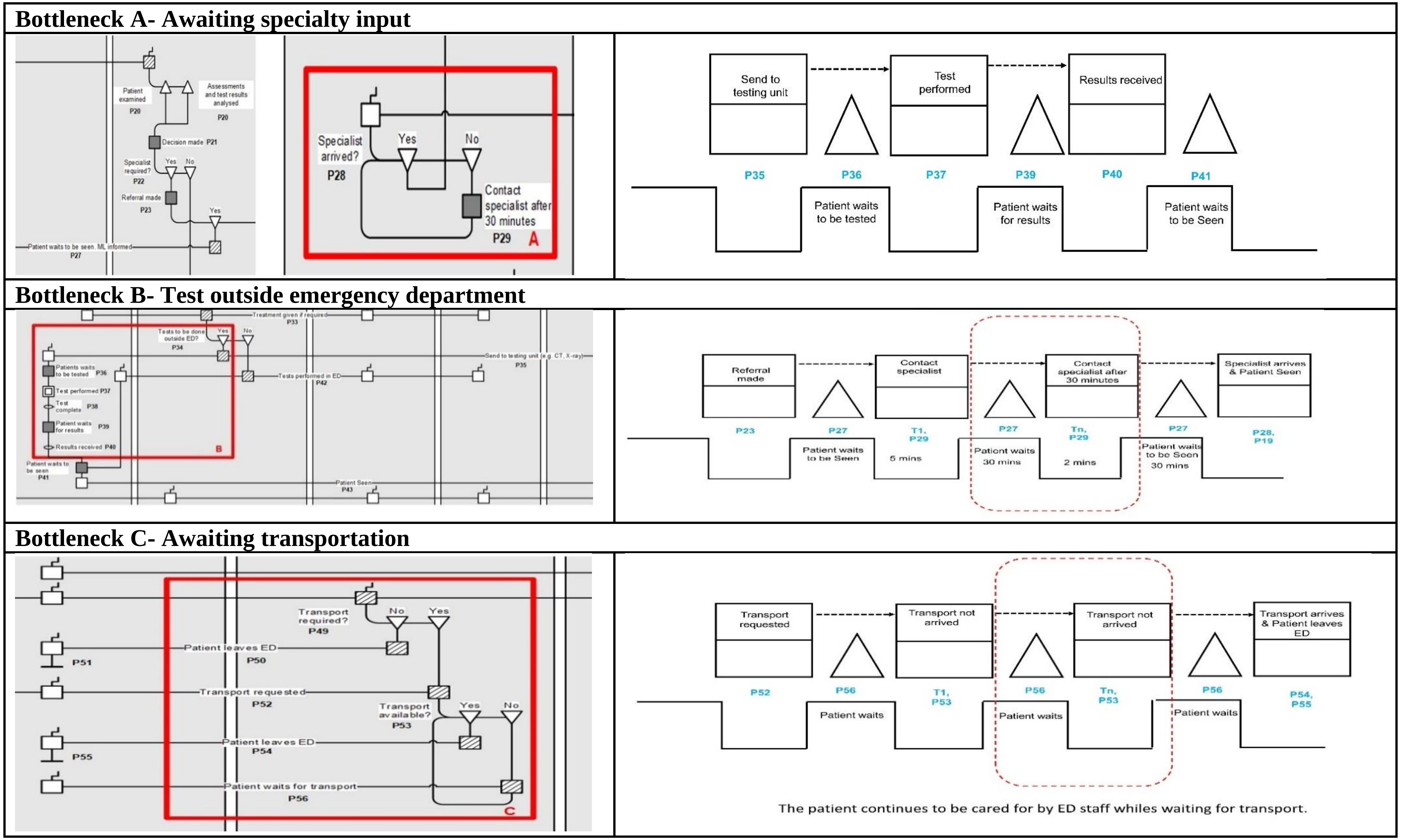


Figure 7.1 A comparison of RAD and VSM mapping of processes around bottlenecks A, B and C

Source: Author

Furthermore, analysis of the LOS in this study and others reported in literature show that there is a peak in activity close to four hours (Blunt et al., 2010, Eatock et al., 2011, Mason et al., 2012). This peak also applies to patients who do not breach the 4HQI (Eatock et al., 2017). There is therefore a crucial need to examine sub-processes and interactions closely when developing quality indicators. There must be a drive to treat and discharge or admit patients steadily throughout the four hours and not at a particular time to avoid breaching the indicator. Based on the evidence, this study suggests that the patient's LOS should be analysed in three time-blocks i.e., Arrival to Seen, Seen to Medical Decision and Medical Decision to Departure. This can help move patients swiftly along the journey rather than focusing on the final LOS for example, as measured by the 4HQI.

Additionally, a model-based, data-informed alert system (EDPas System) was proposed to be integrated into the ED's electronic patient record system. This will combine the capabilities of the RAD and the statistical models to support better decision-making and monitor patient flow. Current alert systems aim to support decision-making and transmit notifications to decision-makers regarding patient conditions and delays in processing patients (Cho et al., 2011, Kim et al., 2012, Shetty et al., 2021, Van Dort et al., 2021, Dutta et al., 2022). As discussed in Section 4.11.1, information included in the Patient Report Form accompanying ambulance arrivals and the Casualty Card completed for all ED patients can be better utilised (Jenkin et al., 2007, Montan et al., 2017, Altuwaijri et al., 2019). Through this system, the patient disposition can be predicted in advance so that measures can be put in place to minimise the occurrence of bottlenecks, thereby leading to improved timely care delivery and ED waiting time performance.

Despite all the capabilities of RADs, they are static in nature and do not provide any timing information. Generally, DES is the preferred simulation method following the review presented in Section 2.6.2.1. It can model EDs in a dynamic state so that improvements can be tested to see the impact on waiting times. However, current simulation techniques make incorporating granularity a challenge hence this research used an indirect mapping approach to translate the granular information obtained in the RADs to a condensed flow chart for DES application. The RAD helped to overcome this barrier by providing granular information which other process mapping tools cannot at present.

A DES simulation model was developed for the Majors unit and utilised in testing the improvement suggestions for addressing three bottlenecks, A-awaiting specialty input, B-tests outside ED, and C-awaiting transportation. Addressing bottleneck, A (awaiting specialty input) involved introducing an ACP in triage to support early requests for investigations ahead of patients being seen by an ED doctor. The ACP could alert the specialities early (at Triage) which would be confirmed at the point of patient being Seen by an ED doctor. The scenario testing in Section 6.11.1.1 showed how this would improve the LOS for a group of low-acuity patients. Moreover, to address bottleneck B (test outside ED), information available to the ED pre-hospital (PRF) and pre-Majors (CAS Card) could be efficiently utilised to reduce the number of investigations and subsequently, patient waiting time. This was tested in DES as discussed in Section 6.11.2.1. Finally, bottleneck C (awaiting transportation) was addressed through the use of a discharge lounge for ED patients which was also tested in DES in Section 6.11.3.1. This lounge was applicable to discharges during the day (8:00 am to 8:00 pm).

7.3 Research Contributions

This research makes a number of contributions which can be divided into three main areas namely scientific, operational and implications on policy making.

1. **Scientific Contribution**
    a. The scientific contribution is firstly on the methodology development achieved in this research for bottleneck identification and solution. In addressing the lack of flow in EDs due to bottlenecks (Zhao et al., 2015, DeAnda, 2018, Amissah and Lahiri, 2022), this research developed a model-driven methodology to address ED inefficiencies to enhance flow and improve waiting times. This is presented as a four-step approach and was achieved by highlighting the need for granularity in examining and understanding complex systems. Problems had to be understood first before attempts could be made at solving them. Embarking on problem identification revealed the importance of process modelling to derive the systems model as the first step in this methodology. Granularity of processes being a key focus of this research led to exploring process mapping tools to yield the required level of granularity. Role activity diagram emerged as having the necessary granular capability. This study is the first to apply role activity diagram in modelling an emergency department for bottleneck identification. The application of role activity diagram is also an approach for capturing tacit knowledge involving emergency department processes of care. These processes, implicitly known by staff needed to be explicitly captured for benefits including improvement initiatives, planning and training of staff. The maps provided a graphical representation of processes which had not been illustrated at such a granular level. The second step in the methodology involved the analysis of routinely

collected hospital data to understand decisions made regarding the patient and to gain insights into the patient flow. The third step is the integration of the qualitative analysis in step two and the quantitative analysis in step three to merge lessons and develop solutions for addressing the problems identified. The final step of the methodology is the simulation of improvement suggestions to assess the impact on waiting time. The technique for identifying bottlenecks was also shown to support identifying solutions through the application of a Loop Disintegration Approach. This approach sought to convert loops into activities to enhance smooth flow.

b. The indirect mapping of role activity diagrams to discrete event simulation modelling is another scientific contribution. This was achieved by extracting essential processes which were embedded with quantitative data to develop a condensed RAD-informed flowchart. This flow chart was used to develop the DES model for testing improvement suggestion scenarios. Current process modelling techniques used in hospitals often use simple tools which do not capture realities and associated variations in patient care. Hence, the developed models are not accurate representations of the care processes and do not account for complexities in the system to enhance bottleneck identification. These models are used as inputs in simulation analysis which affect the results. In this study, RAD provided the granularity needed to identify bottlenecks yet was too detailed to be transferred directly into a DES model as explained in Section 6.4. An indirect mapping of RAD to DES through a condensed RAD-informed flowchart was developed to overcome this challenge. As stated in Section 1.5, RAD has granularity but lacks time-based data and DES has time-based data but does not have an equivalent level of granularity as RAD. The indirect mapping of RAD to DES in this study has addressed this gap by bringing the two methods together with RAD enhancing DES input as a complementary tool.

c. Another scientific contribution is the development of quality indicators from a research perspective. The use of a time-based quality indicator is generally accepted and has a widespread interest. However, emergency departments nationally and internationally have been struggling to meet time-based quality indicators with calls to examine these. Due to the complex nature of the departments, it is essential that research is conducted to examine the processes of care including sub-processes and interactions closely when developing quality indicators. Through the modelling of granular information and integration with data, this study has presented a plan for consideration when developing quality indicators to measure ED waiting times.

d. This study also sheds light on the development of an information technology system for the emergency department. It demonstrated through the discussion in Sections 5.15 through 5.17, the need for monitoring patients' length of stay in meeting waiting time expectations. The emergency department could benefit from such a monitoring system to support decision-making and manage delays relating to the patient journey. In addition to the information technology infrastructure required to build such a system, an important consideration is the underpinning knowledge of the system it will be utilised for. The process modelling and data analysis to develop predictive models have provided insights into the system knowledge for alert system development. This constitutes another scientific contribution.

2. Operational Contribution in Practice Settings

a. The operational contribution of this research stemmed from the analysis of routinely collected hospital data to develop statistical models for predicting length of stay and breach of the four-hour quality indicator. The data analysis also shed light on the need to monitor the length of stay regularly to address the phenomenon of a peak in activity a few minutes before the end of the quality indicator as reported in other studies (Blunt et al., 2010, Eatock et al., 2011, Mason et al., 2012). This research is proposing that the length of stay should be monitored in three time-blocks. This implies that rather than monitoring the time of arrival and time of departure alone, LOS should be monitored as Time-block 1-Arrival to Seen, Time-block 2- Seen to Medical Decision and Time block 3- Medical Decision to Departure. The average times for these time-blocks obtained from historic data could be used as a guide.

b. The need for specialty input is creating bottlenecks as identified in this study and reported in literature. This is partly due to the delay in specialties responding to referral requests. Moreover, the need to request and wait to receive test results is adding to the delay in doctors arriving at a medical decision. Hence, another operational contribution is the introduction of an advanced clinical practitioner at Triage in the Majors unit. This role is not usually based in Triage, but scenario testing has demonstrated that having an ACP in triage can support requests for diagnostic tests ahead of patients being seen by an ED doctor. Specialty input requests can also be submitted in advance and confirmed following an agreement with the ED doctor.

c. Furthermore, a model-driven, data-informed alert system (EDPas System) has been proposed which can potentially be integrated into the electronic patient record system. This alert system can support monitoring patients for a smooth flow and timely care delivery. However, careful consideration must be given to alert fatigue compatibility, data security and confidentiality of data systems. Further development of this system has been recommended for future work.

3. Implications on Policy Making

a. This research shows that the entire emergency department does not need to be modelled to address flow inefficiencies. ED managers and policymakers can identify and target problematic areas for improvement initiatives considering the limited resources available to the department. This study identified the Majors unit as the most crowded unit in the department in terms of bottlenecks that affect ED flow. Further analysis, therefore, focused on this unit as the area of interest.

b. The methodology developed in this study provides policymakers with an informed way of analysing and monitoring patients' length of stay. This offers information for consideration in the development of quality indicators to improve ED waiting time performance and standardisation of ED processes. The complex nature of emergency departments necessitates the need for a close examination of processes when developing quality indicators. The department is characterised by high levels of uncertainties and variations, both in patient characteristics (clinical) and operational processes (non-clinical). Hence this study employed an exploratory framework to model and analyse processes of care in the department to understand and examine patient flow.

7.4 Limitations and Future Work

This research had a number of limitations. The interviews were conducted in a single-site emergency department even though it is in one of the biggest NHS Acute Trusts in the UK. Evidence indicates that this study site's problems are similar to other EDs in the country and internationally. For this reason, lessons learnt can assist other EDs to develop contextualised and robust processes when tackling waiting times. The interviews were skewed towards nursing staff as they are mostly involved in the daily operations of the ED and as such, it was important to get their views. The exact information about processes that were captured during the interviews would have changed over time, but the main principles remain the same. Moreover, new process maps provide avenues for modelling and comparing past, current and future processes. The RADs do not have arrows to show the direction of flow and do not provide time-related information. This is an opportunity for future development of this process mapping tool. Also, the RAD-based process mapping was not able to model issues of shared resources and or duplicating processes as there is currently no way of modelling such processes wherein two different staff members perform the same role depending on the prevailing conditions for example, when the department is busy, and some tasks have to be delegated to other roles.

The problems identified in relation to patient flow and waiting times are prevalent, making the focus of this research and contributions still relevant. In order to simplify the RAD, it was assumed that each member of staff was attending to one patient at a time and therefore completed one task before moving on to another patient. Also, tasks performed by staff were simplified to exclude non-patient related activities such as answering the telephone, reporting broken equipment to the relevant department, contacting IT, liaising with potters to move things around the department, attending to relatives or friends of patients, and contacting security among many others. Activities performed and interactions between roles were not matched with resource utilisation which provides an opportunity for future research. Furthermore, the interviews were conducted before the global pandemic which had an impact on processes in ED. The data for the statistical analysis was limited to two years and to what the hospital was willing to provide in keeping with information governance requirements. Independent variables such as triage categories, identification of patients who were sent home with transportation and those who required specialty input were not available in the dataset. These variables need to be considered in future analysis.

The improvement suggestions were only tested in a simulation environment and not implemented in practice, providing an avenue for future work. The simulation was built and run using a 24-hour clock to replicate the ED being open 24 hours a day. The arrival rate which is an average over 24 hours for the dataset seems low which is being recognised as a limitation since it does not reflect how crowded the ED is at specific times of the day. Future modelling can take into consideration different arrival rates for different times of the day.

The bed search and handover bottlenecks which are interlinked were not addressed in this study, this is also an opportunity for future research. The bed issue represents a larger concern affecting the wider healthcare system. The underpinning theory for a model-driven, data-informed alert system was developed which can be further explored to develop the technology for integration into a patient electronic record system. The development of a new quality indicator for the ED could incorporate the proposed three time-blocks into the specification in addition to an overall length of stay measurement. The timings could be based on local or nationally generated averages, however, the use of the alert system proposed in this study will enable these averages to be generated based on the independent variables of individual patients or groups of patients. This is also an opportunity for future development where the grouping can be based on factors such as number of investigations, disposal status, arrival time, arrival location and age which emerged as strong predictors of length of stay. Different statistical techniques could be employed to explore these factors further to improve the predictive ability of the derived models which impact correct estimation of breach and LOS. It was noted that some of the odds ratio interpretations were not consistent with practice and literature and must therefore be applied cautiously by considering clinical judgment and evidence from literature. The variables used for references could be changed to analyse the impact on the resulting model. Moreover, different methods of data transformation apart from the natural log could be used. The reference variables used in the model development could also be changed to see the impact on the results.

7.5 Concluding Remarks

Numerous factors have contributed to the rise in demand and increasing case mix in emergency departments which have triggered complexities in care delivery resulting in the need for better care at the individual patient level while driving up demands for efficiency and reducing delays at the health system level. In the face of growing demand, EDs are struggling to meet quality indicators.

The department is a complex system characterised by a high degree of uncertainties and variations which impact the whole healthcare system. Hence, it was important to ensure that bottlenecks affecting the patient journey were addressed to benefit patient care overall. Processes of care in the ED needed to be accurately understood and modelled in light of the increasing demand and changing case mix.

Granular information, once gathered, was modelled, and analysed to address identified bottlenecks. This resulted in the development of a systematic model-driven approach for assessing processes of care in the emergency department for quality improvements. The methodology developed and insights discovered have helped to improve patient flow and waiting times. Emergency departments will continue to be a source of care for many people. The results from this study would benefit patient care and contribute towards efficiency at the system level.

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Appendices

Appendix C.1 Semi-structured Interview Topics

Participation is completely voluntary, and participants are free to skip a question at any point.

1. **Role in the A&E care process**
    - Starting point of the role in the A&E care process
    - Most frequent tasks/steps/activities done during the care process-Sequence of tasks /Simultaneous activities
    - Interactions role has with other staff (who are they)

2. **Decision-making**
    - Key decisions made and factors influencing decision-making
    - Are there guidelines or protocols that provide support
    - Steps or decision-making done in role towards admission deterrence
    - Once ED makes the decision to admit; what then, in the opinion of the participants, is the decision-making that is triggered at the ward level
3. **Quality expectations**
    - Key quality targets, if any, that participant must follow
    - Managing scenarios where targets are about to be breached or not met
    - Participants' perception on particular quality indicator
4. **Data and information**
    - Types of data system(s) and information used to perform tasks for e.g. lab tests, CT scans, ECGs etc.
    - Types of data that participant collects in his/her role
    - Type of data not collected currently but would be useful to gather
5. **Resources utilisation**
    - Resources that are needed to carry out the care processes for example, databases, mobile phone etc.
    - Availability of resources (e.g., are they always available and if not, then what might be some reasons)
6. **Improvement processes**
    - Participant's previous experience in any process improvement projects

- Suggestions participant might want to share about doing things differently
- Anything else participant would like to say about the impact of non-urgent patients on the ED patient flow
- What are some of the major problems around patient flow that the participant sees in her/his role capacity; views on the hospital's discharge planning and need for efficiency, beds management.
- According to the interviewee, what is the key problem that could be solved which could then have the highest return on investment on the patient flow problem

7. **End point of the role in the care process**

Anything else that participant would like to add that they feel that has not been discussed but will be important to be considered in this research.

Appendix C.2 Participant Information Sheet

THE UNIVERSITY OF WARWICK

PARTICIPANT INFORMATION LEAFLET

Date:	1st February 2017
Study Title:	A model-driven approach for assessment and optimisation of hospital systems
Name of Researcher(s):	Marian A Amissah
Name of academic supervisor:	Dr. Sudakshina (Sudi) Lahiri

Introduction

You are invited to take part in a research study. Before you decide, you need to understand why the research is being done and what it would involve for you. Please take the time to read the following information carefully. Talk to others about the study if you wish.

Part 1 tells you the purpose of the study and what will happen to you if you take part. Part 2 gives you more detailed information about the conduct of the study

Please ask us if there is anything that is not clear or if you would like more information. Take time to decide whether or not you wish to take part.

PART 1

What is the study about?

Every year in the UK, the National Health Service (NHS) deals with an increasing number of patients putting an enormous pressure on hospitals to treat patients at a faster rate to ensure smooth flow. As the demand for service increases, hospitals are also expected to meet care quality targets and thresholds. This has created an urgent need for service improvement approaches that can benefit patient care while also ensuring a cost-effective health system. This study aims to address this gap through the development of a systematic approach for assessing and optimising processes in a hospital with a focus on the Accident & Emergency Department, which being one of the entry points in the hospital, is also under pressure to meet a lot of national target which are used as a measurement of the quality of care patients receive.

Do I have to take part?

It is entirely up to you to decide. We will describe the study and go through this information sheet, which we will give you to keep. If you choose to participate, we will ask you to sign a consent form to confirm that you have agreed to take. You will be free to withdraw at any time, without giving a reason and this will not affect you or your circumstances in any way.

What will happen to me if I take part?

You will be asked a series of questions in a semi- structured interview. This will take approximately 60 minutes.

What are the possible disadvantages, side effects, risks, and/or discomforts of taking part in this study?

There are no known disadvantages, side effects, risks, and/or discomforts of taking part in this study. Participants can choose not to answer any questions if they are uncomfortable to do so.

What are the possible benefits of taking part in this study?

By taking part in the study, you will be contributing to service improvements which can benefit patients and staff and the hospital as a whole. This can also benefit other hospitals.

Expenses and payments

No expenses can be claimed and no payments will be made for taking part in this study.

What will happen when the study ends?

The audio recording of the interview will be transcribed and used as data for analysis in the research project. Your identity will remain anonymous.

Will my taking part be kept confidential?

Yes. We will follow strict ethical and legal practice and all information about you will be handled in confidence. All information which is collected about you during the course of the research will be kept strictly confidential, and any information will be kept within a locked filing cabinet in the office at the research office located at the University of Warwick Department of WMG. You will only be asked to provide basic information (for example, if you are a healthcare professional) and your name will not be taken. During the study data will be stored within a locked filing cabinet and on university owned computers which require a username and password by Marian Amissah. This data will be accessed only by Marian Amissah and academic supervisor, Doctor Sudi Lahiri. After the study the data will be kept for 5 years until the PhD has been completed and passed after which it will be destroyed. It will not be possible to identify you from any published material arising from the study as anonymity will be ensured as all participants will be given a participant identification number.

What if there is a problem?

If there is a problem with the research the University has in force a Public and Products Liability policy which provides cover for claims for "negligent harm" and the activities here are included within that coverage subject to the terms, conditions and exceptions of the policy. Any complaint about the way you have been dealt with during the study or any possible harm you might have suffered will be addressed. Please address your complaint to the person below who is a senior university official entirely independent of the study:

Director of Delivery Assurance
Registrar's Office
University House
University of Warwick
Coventry CV4 8UW

Complaints@Warwick.ac.uk

024 7657 4774

This concludes Part 1.

If the information in Part 1 has interested you and you are considering participation, please read the additional information in Part 2 before making any decision.

PART 2

Who is organising and funding the study?

This study is part of my PhD research training conducted at the University of Warwick's WMG Department.

What will happen if I don't want to carry on being part of the study?

Participation in this study is entirely voluntary. Refusal to participate will not affect you in any way. If you decide to take part in the study, you will need to sign a consent form, which states that you have given your consent to participate.

If you agree to participate, you may nevertheless withdraw from the study at any time without affecting you in any way.

You have the right to withdraw from the study completely and decline any further contact by study staff after you withdraw.

What if there is a problem?

If there is a problem with the research the University has in force a Public and Products Liability policy which provides cover for claims for "negligent harm" and the activities here are included within that coverage subject to the terms, conditions and exceptions of the policy. Any complaint about the way you have been dealt with during the study or any possible harm you might have suffered will be addressed. Please address your complaint to the person below who is a senior university official entirely independent of the study:

Director of Delivery Assurance

Registrar's Office

University House

University of Warwick

Coventry

CV4 8UW

Complaints@Warwick.ac.uk

024 7657 4774

Who should I contact if I wish to make a complaint?

Any complaint about the way you have been dealt with during the study or any possible harm you might have suffered will be addressed. Please address your complaint to the person below, who is a senior University of Warwick official entirely independent of this study:

Director of Delivery Assurance

Registrar's Office

University House

University of Warwick

Coventry

CV4 8UW

Complaints@Warwick.ac.uk

024 7657 4774

Will my taking part be kept confidential?

Yes. We will follow strict ethical and legal practice and all information about you will be handled in confidence. All information which is collected about you during the course of the research will be kept strictly confidential, and any information will be kept within a locked filing cabinet in the office at the research office located at the University of Warwick Department of WMG. You will only be asked to provide basic information (for example, if you are a healthcare professional) and your name will not be taken. During the study data will be stored within a locked filing cabinet and on university owned computers which require a username and password by Marian Amissah. This data will be accessed only by Marian Amissah and academic supervisor, Doctor Sudi Lahiri. After the study the data will be kept for 5 years until the PhD has been completed and passed after which it will be destroyed. It will not be possible to identify you from any published material arising from the study as anonymity will be ensured as all participants will be given a participant identification number.

What will happen to the results of the study?

The results of this research will be discussed in the PhD dissertation and also presented at conferences. Result will also be published in refereed journals. Participants can request for copies of the findings to be sent to them by email or post.

Who has reviewed the study?

This study has been reviewed and given favourable opinion by the University of Warwick's Biomedical and Scientific Research Ethics Committee (BSREC):

REGO-2015-1715

What if I want more information about the study?

If you have any questions about any aspect of the study, or your participation in it, not answered by this participant information leaflet, please contact:

Marian A Amissah

International Manufacturing Centre

University of Warwick

Coventry, CV4 7AL

m.ameyaw-amissah@warwick.ac.uk

or

Dr. Sudakshina (Sudi) Lahiri

International Manufacturing Centre

University of Warwick

Coventry, CV4 7AL

s.lahiri@warwick.ac.uk

Thank you for taking the time to read this participant information leaflet.

Appendix C.3 Interview De-briefing Sheet

Thank you very much for taking part in the interview today.

The results of the interview will be used in my doctoral project and may be published in relevant journals. They also may be presented at conferences as presentation to an audience or a poster presentation showing the key findings from the research. However, please note that your individual identity will not be disclosed at any time. Your participation in this research is entirely anonymous and no one will ever be able to identify you in the study.

If you have any concerns about the topics raised in today's session, please you are welcome to talk with me in private after the interview or you can contact me later. I can be reached at m.amissah@warwick.ac.uk

Please also let me know if you would like a copy of the findings which can be sent to you by email or post.

Many thanks,

Marian Amissah
PhD student
WMG Department, University of Warwick

Appendix C.4 Ethics Approval

WARWICK

MEDICAL SCHOOL

PRIVATE
Mrs Marian A Amissah
International Manufacturing Centre
WMG
University of Warwick
Coventry
CV4 7AL

11th December 2015

Dear Mrs Amissah,

Study Title and BSREC Reference: *A model-driven approach for assessment and optimisation of hospital systems* REGO-2015-1715

Thank you for submitting your revisions to the above-named study to the University of Warwick's Biomedical and Scientific Research Ethics Sub-Committee for approval.

I am pleased to confirm that approval is granted and that your study may commence.

In undertaking your study, you are required to comply with the University of Warwick's *Research Data Management Policy*, details of which may be found on the Research and Impact Services' webpages, under "Codes of Practice & Policies" » "Research Code of Practice" » "Data & Records" » "Research Data Management Policy", at: http://www2.warwick.ac.uk/services/ris/research_integrity/code_of_practice_and_policies/research_code_of_practice/datacollection_retention/research_data_mgt_policy

You are also required to comply with the University of Warwick's *Information Classification and Handling Procedure*, details of which may be found on the University's Governance webpages, under "Governance" » "Information Security" » "Information Classification and Handling Procedure", at:
http://www2.warwick.ac.uk/services/gov/informationsecurity/handling.
Investigators should familiarise themselves with the classifications of information defined therein, and the requirements for the storage and transportation of information within the different classifications:

> *Information Classifications:*
> http://www2.warwick.ac.uk/services/gov/informationsecurity/handling/classifications
> *Handling Electronic Information:*
> http://www2.warwick.ac.uk/services/gov/informationsecurity/handling/electronic/
> *Handling Paper or other media*
> http://www2.warwick.ac.uk/services/gov/informationsecurity/handling/paper/.

Please also be aware that BSREC grants **ethical approval** for studies. **The seeking and obtaining of *all* other necessary approvals is the responsibility of the investigator.**

These other approvals may include, but are not limited to:

www.warwick.ac.uk

1. Any necessary agreements, approvals, or permissions required in order to comply with the University of Warwick's Financial Regulations and Procedures.
2. Any necessary approval or permission required in order to comply with the University of Warwick's Quality Management System and Standard Operating Procedures for the governance, acquisition, storage, use, and disposal of human samples for research.
3. All relevant University, Faculty, and Divisional/Departmental approvals, if an employee or student of the University of Warwick.
4. Approval from the applicant's academic supervisor and course/module leader (as appropriate), if a student of the University of Warwick.
5. NHS Trust R&D Management Approval, for research studies undertaken in NHS Trusts.
6. NHS Trust Clinical Audit Approval, for clinical audit studies undertaken in NHS Trusts.
7. Approval from Departmental or Divisional Heads, as required under local procedures, within Health and Social Care organisations hosting the study.
8. Local ethical approval for studies undertaken overseas, or in other HE institutions in the UK.
9. Approval from Heads (or delegates thereof) of UK Medical Schools, for studies involving medical students as participants.
10. Permission from Warwick Medical School to access medical students or medical student data for research or evaluation purposes.
11. NHS Trust Caldicott Guardian Approval, for studies where identifiable data is being transferred outside of the direct clinical care team. Individual NHS Trust procedures vary in their implementation of Caldicott guidance, and local guidance must be sought.
12. Any other approval required by the institution hosting the study, or by the applicant's employer.

There is no requirement to supply documentary evidence of any of the above to BSREC, but applicants should hold such evidence in their Study Master File for University of Warwick auditing and monitoring purposes. You may be required to supply evidence of any necessary approvals to other University functions, e.g. The Finance Office, Research & Impact Services (RIS), or your Department/School.

May I take this opportunity to wish you success with your study, and to remind you that any Substantial Amendments to your study require approval from BSREC before they may be implemented.

Yours sincerely

p.p. Graham Hewitt

Professor Scott Weich
Chair
Biomedical and Scientific
Research Ethics Sub-Committee

Biomedical and Scientific Research Ethics Sub-Committee
A010 Medical School Building
Warwick Medical School,
Coventry, CV4 7AL.
T: 02476-528207
E: BSREC@Warwick.ac.uk

http://www2.warwick.ac.uk/services/ris/research_integrity/researchethicscommittees/biomed

Appendix C.5 Consent Form

THE UNIVERSITY OF WARWICK

BIOMEDICAL AND SCIENTIFIC RESEARCH ETHICS COMMITTEE CONSENT FORM

Study Number: **REGO-2015-1715**

Title of Project: A model-driven approach for assessment and optimisation of hospital systems

Name of Researcher(s): Marian A Amissah

Name of academic supervisor: Dr. Sudakshina (Sudi) Lahiri

Please initial all boxes

1. I confirm that I have read and understand the information sheet dated **1st February 2017** for the above study. I have had the opportunity to consider the information, ask questions and have had these answered satisfactorily. ☐
2. I understand that my participation is voluntary and that I am free to withdraw at any time without giving any reason, without-being affected. ☐
3. I understand that my information will be held and processed to be used anonymously for internal publication for a PhD thesis. I also understand that such anonymous data may be used for future research, including that for publication. ☐
4. I agree to take part in the above study and am willing to have my involvement in the interview noted and electronically recorded ☐

____________________	____________________	____________________
Name of Participant	Date	Signature
____________________	____________________	____________________
Name of Person taking consent	Date	Signature

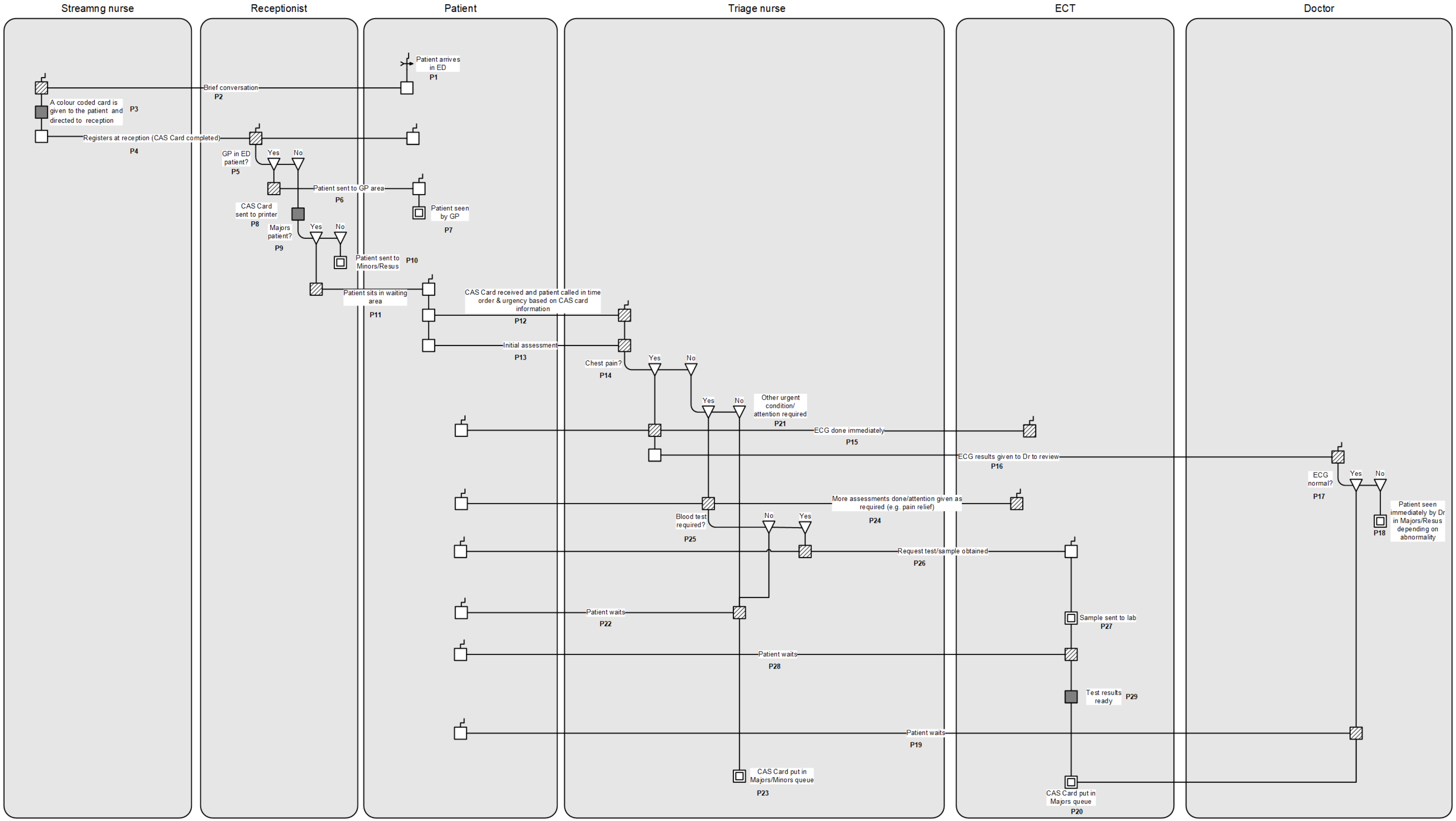
Appendix D.1 Python Script for Matrices

```
# -*- coding: utf-8 -*-

"""

@author: amissa_m

"""

#Importing pandas and numpyimport pandas as pd

import numpy as np

import pandas as pd


#Specifying data path and file name. Remember to change for each file name

data_path= r"C:\Users\amissa_m\OneDrive - University of Warwick\Documents\Transcript Tables/"

file_name = "Majors unit.xlsx"

intermediate_matrix_data = pd.read_excel(data_path + file_name, "Sheet1")

role = list(intermediate_matrix_data['Role'])

role_unique = list(set(role))

activity_type_unique = list(set(intermediate_matrix_data['Action_type']))

action_length = len(intermediate_matrix_data)


#Interaction role list

interaction_roles =
list(set(intermediate_matrix_data['Interaction_driver1']).union(set(intermediate_matrix_data['Interaction_
receiver1'])).union(set(intermediate_matrix_data['Interaction_receiver2'])).union(set(role_unique)))

interaction_roles = [i for i in interaction_roles if i is not np.nan]

role_count = len(interaction_roles)


#Identifying the number of times the interaction has taken place to know the interaction matrix size

interaction_count = 0
```

```
for i in range(action_length):
    if intermediate_matrix_data['Action_type'][i] == "Interaction":
        interaction_count = interaction_count + 1
interaction_action_list = ['']*interaction_count

#All empty matrices declared
activity_type_length = len(activity_type_unique)
Action_type_matrix = np.zeros((action_length, activity_type_length))
Action_role_matrix = np.zeros((action_length, role_count))
interaction_type_matrix = np.zeros((interaction_count, role_count))

#Generating the individual matrices
#Action type matrix
for i in range(action_length):
    for j in range(activity_type_length):
        if intermediate_matrix_data['Action_type'][i] == activity_type_unique[j]:
            Action_type_matrix[i][j] = 1

for i in range(action_length):
    for j in range(role_count):
        if intermediate_matrix_data['Role'][i] == interaction_roles[j]:
            Action_role_matrix[i][j] = 1

#Include the roles in the interaction_drivers
c = 0
for i in range(action_length):
    if intermediate_matrix_data['Action_type'][i] == "Interaction":
```

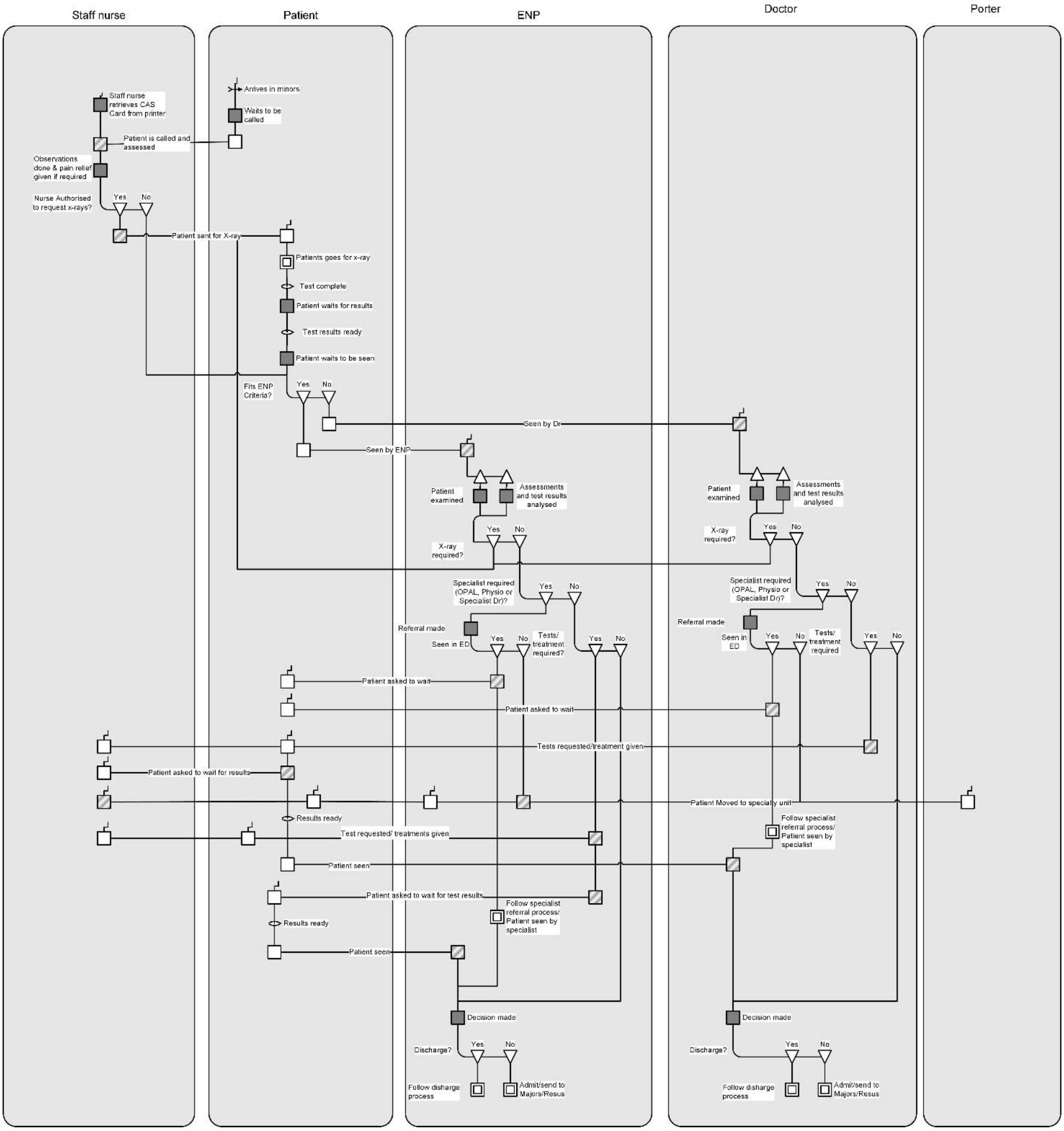
```
        interaction_action_list[c] = intermediate_matrix_data['Activities'][i]
        for j in range(role_count):
            if intermediate_matrix_data['Interaction_driver1'][i] == interaction_roles[j]:
                interaction_type_matrix[c][j] = 1

            if intermediate_matrix_data['Interaction_receiver1'][i] == interaction_roles[j]:
                interaction_type_matrix[c][j] = 2
            if intermediate_matrix_data['Interaction_receiver2'][i] == interaction_roles[j]:
                interaction_type_matrix[c][j] = 2
        c = c + 1

df_action_type1 = pd.DataFrame(intermediate_matrix_data['Activities'])
df_action_type2 = pd.DataFrame(Action_type_matrix, columns = activity_type_unique)
df_action_type = pd.concat([df_action_type1, df_action_type2], axis = 1)

df_action_role1 = pd.DataFrame(Action_role_matrix, columns = interaction_roles)
df_action_role = df = pd.concat([df_action_type1, df_action_role1], axis =1)

df1 = pd.DataFrame(pd.Series(interaction_action_list), columns = ["Activities"])
df2 = pd.DataFrame(interaction_type_matrix, columns = interaction_roles)
df_interaction_roles = pd.concat([df1, df2], axis = 1)

writer = pd.ExcelWriter(data_path + 'Intermediate_results_sheet.xlsx')
df_action_type.to_excel(writer, "Action_type_matrix", index=False)
df_action_role.to_excel(writer, "Action_role_matrix", index=False)
df_interaction_roles.to_excel(writer, "Interaction_role_matrix", index=False)
writer.save()
```

Appendix D.2 Streaming and Triage Role Activity Diagram



Source: Author, Note: ECT-Emergency Care Technician, GP-General Practitioner, CAS Card- Casualty Card, ECG-Electrocardiogram

Appendix D.3 Minors Role Activity Diagram



Source: Author, Note: ENP-Emergency Nurse Practitioner, GP-General Practitioner, CAS Card- Casualty Card, Physio-Physiotherapist, OPAL- Old Persons Assessemnt and Liaison Team

Appendix E.1 Description of Variables Received in Dataset

Number	Variable name	Format/Example
1	Hashbytes unitno	Long string of numbers
2	A&E activity reference number	Long string of numbers
3	Age group	5 year group- 17-21 years
4	Gender	M, F, U,X
5	Mode of arrival	999, Private transport
6	Complaints	Abdo pain, injury head
7	Referral Source	Self/Parent, GP no letter
8	Partial patient post code	First three characters of postcode
9	GP postcode	First three characters of postcode
10	Arrival location	Major, See & Treat
11	Date and time of arrival	01/01/2017 00:08
12	Triage date and time	02/01/2017 00:08
13	Seen date and time	03/01/2017 00:08
14	Medical discharge date and time	04/01/2017 00:08
15	Departure date and time	05/01/2017 00:08
16	Diagnosis 1	Head Injury (Minor)
17	Diagnosis 2	Head Injury (Minor)
18	Diagnosis 3	Head Injury (Minor)
19	Procedure 1	Active warming, Advice-Verbal
20	Procedure 2	Active warming, Advice-Verbal
21	Procedure 3	Active warming, Advice-Verbal
22	Investigation 1	X-ray plain film, Venous Blood Gas
23	Investigation 2	X-ray plain film, Venous Blood Gas
24	Investigation 3	X-ray plain film, Venous Blood Gas
25	Disposal Status	Admitted, Discharged - No further treatment required
26	EM-HRG codes	VB08Z, VB11Z
27	Spell number	Long string of numbers
28	Admission date and time	05/01/2017 00:08
29	Number of episodes	1,2
30	First ward of discharge	Ward number/number
31	Last ward of discharge	Ward number/number
32	ICD and diagnosis code 1	A020
33	Description of diagnosis 1	Chest pain, unspecified,"Tachycardia, unspecified"
34	ICD and diagnosis code 2	A020
35	Description of diagnosis 2	Chest pain, unspecified,"Tachycardia, unspecified"
36	FCE-HRG code	AA02A
37	Discharge date and time	05/01/2017 00:08
38	Discharge Destination	The usual place of residence, including no fixed abode

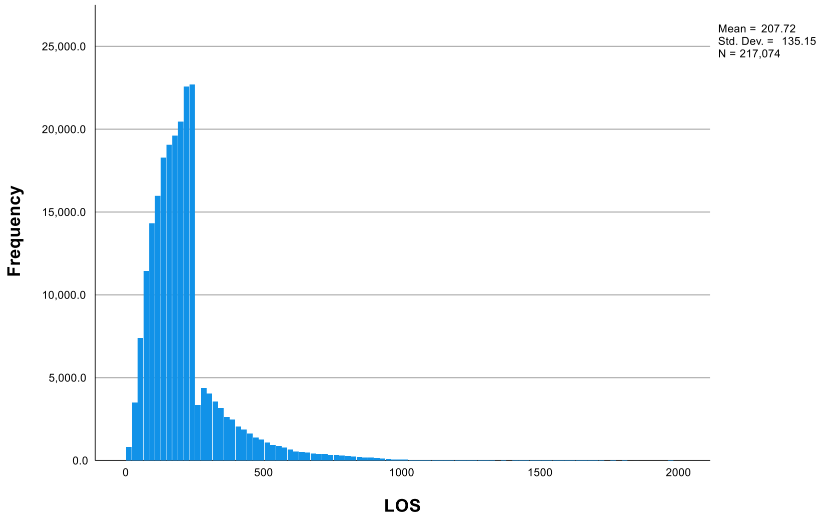
Appendix E.2 Data Size After Cleansing

Data size (number of visits)	Amendments	Final size
229,094	3 categories of 'dead' removed • Dead on arrival at hospital (finding)-2 • Died in Department-163 • Emergency room admission, died in emergency room (procedure)-193 • Total-358	228,736
228,736	Patients with wards of admission but ambiguous disposal status such as discharged and LWBS-516	228,220 Admitted- 80,339 Not admitted- 147,881

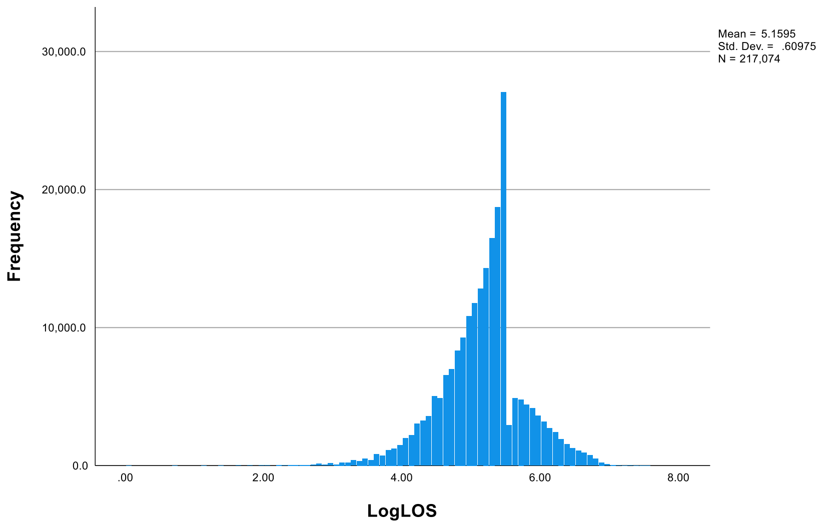
Appendix E.3 Left Without Being Seen Analysis

Arrival location	Count (N)	Percentage (%)
0-GP	233	2.12%
1-See&Treat	8089	73.48%
2-Major	2529	22.97%
3-Resus	158	1.44%
Age		
17-21	1609	14.62%
22-26	1700	15.44%
27-31	1457	13.23%
32-36	1417	12.87%
37-41	1063	9.66%
42-46	865	7.86%
47-51	877	7.97%
52-56	684	6.21%
57-61	429	3.90%
62-66	277	2.52%
67-71	214	1.94%
72-76	152	1.38%
77-81	132	1.20%
82-101	133	1.21%
Referral source		
All others	1552	7.58%
Self	18914	92.42%
Mode of arrival		
EMS	3971	22.00%
Non-EMS	14076	78.00%

Appendix E.4 LOS before log transformation



Appendix E.5 LOS after log transformation

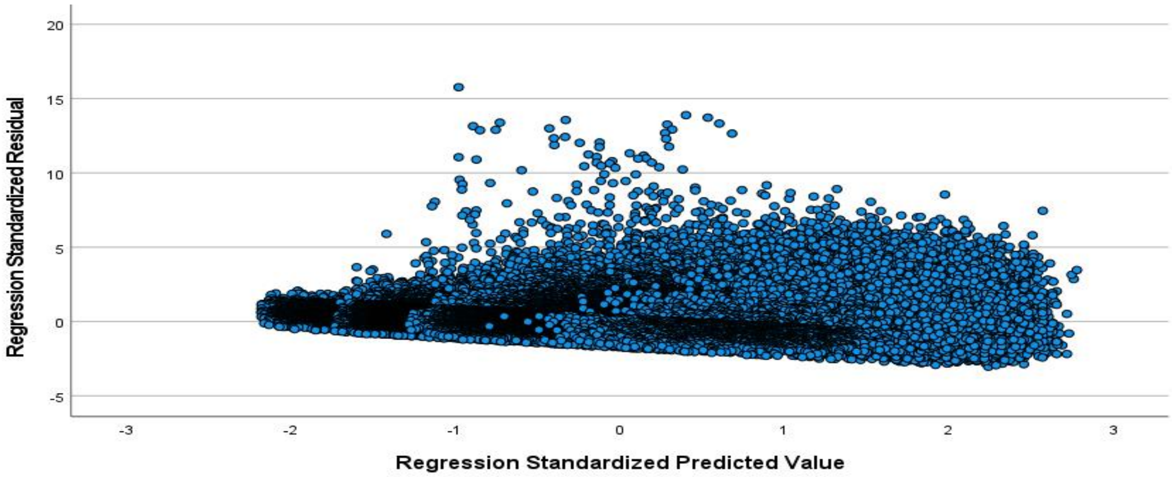


Appendix E.6 Wald Values for Independent Variables

Independent variable	**Wald**
Disposal status	2825.851
Arrival location	2804.420
Arrival time (In/Out of hours)	2540.684
Number of investigations	1364.161
Age	1137.541
Day of the week	1054.888
Mode of arrival	587.571
Weekday_Weekend	486.636
Year of arrival	179.330
Frequent user	156.167
Presenting complaint	96.758
Number of procedures	87.142
Gender	66.801
Month of arrival	39.595
Referral source	24.712
Number of diagnosis	23.090

Appendix E.7 Scatter Plot to Test Logistic Regression Assumption

(Independent Observation)



Appendix E.8 Logistic Regression R Squared Results

Step	Cox & Snell R Square	Nagelkerke R Square
1	.123	.197
2	.145	.233
3	.154	.246
4	.160	.256
5	.165	.265
6	.167	.268
7	.169	.270
8	.170	.272
9	.171	.273
10	.171	.274
11	.171	.274
12	.172	.274
13	.172	.274

Appendix E.9 Hosmer and Lemeshow Test Results in Logistic Regression

Hosmer and Lemeshow Test			
Step	Chi-square	df	Sig.
1	.000	2	1.000
2	414.575	5	.000
3	643.193	5	.000
4	572.309	8	.000
5	869.013	8	.000
6	720.444	8	.000
7	904.483	8	.000
8	816.490	8	.000
9	823.916	8	.000
10	794.514	8	.000
11	778.309	8	.000
12	748.581	8	.000
13	721.276	8	.000

Appendix E.10 Generalised Linear Model Parameters

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
(Intercept)	5.664	0.0078	5.649	5.679	526188.579	1	0
[Age=17-31]	-0.159	0.0036	-0.166	-0.152	1976.859	1	0
[Age=32-51]	-0.136	0.0035	-0.143	-0.129	1518.097	1	0
[Age=52-71]	-0.084	0.0035	-0.091	-0.077	574.89	1	0
[Age=72-101]	0[a]	.	.	.	.	.	.
[Mode of arrival=EMS]	0.079	0.0031	0.073	0.085	657.302	1	0
[Mode of arrival=Non-EMS]	0[a]	.	.	.	.	.	.
[Referral source=All others]	0.008	0.0028	0.003	0.013	8.566	1	0.003
[Referral source=Self]	0[a]	.	.	.	.	.	.
[Arrival location=GP]	-0.216	0.0081	-0.232	-0.201	721.8	1	0
[Arrival location=See & Treat]	-0.182	0.0055	-0.193	-0.172	1115.483	1	0
[Arrival location=Majors]	0.052	0.0047	0.043	0.061	121.655	1	0
[Arrival location=Resus]	0[a]	.	.	.	.	.	.
[Disposal status=Discharged]	-0.213	0.0029	-0.219	-0.207	5351.202	1	0
[Disposal status=Admitted]	0[a]	.	.	.	.	.	.
[Number of procedures=0]	-0.136	0.0044	-0.144	-0.127	939.757	1	0
[Number of procedures=1]	-0.1	0.003	-0.106	-0.094	1118.914	1	0
[Number of procedures=2]	-0.049	0.0031	-0.055	-0.043	255.407	1	0
[Number of procedures=3]	0[a]	.	.	.	.	.	.
[Number of investigations=0]	-0.261	0.0035	-0.267	-0.254	5497.679	1	0
[Number of investigations=1]	-0.126	0.0034	-0.132	-0.119	1397.332	1	0
[Number of investigations=2]	-0.057	0.0039	-0.065	-0.05	218.63	1	0
[Number of investigations=3]	0[a]	.	.	.	.	.	.
[Day of arrival=Weekday]	-0.008	0.0025	-0.013	-0.003	10.82	1	0.001
[Day of arrival =Weekend]	0[a]	.	.	.	.	.	.
[Frequent user=No]	-0.045	0.0037	-0.052	-0.038	150.758	1	0
[Frequent user=Yes]	0[a]	.	.	.	.	.	.
[Year of arrival=2017]	-0.053	0.0022	-0.057	-0.048	552.943	1	0
[Year of arrival=2018]	0[a]	.	.	.	.	.	.
[Arrival time=Out of hours]	0.158	0.0023	0.154	0.163	4813.841	1	0
[Arrival time =In hours]	0[a]	.	.	.	.	.	.

Appendix E.10 Generalised Linear Model Parameters (cont'd)

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test		
			Lower	Upper	Wald Chi-Square	df	Sig.
[Gender=Others]	-0.062	0.0453	-0.151	0.026	1.89	1	0.169
[Gender=Female]	0.017	0.0022	0.012	0.021	56.721	1	0
[Gender=Male]	0[a]	.	.	.	.	.	.
[Presenting Complaint= Airway / Breathing/Circulation / Chest]	-0.077	0.0041	-0.085	-0.069	354.93	1	0
[Presenting Complaint= Environmental/General / Minor / Admin]	0.008	0.0042	0	0.016	3.459	1	0.063
[Presenting Complaint= Gastrointestinal]	-0.015	0.0045	-0.024	-0.006	10.821	1	0.001
[Presenting Complaint= Head and neck/Neurological /Eye]	0.019	0.0046	0.01	0.028	18.06	1	0
[Presenting Complaint= Trauma / Musculoskeletal]	-0.047	0.0036	-0.054	-0.04	166.946	1	0
[Presenting Complaint=All others]	0[a]	.	.	.	.	.	.
(Scale)	.260[b]	0.0008	0.258	0.261			

Dependent Variable: LogLOS
Model: (Intercept), Age, Mode of arrival, Referral source, Arrival location, Disposal status, Number of procedures, Number of investigations, Day of arrival, Frequent user, Year of arrival, Arrival time, Gender, Presenting Complaint.

a. Set to zero because this parameter is redundant.

b. Maximum likelihood estimate.

Appendix E.11 Generalized Linear Model Goodness of Fit

	Value
Bayesian Information Criterion (BIC)	323577.673
Consistent AIC (CAIC)	323605.673

Appendix E.12 Generalized Linear Model Tests of Model Effects

Tests of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	116819.051	1	.000
Age	2189.807	3	.000
Mode of arrival	657.302	1	.000
Referral source	8.566	1	.003
Arrival location	5611.177	3	.000
Disposal status	5351.202	1	.000
Number of procedures	1498.748	3	.000
Number of investigations	6071.250	3	.000
Day of arrival	10.820	1	.001
Frequent user	150.758	1	.000
Year of arrival	552.943	1	.000
Arrival time	4813.841	1	.000
Gender	59.184	2	.000
Presenting Complaint	864.028	5	.000

Dependent Variable: LogLOS
Model: (Intercept), Age, Mode of arrival, Referral source, Arrival location, Disposal status, Number of procedures, Number of investigations, Day of arrival, Frequent user, Year of arrival, Arrival time, Gender, Presenting Complaint

Appendix E.13 Length of stay per disposal status

Length of stay for overall dataset					
Disposal status	**N**	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
Admitted	80298	2	1427	275.85	158.727
Discharged	136776	1	1965	167.73	99.365
Length of stay for patients who violated the QI					
Disposal status	**N**	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
Admitted	28443	241	1427	436.57	162.192
Discharged	13443	241	1965	376.64	151.595

Appendix F.1 Time blocks for admitted and discharged Majors violators

Time-blocks	Admitted Patients						Discharged Patients				
	N	**Min**	**Max**	**Mean**	**Std. Deviation**		**N**	**Min**	**Max**	**Mean**	**Std. Deviation**
Arrival to Triage	19323	0	965	13.21	28.702		7954	0	704	14.22	32.875
Triage to Seen	19323	0	1017	106.01	76.766		7954	0	1167	136.39	91.917
Seen to MD	19323	0	1330	109.69	100.737		7954	0	1751	203.32	177.881
Boarding	19323	0	720	216.58	167.102		7954	0	1340	48.15	88.853
LOS	19323	241	1427	445.48	168.489		7954	241	1965	402.08	172.471

Appendix F.2 Discharged patients who stayed more than 30 minutes before departure

Arrival time	Frequency	Percent
In hours	1157	41.69
Out of hours	1618	58.31
Total	2775	100

Appendix F.3 Hourly Emergency Department Arrivals Per Arrival Location

Hourly arrivals	Arrival location							
	GP number of attendance	GP average attendance	Minors number of attendance	Minors average attendance	Majors number of attendance	Majors average attendance	Resus number of attendance	Resus average attendance
1	5	0.01	2196	3.01	2592	3.55	573	0.78
2	2	0.00	1472	2.02	2357	3.23	492	0.67
3	11	0.02	1192	1.63	2037	2.79	390	0.53
4	14	0.02	956	1.31	1894	2.59	398	0.55
5	14	0.02	858	1.18	1859	2.55	341	0.47
6	37	0.05	806	1.10	1754	2.40	356	0.49
7	50	0.07	1069	1.46	1646	2.25	317	0.43
8	147	0.20	1814	2.48	1728	2.37	327	0.45
9	295	0.40	3102	4.25	2386	3.27	468	0.64
10	717	0.98	5573	7.63	3532	4.84	629	0.86
11	989	1.35	7110	9.74	4427	6.06	758	1.04
12	1095	1.50	8039	11.01	4999	6.85	835	1.14
13	976	1.34	7819	10.71	4903	6.72	896	1.23
14	894	1.22	7515	10.29	4667	6.39	836	1.15
15	709	0.97	7221	9.89	4351	5.96	835	1.14
16	473	0.65	7136	9.78	4512	6.18	802	1.10
17	345	0.47	7031	9.63	4485	6.14	797	1.09
18	309	0.42	7118	9.75	4838	6.63	868	1.19
19	329	0.45	7437	10.19	4567	6.26	844	1.16
20	300	0.41	7054	9.66	3970	5.44	751	1.03
21	175	0.24	6410	8.78	4095	5.61	754	1.03
22	84	0.12	5290	7.25	3660	5.01	701	0.96
23	23	0.03	4316	5.91	3761	5.15	701	0.96
24	5	0.01	3080	4.22	3187	4.37	586	0.80
Total	7998	10.96	111614	152.90	82207	112.61	15255	20.90